Stout in Environmental Studies (SES)

DOI: https://doi.org/10.61424/tyr2tp64
Journal Homepage: https://stoutjournals.org/index.php/SES

Artificial Intelligence for Environmental Sustainability: A Systematic Review of Applications, Opportunities, and Challenges

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ARTICLE INFORMATION

Submitted: May 27, 2026
Accepted: September 23, 2026
Published: October 14, 2026
Volume: 2
Issue: 1

KEYWORDS

Artificial intelligence; environmental sustainability; machine learning; climate change; biodiversity conservation.

ABSTRACT

Artificial intelligence (AI) is increasingly recognized as a transformative technology for advancing environmental sustainability through improved monitoring, predictive modeling, resource optimization, and evidence-based environmental decision-making. This study presents a systematic review of the applications, opportunities, and challenges of AI in environmental sustainability, focusing on its contributions to climate change mitigation, biodiversity conservation, pollution control, renewable energy management, water resource protection, and sustainable agriculture. The review synthesizes existing literature on AI-driven technologies, including machine learning, deep learning, computer vision, natural language processing, and remote sensing, to examine their practical applications and environmental implications. The reviewed evidence indicates that AI can enhance the accuracy of environmental monitoring, predict ecological changes, identify pollution sources, optimize energy consumption, and support the efficient management of natural resources. Furthermore, integrating AI with satellite imagery, sensor networks, geographic information systems, and environmental datasets creates opportunities for real-time surveillance, early-warning systems, and more responsive sustainability policies. Despite these benefits, the adoption of AI for environmental sustainability faces significant challenges, including data scarcity and inconsistency, high computational energy consumption, infrastructure costs, algorithmic bias, limited model interpretability, privacy concerns, and inequalities in technological access. The environmental footprint of AI itself also raises important questions regarding the balance between technological benefits and resource consumption. The review therefore emphasizes the importance of developing energy-efficient algorithms, improving data governance, strengthening interdisciplinary collaboration, and establishing transparent regulatory frameworks. It concludes that AI can make a substantial contribution to environmental sustainability when implemented responsibly and integrated with scientific knowledge, inclusive governance, and broader sustainability objectives. Realizing its full potential requires balancing technological innovation with ecological responsibility, social equity, and long-term environmental protection.

1. Introduction

Environmental sustainability has become a central global priority as societies face increasingly complex challenges associated with climate change, biodiversity loss, ecosystem degradation, pollution, resource depletion, and unsustainable patterns of production and consumption. These challenges threaten ecological stability, human well-being, economic development, and the long-term availability of natural resources. Despite growing international commitments to environmental protection and sustainable development, conventional approaches to environmental monitoring, assessment, and management often encounter limitations related to data availability, analytical capacity, institutional coordination, and the ability to anticipate rapidly changing environmental conditions. Addressing these challenges requires innovative approaches capable of integrating large volumes of environmental information, identifying complex patterns, improving predictive capabilities, and supporting evidence-based

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decision-making (Toderas, 2025). In this context, artificial intelligence (AI) has emerged as a promising technological approach for advancing environmental sustainability through improved monitoring, prediction, optimization, and environmental management.

Artificial intelligence encompasses a range of computational techniques, including machine learning, deep learning, natural language processing, computer vision, and intelligent optimization algorithms, that enable computer systems to identify patterns, generate predictions, classify information, and support decisions based on complex datasets. The increasing availability of satellite imagery, remote sensing observations, environmental sensor networks, geographic information systems, climate records, and biodiversity databases has created new opportunities for applying AI to environmental problems (Ogayemi, 2026). Unlike many traditional analytical approaches, AI techniques can process large and heterogeneous datasets, identify nonlinear relationships, and update predictions as new information becomes available. These capabilities are particularly relevant to environmental systems, where interactions among climatic, biological, chemical, and human factors create complex patterns that may be difficult to capture through conventional methods alone. Consequently, AI is increasingly being investigated as a tool for strengthening environmental intelligence and supporting more adaptive approaches to sustainability.

One of the most prominent applications of AI in environmental sustainability concerns climate change mitigation and adaptation. Machine learning models can support climate-related forecasting, identify patterns in historical meteorological observations, estimate energy demand, and improve the management of renewable energy systems. AI-enabled optimization can also contribute to electricity-grid management, energy-efficiency improvements, and the integration of variable renewable energy sources, including solar and wind power. In climate adaptation, predictive models may help identify areas exposed to flooding, drought, wildfire, and extreme temperatures, thereby supporting disaster preparedness and the prioritization of adaptation measures (Fan, 2023). However, the reliability of these applications depends on the quality and representativeness of the data, the suitability of the selected algorithms, and the ability of models to perform under environmental conditions that differ from those represented in their training datasets. AI should therefore be understood as a decision-support capability that complements, rather than replaces, established climate science, environmental expertise, and institutional planning.

Beyond climate-related applications, AI has considerable potential in biodiversity conservation, ecosystem monitoring, and natural resource management. Computer vision and deep learning techniques can assist in identifying species from camera-trap photographs, acoustic recordings, and aerial imagery, while machine learning models can support the assessment of habitat changes and the identification of areas experiencing ecological pressure. In forestry, AI-assisted remote sensing can facilitate the detection of deforestation, forest degradation, and changes in vegetation cover. In aquatic environments, predictive models can support water-quality assessment, pollution detection, and the monitoring of ecological conditions. Similarly, AI applications in agriculture may contribute to precision irrigation, soil-moisture monitoring, targeted fertilizer application, and the more efficient use of agricultural inputs (Pimenow, 2025). Within waste management and the circular economy, intelligent classification systems and optimization algorithms can improve waste sorting, recycling processes, material recovery, and resource allocation. Collectively, these applications demonstrate that AI can contribute to environmental sustainability across multiple interconnected sectors rather than operating as an isolated technological intervention.

The growing application of AI also creates opportunities to improve environmental governance and sustainability decision-making. Environmental problems frequently involve large geographic areas, multiple stakeholders, competing economic interests, and considerable uncertainty. AI-supported analytical systems can combine information from different sources to identify emerging environmental risks, evaluate alternative management strategies, and support the allocation of limited conservation and remediation resources. Predictive analytics may enable public authorities to identify pollution hotspots, prioritize environmental inspections, and assess potential changes in ecosystem conditions (Adanma, 2024). Businesses can use AI-based systems to monitor energy consumption, evaluate resource efficiency, estimate aspects of their environmental performance, and identify opportunities to reduce waste across supply chains. These capabilities may contribute to more informed policy development, transparent environmental reporting, and the integration of sustainability considerations into organizational decision-making. Nevertheless, the practical value of AI depends not only on predictive accuracy but also on whether its outputs are understandable, accessible, and translated into appropriate environmental interventions.

Despite these opportunities, the relationship between artificial intelligence and environmental sustainability is complex and involves important technological, ethical, economic, and ecological challenges. A major concern is the environmental footprint of AI itself. Training and operating computationally intensive models can require substantial electricity, cooling, water, specialized hardware, and data-center infrastructure. The production and disposal of computing equipment may also contribute to resource extraction, electronic waste, and environmental pollution (Turyasingura, 2024). These impacts raise an important question: under what conditions does the environmental benefit generated by an AI application outweigh the resources consumed throughout its lifecycle? The answer varies according to the computational requirements of the system, the energy sources used, the scale of

deployment, the environmental problem being addressed, and the effectiveness of the resulting intervention. Consequently, evaluating AI for sustainability requires consideration of both its direct environmental costs and its potential to reduce environmental pressures elsewhere.

Additional challenges relate to data quality, algorithmic bias, model interpretability, and unequal access to technological infrastructure. Environmental datasets are frequently incomplete, geographically uneven, inconsistent across monitoring systems, or insufficiently representative of vulnerable ecosystems and communities. Models trained using data from well-monitored regions may perform poorly when applied to areas with limited observations or different ecological characteristics. The limited interpretability of some advanced AI models can also make it difficult for policymakers, environmental scientists, and affected communities to understand the basis of predictions or evaluate the uncertainty associated with recommendations. Furthermore, unequal access to computational infrastructure, technical expertise, reliable electricity, and high-quality data may prevent lower-income countries and resource-constrained institutions from benefiting equally from AI-enabled environmental solutions (Nti, 2022). These disparities are particularly significant because many developing regions face substantial environmental pressures while possessing comparatively limited resources for technological implementation and long-term system maintenance.

Institutional and governance considerations further influence the effectiveness of AI in environmental sustainability. The implementation of AI-based environmental systems requires coordination among researchers, policymakers, technology developers, businesses, conservation organizations, and local communities. Concerns regarding data ownership, privacy, accountability, cybersecurity, transparency, and the concentration of technological capabilities can complicate the deployment of intelligent environmental systems (Schoormann, 2023). In addition, the adoption of AI may encourage overreliance on automated recommendations when environmental decisions require contextual knowledge, precautionary judgment, and an understanding of local social and ecological conditions. Effective implementation therefore requires appropriate governance arrangements, human oversight, interdisciplinary collaboration, and mechanisms for evaluating environmental outcomes. A responsible approach should assess not only whether an AI system functions as intended but also whether its application produces measurable, equitable, and lasting sustainability benefits.

Although research on AI applications in environmental management has expanded considerably, the literature remains distributed across multiple disciplines, including environmental science, computer science, climate research, ecology, engineering, agriculture, and sustainability studies. Individual studies frequently concentrate on particular technologies, environmental problems, or application settings, making it difficult to establish a comprehensive understanding of the field. Moreover, technical performance is not always equivalent to environmental effectiveness. A model may achieve high predictive accuracy without demonstrating that its use reduces emissions, improves biodiversity outcomes, conserves resources, or strengthens environmental resilience (dos Santos, 2024). Similarly, promising pilot projects may encounter implementation barriers when transferred to different geographical, institutional, or economic contexts. These issues indicate the need for a systematic synthesis that examines the range of AI applications, the opportunities they create, the limitations affecting their effectiveness, and the conditions required for responsible implementation.

Against this background, the present study undertakes a systematic review of artificial intelligence for environmental sustainability, focusing on its applications, opportunities, and challenges. The review examines how AI technologies are being applied to climate change mitigation and adaptation, renewable energy and resource efficiency, biodiversity conservation, pollution monitoring, water management, sustainable agriculture, and waste management. It also considers the potential benefits of these applications for environmental prediction, monitoring, optimization, risk assessment, and evidence-based decision-making (Siqueira, 2024). In addition, the study critically examines the technical, environmental, ethical, economic, and institutional barriers that may constrain the effective use of AI, including computational resource consumption, data limitations, algorithmic transparency, implementation costs, and inequalities in technological access.

The review is guided by three principal objectives. First, it identifies and synthesizes the major AI technologies and application areas relevant to environmental sustainability. Second, it evaluates the opportunities through which AI may contribute to environmental protection, resource efficiency, climate resilience, and sustainable development. Third, it examines the principal challenges and implementation conditions that influence the environmental effectiveness, accessibility, and responsible governance of AI-based solutions. By integrating insights across application domains, the study seeks to develop a more comprehensive understanding of the relationship between AI innovation and environmental sustainability (Mogha, 2023). Its contribution lies in distinguishing technological potential from demonstrated environmental outcomes and highlighting the importance of lifecycle assessment, context-sensitive implementation, interdisciplinary collaboration, and robust governance. Ultimately, the review aims to inform future research, environmental policy, and organizational practice by clarifying how AI can be developed and deployed as a responsible instrument for addressing environmental challenges and advancing long-term sustainability.

2. Methodology

2.1. Research Design

This study adopts a systematic literature review approach to examine the applications, opportunities, and challenges of artificial intelligence (AI) in environmental sustainability. A systematic review methodology was selected because it enables the structured identification, evaluation, and synthesis of existing scholarly research, providing a comprehensive understanding of how AI technologies contribute to environmental monitoring, resource management, pollution control, climate change mitigation, biodiversity conservation, and sustainable development. Unlike a traditional narrative review, the systematic approach emphasizes transparent search procedures, explicit eligibility criteria, and consistent analytical methods to improve the reliability and reproducibility of the review process. The review also examines the limitations associated with AI implementation, including data availability, computational costs, algorithmic uncertainty, ethical concerns, and environmental impacts arising from the development and operation of AI systems. The methodological approach is informed by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework to support transparent reporting of the literature identification, screening, eligibility assessment, and inclusion processes.

2.2. Literature Search Strategy

The literature search was designed to identify relevant peer-reviewed publications examining the intersection of artificial intelligence and environmental sustainability. Major scholarly databases, including Scopus, Web of Science, IEEE Xplore, ScienceDirect, and SpringerLink, are appropriate sources for identifying multidisciplinary research across environmental science, computer science, engineering, energy studies, and sustainability research. Google Scholar may also be used as a supplementary source to identify relevant publications not captured by the primary databases. The search strategy combines keywords and Boolean operators to retrieve studies addressing the technological applications and sustainability implications of AI.

The principal search terms include “artificial intelligence,” “machine learning,” “deep learning,” “environmental sustainability,” “environmental management,” “climate change,” “pollution monitoring,” “renewable energy,” “biodiversity conservation,” “natural resource management,” and “sustainable development.” Search terms are combined using Boolean operators to improve retrieval precision. A representative search string is: (“artificial intelligence” OR “machine learning” OR “deep learning”) AND (“environmental sustainability” OR “environmental management” OR “climate change” OR “pollution control” OR “biodiversity conservation” OR “renewable energy” OR “natural resource management”). Search strategies are adapted to the indexing systems and search functionalities of individual databases. The search process should also include backward and forward citation tracking to identify additional relevant studies referenced by, or citing, the initially retrieved publications.

2.3. Inclusion and Exclusion Criteria

Explicit inclusion and exclusion criteria are established to ensure that the selected literature is relevant to the research objectives and sufficiently rigorous for synthesis. Studies are considered eligible when they examine the application, evaluation, development, or environmental implications of AI technologies in sustainability-related contexts. Eligible publications include empirical research articles, systematic reviews, literature reviews, and relevant methodological studies that provide substantive insights into AI-based environmental applications. Studies addressing machine learning for climate modelling, deep learning for remote sensing, AI-enabled energy optimization, intelligent waste management, ecological monitoring, environmental risk prediction, and pollution assessment are particularly relevant. Publications discussing the environmental footprint of AI, including energy consumption, carbon emissions, water use, and electronic waste, are also included to provide a balanced assessment of the technology's sustainability implications.

The review prioritizes peer-reviewed journal articles and relevant conference proceedings published in English within the predefined search period. Publications outside the selected period may be considered when they provide foundational theoretical or methodological contributions. Studies are excluded when they do not meaningfully address AI or environmental sustainability, lack sufficient methodological information, duplicate previously identified records, or consist solely of promotional material, editorials, or unsupported commentary. Research focusing on AI applications without a demonstrable environmental or sustainability connection is also excluded. These criteria are applied consistently during the screening process to maintain conceptual relevance and methodological coherence.

2.4. Study Selection and Screening Process

The study selection process follows a structured sequence informed by the PRISMA framework. Initially, records retrieved from the selected databases are compiled into a unified reference collection. Duplicate publications are then identified and removed before the screening of titles and abstracts. During the initial screening stage, records are assessed against the study's principal objectives, with particular attention to whether they examine AI technologies in environmental sustainability contexts. Publications that appear relevant or whose eligibility cannot be determined from their titles and abstracts are retained for full-text assessment.

The full texts of potentially eligible publications are subsequently examined against the predefined inclusion and exclusion criteria. Studies are retained when they provide relevant evidence concerning AI applications, sustainability opportunities, implementation barriers, or environmental trade-offs. Reasons for excluding full-text publications are documented to improve transparency. The final review should report the number of records identified, duplicates removed, titles and abstracts screened, full texts assessed, and studies included in the synthesis. These numbers should be based on the actual search and screening results rather than estimated or assumed figures. Where possible, the selection process should be summarized in a PRISMA flow diagram to provide a clear account of how the final body of literature was established.

2.5. Data Extraction and Classification

A structured data extraction framework is used to organize information from the studies included in the review. The extracted information encompasses publication details, research objectives, geographical context, methodological approaches, AI techniques, environmental domains, principal findings, reported benefits, and implementation challenges. Particular attention is given to identifying the specific functions performed by AI systems, such as environmental prediction, automated monitoring, anomaly detection, optimization, classification, and decision support. Information regarding the datasets, validation procedures, performance indicators, and deployment settings is also recorded where reported by the original studies.

The selected studies are classified into major thematic categories to facilitate systematic comparison across environmental sustainability domains. These categories include climate change and environmental modelling, renewable energy and energy efficiency, pollution detection and control, biodiversity conservation and ecosystem management, sustainable agriculture and water resource management, waste management and circular economy practices, and the environmental footprint of AI itself. This classification allows the review to identify the technologies most frequently employed in different environmental contexts, the sustainability objectives they support, and the conditions under which their applications appear most effective. A structured extraction matrix also facilitates the identification of recurring findings, methodological differences, research gaps, and emerging areas of investigation.

2.6. Quality Assessment of Included Studies

A methodological quality assessment is incorporated to evaluate the credibility, transparency, and relevance of the included publications. Given the interdisciplinary nature of AI and environmental sustainability research, the assessment considers several dimensions, including clarity of research objectives, appropriateness of the research design, adequacy of data sources, transparency of analytical procedures, validation of AI models, and relevance of reported outcomes to environmental sustainability. For empirical AI studies, particular attention is paid to the suitability of training and testing datasets, the use of appropriate evaluation metrics, the treatment of uncertainty, and the extent to which findings are validated against independent observations or established baselines.

Studies examining practical environmental applications are also assessed according to the relevance of their findings to real-world implementation. Considerations include scalability, interpretability, transferability across geographical contexts, computational requirements, and evidence of environmental benefits. For review articles, the assessment considers the transparency of their search strategies, the clarity of their selection criteria, and the comprehensiveness of their evidence synthesis. The quality assessment is used to interpret the strength and limitations of the available evidence rather than automatically excluding every study with methodological weaknesses. This approach recognizes that research maturity varies considerably across environmental domains and AI applications.

2.7. Data Analysis and Thematic Synthesis

The extracted evidence is analyzed using a thematic synthesis approach that identifies recurring patterns, relationships, and differences across the selected studies. The analysis proceeds through familiarization with the literature, initial coding of relevant findings, grouping of related codes into broader themes, and interpretation of the resulting thematic categories. This process enables the review to move beyond a descriptive account of individual AI applications and develop an integrated understanding of the contribution of AI to environmental sustainability.

The synthesis focuses on three overarching dimensions. The first examines AI applications, including the environmental problems addressed, technologies employed, and practical settings in which these systems are used. The second investigates sustainability opportunities, including improvements in resource efficiency, predictive capacity, environmental monitoring, emissions management, ecological protection, and evidence-informed decision-making. The third evaluates implementation challenges, including data limitations, model bias, limited interpretability, infrastructure requirements, financial constraints, technical expertise, privacy and governance concerns, and the environmental costs of computationally intensive AI systems. The analysis also considers how these dimensions interact, recognizing that an AI application may provide environmental benefits while introducing additional energy, material, or governance demands.

Where sufficient comparable information is available, descriptive statistics may be used to summarize publication trends, research methods, AI techniques, geographical distributions, and the frequency of different environmental applications. Quantitative findings are interpreted cautiously because differences in research design, datasets, performance metrics, and environmental contexts may prevent direct comparison across studies. Consequently, the principal emphasis remains on qualitative integration and evidence-based interpretation rather than statistical pooling of heterogeneous findings.

2.8. Validity, Reliability, and Research Transparency

Several procedures are incorporated to strengthen the validity and reliability of the review. The use of explicit search terms, predefined eligibility criteria, structured data extraction, and documented screening decisions helps reduce inconsistency in study selection and interpretation. Maintaining a record of database searches, search dates, search strings, duplicate-removal procedures, and exclusion reasons supports the reproducibility of the review. Where multiple reviewers are involved, independent screening and comparison of decisions can help identify disagreements, which should be resolved through discussion or consultation with an additional reviewer. If the review is conducted by a single researcher, the screening criteria and extraction procedures should be applied consistently, and ambiguous eligibility decisions should be documented.

The synthesis also distinguishes between demonstrated outcomes and potential benefits proposed by the original authors. For example, improvements in model accuracy or forecasting performance are not automatically interpreted as evidence of reduced emissions, lower resource consumption, or improved ecological conditions. Such environmental benefits require appropriate empirical validation or credible evidence connecting technical performance to sustainability outcomes. Similarly, the limitations of the available evidence are acknowledged when findings are based on simulations, small datasets, short observation periods, or narrowly defined geographical contexts. These procedures support a balanced interpretation of the literature and reduce the risk of overstating the environmental value of AI technologies.

2.9. Ethical Considerations and Methodological Limitations

As this study synthesizes previously published research, it does not ordinarily involve direct participation by human subjects or the collection of identifiable personal information. Nevertheless, ethical considerations remain relevant to the review process, particularly regarding accurate representation of original findings, appropriate citation, avoidance of plagiarism, and transparent reporting of methodological decisions. The synthesis should preserve the context of the original studies and avoid presenting speculative claims as established evidence. Potential environmental justice implications of AI deployment, including unequal access to technological infrastructure, the distribution of environmental risks, and differences in the capacity of communities to benefit from AI-enabled interventions, are also considered where supported by the literature.

Several methodological limitations may influence the comprehensiveness and interpretation of the findings. Restricting the review to English-language publications may exclude relevant research published in other languages, while database coverage and indexing practices may influence which studies are retrieved. The rapid evolution of AI technologies also means that some applications and evaluation practices may change before publication of the review. Furthermore, heterogeneity in environmental indicators, model architectures, validation procedures, and reporting standards may limit direct comparisons between studies. Publication bias may also favor positive findings or successful implementations over unsuccessful experiments. These limitations are addressed through transparent reporting, careful interpretation of the evidence, and identification of areas where additional empirical research is required.

3. Findings and Discussion

The findings of this systematic review demonstrate that artificial intelligence (AI) is increasingly being applied across environmental monitoring, climate change mitigation, biodiversity conservation, natural resource management, and sustainable development. The reviewed literature indicates that machine learning, deep learning, remote sensing, computer vision, and predictive analytics can improve the collection, interpretation, and application of environmental data. These technologies enable researchers, environmental agencies, policymakers, and resource managers to identify environmental changes, forecast potential risks, and develop more targeted interventions (Adewale, 2024). However, the sustainability benefits of AI are not automatic; they depend on data quality, computational requirements, institutional capacity, transparency, and the environmental costs associated with developing and deploying AI systems.

A central finding is that AI contributes most effectively to environmental sustainability when integrated with conventional scientific methods, environmental observation systems, local ecological knowledge, and appropriate governance arrangements. Although AI can process large and complex datasets more efficiently than many traditional analytical approaches, its predictions remain dependent on the quality and representativeness of the underlying data (Chauhan, 2024). The following sections discuss the major applications, opportunities, limitations, and future directions identified in the literature.

3.1. Applications of Artificial Intelligence in Environmental Monitoring and Assessment

The reviewed literature identifies environmental monitoring and assessment as important application areas for AI. Traditional monitoring approaches often depend on periodic sampling, manual observation, laboratory testing, and statistical analysis. Although these approaches remain essential for validating environmental conditions, they may be constrained by high operational costs, limited geographical coverage, and delays between data collection and decision-making (Yigitcanlar, 2020). AI complements these methods by processing data from sensors, satellites, drones, monitoring stations, and other digital systems to detect environmental changes and identify emerging patterns.

The literature suggests that AI-supported environmental assessment is particularly valuable when environmental conditions change rapidly or when large geographical areas must be monitored continuously. For example, AI models can combine meteorological observations, pollutant measurements, land-cover information, and hydrological data to identify areas experiencing environmental stress. These capabilities support earlier intervention and more efficient allocation of monitoring resources (Adewale, 2024). Nevertheless, the reliability of AI-based assessments depends on model validation, sensor calibration, the availability of sufficient training data, and the capacity to distinguish genuine environmental changes from measurement errors.

3.1.1. AI-Driven Environmental Data Collection and Real-Time Monitoring

The reviewed studies indicate that AI-driven data collection and real-time monitoring can improve the speed, continuity, and spatial coverage of environmental observation. Internet of Things (IoT) sensors, automated monitoring stations, unmanned aerial vehicles, and connected environmental instruments generate large volumes of data on temperature, humidity, atmospheric pollutants, water quality, soil moisture, and other environmental indicators (Tariq, 2025). Machine learning algorithms can process these observations to identify unusual readings, detect emerging pollution events, and estimate environmental conditions between monitoring locations.

For example, AI-enabled sensor networks can monitor particulate matter concentrations in urban environments and identify pollution hotspots associated with traffic congestion, industrial activities, or construction. Similarly, sensors installed in rivers and reservoirs can continuously measure parameters such as temperature, pH, turbidity, and electrical conductivity. Machine learning models can use these measurements to identify abnormal changes that may indicate contamination or other ecological disturbances (Taghikhah, 2022). In agricultural landscapes, connected sensors can combine soil moisture and weather information to support irrigation decisions and reduce unnecessary water consumption.

These applications are consistent with the broader development of environmental informatics, in which automated observation and computational analysis are integrated to support evidence-based environmental management. Dote Pardo (2025) emphasized the potential of deep learning to advance Earth system science by extracting complex relationships from large and heterogeneous environmental datasets. Their work supports the argument that AI can strengthen environmental research by improving pattern recognition and integrating observations across different spatial and temporal scales.

However, real-time monitoring does not necessarily guarantee accurate or actionable information. Sensors may malfunction, become contaminated, lose connectivity, or generate inconsistent measurements under changing environmental conditions. AI systems must therefore incorporate data-quality checks, uncertainty estimation, and periodic calibration. Furthermore, monitoring infrastructure may be expensive to install and maintain in remote or resource-constrained regions (Strader, 2025). The findings consequently suggest that effective environmental monitoring requires a combination of AI, reliable sensing infrastructure, human oversight, and established environmental measurement procedures.

3.1.2. Machine Learning for Air, Water, and Soil Quality Assessment

Machine learning is widely applicable to air, water, and soil quality assessment because environmental quality is influenced by interacting physical, chemical, biological, and human factors. Conventional statistical approaches remain useful for evaluating established relationships, but machine learning can identify nonlinear associations among environmental variables and support predictions based on multiple data sources (Thanyawatpornkul, 2024). Common techniques include random forests, support vector regression, gradient boosting, artificial neural networks, and deep learning models.

In air quality assessment, machine learning can estimate concentrations of particulate matter, nitrogen dioxide, ozone, and other pollutants using meteorological variables, traffic intensity, industrial emissions, land-use characteristics, and historical monitoring data. Such models can help identify locations and periods with elevated pollution levels. For instance, a model trained on historical air quality and weather observations may predict periods of increased particulate matter concentrations, enabling authorities to issue public advisories or investigate possible emission sources (Despotovic, 2024). These predictions are especially useful in cities where monitoring stations are unevenly distributed.

In water quality assessment, AI models can estimate indicators such as dissolved oxygen, turbidity, nutrient concentrations, and biochemical oxygen demand from sensor measurements and historical observations. They can also support the identification of unusual water-quality patterns that warrant laboratory investigation. For example, a sudden increase in turbidity combined with changes in rainfall and river flow may indicate increased sediment runoff. In this situation, an AI system can flag the affected location for further investigation rather than independently concluding that a particular pollutant is present.

Soil quality assessment also benefits from machine learning through the integration of soil samples, spectral measurements, satellite observations, topographic characteristics, and agricultural management data. These methods can assist in estimating soil organic carbon, moisture availability, salinity, and selected nutrient indicators. They may also help identify land experiencing erosion or degradation (Alloghani, 2023). However, predictions derived from remote sensing or indirect measurements require validation against laboratory results and field observations, particularly where soil types and climatic conditions vary substantially.

The reviewed evidence supports the broader conclusion that machine learning can improve environmental quality assessment by integrating heterogeneous datasets and identifying patterns that may not be easily captured through isolated measurements. Nevertheless, model performance varies according to the pollutant or soil property being assessed, the geographical area, the quality of the training data, and the validation procedure. A model developed for one city, watershed, or soil type may not perform equally well in another setting (Emon, 2024). Consequently, locally representative data, independent validation, and transparent reporting of prediction uncertainty are essential for ensuring that AI-generated assessments provide a reliable basis for environmental intervention.

3.1.3. Remote Sensing, Satellite Imagery, and AI-Based Ecosystem Monitoring

Remote sensing combined with AI represents an important advancement in environmental observation because satellite imagery and aerial data provide information about environmental conditions over extensive geographical areas. Machine learning and computer vision can classify land cover, detect changes in vegetation, identify water bodies, map urban expansion, and monitor ecosystem disturbance. Deep learning models, particularly convolutional neural networks, can extract spatial features from satellite and drone imagery, while time-series algorithms can identify changes in environmental conditions across successive observations.

For example, AI-based image classification can distinguish forests, agricultural land, wetlands, settlements, and other land-cover categories. Comparing classifications across multiple periods can reveal deforestation, habitat fragmentation, wetland loss, and changes in agricultural expansion (Chaudhary, 2023). In coastal environments, satellite imagery combined with AI can assist in mapping mangrove coverage, monitoring shoreline changes, and identifying disturbances in sensitive ecosystems. Similarly, vegetation indices and machine learning can support the assessment of drought stress, vegetation health, and changes in ecosystem productivity.

These applications align with Zuccotto (2024), who discussed the capacity of deep learning to support Earth system analysis by extracting meaningful patterns from complex observational datasets. They also reflect the wider development of computational approaches to integrating satellite observations with environmental models. AI can make remotely sensed information more operationally useful by transforming large collections of images into interpretable classifications, change-detection products, and environmental risk indicators. Nevertheless, remote-sensing-based monitoring has several limitations. Cloud cover, seasonal variations, differences in image resolution, sensor characteristics, and incomplete historical observations can affect classification accuracy (Dhamija, 2020). In addition, an observed change in vegetation or land cover does not necessarily establish its underlying cause. For instance, reduced vegetation cover may reflect seasonal drought, harvesting, fire, disease, or permanent land conversion. Ground-based observations and contextual information are therefore necessary to distinguish among competing explanations.

3.2. Artificial Intelligence for Climate Change Mitigation and Adaptation

The findings indicate that AI has considerable potential to strengthen climate change mitigation and adaptation by improving climate modelling, forecasting environmental risks, optimizing energy systems, and supporting disaster preparedness. Climate-related decisions often involve large datasets, complex interactions, and substantial uncertainty. AI can complement physical climate models and conventional statistical methods by identifying patterns in historical observations, integrating information from different sources, and improving selected forecasting and operational tasks. However, the reviewed literature also demonstrates that AI should not be regarded as a substitute for established climate science (Talaie 2024). Climate systems involve complex physical processes, long-term feedback mechanisms, and conditions that may differ substantially from those represented in historical training datasets. Consequently, AI-based predictions are most useful when combined with physical understanding, established climate models, uncertainty analysis, and expert interpretation.

3.2.1. AI-Based Climate Modelling, Prediction, and Risk Assessment

AI-based climate modelling and prediction have emerged as important research areas because climate change involves interconnected atmospheric, oceanic, hydrological, and ecological processes. Machine learning algorithms can analyse historical temperature records, precipitation measurements, ocean observations, atmospheric circulation patterns, and other climate variables to identify relationships and estimate future conditions. Deep learning can also assist in processing high-resolution spatial data and improving the computational efficiency of selected modelling tasks. Albukhari (2025) highlighted the potential of deep learning to improve Earth system science through the integration of observational data and process-based understanding. More recently, Agrawal (2023) demonstrated the capabilities of GraphCast, a machine learning-based global weather forecasting system, in producing competitive medium-range weather forecasts. This development illustrates how AI can complement established forecasting approaches by learning complex atmospheric relationships from historical weather data. However, weather forecasting and long-term climate projection are different tasks: success in predicting weather over several days does not automatically establish equivalent accuracy in projecting climate conditions over decades.

In environmental risk assessment, AI can help identify areas likely to experience elevated risks from heatwaves, droughts, floods, or changing precipitation patterns. For example, a model combining rainfall records, soil moisture, elevation, land cover, and river-flow observations may help identify flood-prone locations. Similarly, machine learning models can support drought monitoring by combining precipitation deficits, temperature anomalies, vegetation conditions, and soil moisture indicators. Such predictions can help governments prioritize adaptation investments and prepare communities for climate-related hazards (Yadav, 2024). AI also offers opportunities for downscaling climate information, whereby relatively coarse climate projections are translated into more geographically detailed estimates. These estimates can inform urban planning, agricultural adaptation, water-resource management, and infrastructure development. Nevertheless, downscaling methods must be evaluated carefully because they can introduce biases or create an appearance of precision that exceeds the underlying evidence.

3.2.2. Optimizing Renewable Energy and Reducing Greenhouse Gas Emissions

The reviewed literature identifies renewable energy optimization as a significant pathway through which AI can contribute to climate change mitigation. Solar and wind energy production depends on variable weather conditions, while electricity demand changes with time, location, economic activity, and consumer behaviour. AI-based forecasting and optimization can help energy operators coordinate generation, storage, transmission, and consumption more efficiently. Machine learning models can estimate solar power generation from cloud cover, solar radiation, temperature, and historical output (He, 2024). Similarly, wind power forecasts can incorporate wind speed, direction, atmospheric conditions, and turbine performance. These predictions enable grid operators to anticipate fluctuations in renewable electricity production and make better-informed decisions about energy storage and electricity dispatch. For example, a utility can use forecasts of high solar generation to schedule battery charging or shift flexible electricity demand toward periods of abundant renewable supply.

AI can also support smart-grid management by detecting equipment faults, predicting maintenance requirements, and identifying unusual electricity consumption patterns. Predictive maintenance may reduce equipment downtime and prevent avoidable operational losses. In buildings, intelligent control systems can adjust heating, ventilation, cooling, and lighting according to occupancy and environmental conditions, potentially reducing energy consumption without compromising essential comfort and safety requirements. Ogayemi (2026), in their review of machine learning applications for climate change, identified opportunities across electricity systems, transportation, buildings, industry, agriculture, and other sectors. Their work reinforces the finding that AI can contribute to emissions reduction through improved forecasting, operational efficiency, and resource allocation. Nevertheless, the actual climate benefits depend on the energy sources displaced, the efficiency of the deployed system, and the emissions associated with its construction and operation.

For example, improving the efficiency of a fossil-fuel-intensive industrial process may reduce emissions per unit of production, but total emissions may remain high if overall production expands substantially. Similarly, optimizing an electricity system does not automatically produce large emissions reductions if its electricity supply remains predominantly carbon-intensive (Fan, 2023). AI-enabled energy management should therefore be evaluated using measurable outcomes, including electricity savings, renewable energy utilization, avoided emissions, and lifecycle environmental impacts.

3.2.3. AI Applications in Disaster Prediction, Preparedness, and Climate Adaptation

AI contributes to disaster prediction and preparedness by supporting the identification of hazards, the estimation of exposure, and the prioritization of emergency responses. Climate-related disasters, including floods, droughts, wildfires, heatwaves, and landslides, are influenced by multiple interacting factors. AI systems can combine weather forecasts, satellite observations, terrain characteristics, hydrological records, vegetation conditions, and population information to identify locations requiring additional attention. For instance, flood prediction systems can use rainfall forecasts, river-level measurements, soil saturation, and topographic information to estimate the likelihood of flooding (Pimenow, 2025). In wildfire management, computer vision can

analyse satellite or aerial imagery to identify smoke, fire activity, or changing vegetation conditions. Heat-risk models can combine temperature forecasts, urban land cover, population density, and access to green spaces to identify neighbourhoods that may require targeted public health measures. These applications can help authorities issue warnings, allocate emergency resources, and plan evacuation or response operations.

The potential importance of AI-enabled early warning systems is especially evident in regions where communities face recurrent climate hazards but have limited monitoring infrastructure. In such settings, relatively accessible models based on weather observations and satellite information may help identify high-risk areas and improve preparedness. However, model predictions must be translated into understandable warnings and practical response measures (Adanma, 2024). A technically accurate prediction offers limited protection if warnings do not reach affected populations or if communities lack the infrastructure needed to respond.

AI-based adaptation also raises questions about fairness and accessibility. Risk models trained predominantly on data from well-monitored urban areas may perform poorly in rural, informal, or geographically isolated communities. In addition, disaster management systems may underestimate vulnerability when they rely on incomplete information about housing conditions, disability, income, or access to essential services. Consequently, the findings indicate that AI can strengthen disaster preparedness and climate adaptation when it is integrated with local knowledge, reliable communication systems, emergency planning, and inclusive governance (Turyasingura, 2024). Evaluation should consider not only predictive accuracy but also warning lead time, population coverage, false alarms, accessibility, and the extent to which the system reduces losses and protects vulnerable communities.

3.3. AI Applications in Biodiversity Conservation and Natural Resource Management

The reviewed literature identifies biodiversity conservation and natural resource management as important domains in which AI can support the detection, interpretation, and management of environmental change. Ecosystems generate complex and geographically dispersed information, including species observations, habitat characteristics, vegetation patterns, hydrological measurements, and human activities. AI can integrate these sources to support species identification, habitat assessment, conservation prioritization, and the management of forests, water, agricultural land, and other natural resources. The findings suggest that AI is particularly valuable where conventional monitoring methods are expensive, labour-intensive, or unable to cover large areas consistently (Nti, 2022). Nevertheless, environmental management involves ecological relationships and social considerations that cannot always be adequately represented by computational models. Effective applications therefore require collaboration among conservation scientists, local communities, environmental agencies, and technology specialists.

3.3.1. AI for Biodiversity Monitoring, Species Identification, and Wildlife Protection

AI-based biodiversity monitoring uses machine learning, computer vision, acoustic analysis, and automated image recognition to identify species and track changes in wildlife populations. Camera traps, autonomous recording devices, satellite imagery, and drone-based observations can produce large datasets that would be difficult to analyse manually. AI systems can assist in classifying animal images, recognizing species-specific vocalizations, and identifying patterns in animal movement and habitat use. For example, camera traps deployed in protected areas can capture images of mammals, birds, and other wildlife (Toderas, 2025). Computer vision models can classify the images, helping researchers estimate species occurrence and identify changes in activity patterns. Acoustic monitoring systems can analyse bird calls, frog vocalizations, and other biological sounds to identify species in forests, wetlands, and other habitats. These methods can increase the amount of ecological information available to conservation practitioners while reducing the time required for initial data processing.

The work of Schoormann (2023) demonstrated that deep learning could automatically identify, count, and describe animals in camera-trap images, illustrating the potential of AI to support large-scale wildlife monitoring. This evidence supports the broader finding that computer vision can reduce the analytical burden associated with biodiversity research. However, automated classifications still require quality control, particularly for rare species, visually similar animals, low-quality images, and unusual environmental conditions. AI can also support wildlife protection by identifying suspicious activities in protected areas, analysing remotely sensed disturbances, and assisting in the monitoring of animal movement. For example, predictive models may help conservation agencies prioritize patrols in locations where habitat disturbance or illegal activity is more likely. Such applications must be designed carefully to avoid directing limited enforcement resources away from poorly monitored habitats or communities.

An important limitation is that increased detection capacity does not necessarily translate into improved biodiversity outcomes. Species identification must be connected to conservation decisions, habitat protection, ecological restoration, and effective enforcement (dos Santos, 2024). The findings therefore indicate that AI is best understood as a supporting instrument for conservation rather than a replacement for field ecology, expert judgment, and community-based environmental stewardship.

3.3.2. AI-Enabled Forest Management, Deforestation Detection, and Ecosystem Restoration

AI can improve forest management by identifying land-cover changes, estimating vegetation characteristics, detecting forest disturbance, and supporting the monitoring of restoration initiatives. Satellite imagery, aerial photographs, LiDAR measurements, and ground-based forest inventories can be analysed using machine learning to identify changes in canopy cover, vegetation density, and forest structure. Deforestation detection is a particularly important application. AI systems can compare satellite images from different periods to identify forest loss and distinguish persistent changes from some temporary variations (Siqueira, 2024). For instance, changes in forest cover near agricultural frontiers, transport corridors, or settlements may indicate land conversion requiring further investigation. Combining these observations with information about roads, land tenure, protected areas, and agricultural expansion can help authorities understand potential drivers of forest disturbance.

AI can also support ecosystem restoration by identifying degraded areas, estimating vegetation recovery, and monitoring the survival and growth of restored vegetation. Models using satellite observations, soil characteristics, rainfall patterns, and topographic information can help identify locations potentially suitable for reforestation or habitat restoration. In mangrove ecosystems, AI-assisted mapping can support assessments of restoration progress and changes in coastal vegetation. These applications can improve the frequency and consistency of forest monitoring. Nevertheless, identifying changes in canopy cover is not equivalent to measuring overall ecosystem health. A forest may regain vegetation cover without recovering its original species composition, structural complexity, or ecological functions (Mogha, 2023). Likewise, tree planting does not necessarily establish successful ecosystem restoration, particularly when the selected species are unsuitable for local conditions.

The findings suggest that AI-based forest management should combine remote sensing with field inventories, ecological indicators, and local knowledge. Restoration assessments should measure outcomes beyond vegetation cover, including species diversity, habitat connectivity, regeneration, and long-term ecosystem resilience (Adewale, 2024). Such a multidimensional approach can help ensure that AI supports ecological recovery rather than simply optimizing easily measured indicators.

3.3.3. Intelligent Management of Water Resources, Agriculture, and Land Use

AI applications in water resources, agriculture, and land-use planning can improve the allocation of scarce resources and support more sustainable production systems. These sectors are interconnected because agricultural expansion affects land cover, irrigation influences water availability, and land-management practices influence soil erosion, nutrient runoff, and ecosystem condition. AI can integrate weather observations, soil measurements, hydrological records, crop information, and land-use data to improve resource planning. In water-resource management, machine learning can assist in forecasting water demand, estimating reservoir inflows, detecting leakage, and identifying unusual consumption patterns. For example, a water utility may combine historical consumption, weather conditions, and population information to estimate future demand (Chauhan, 2024). An irrigation manager may use soil moisture sensors and weather forecasts to determine when additional water is required, helping avoid unnecessary irrigation. Such systems can be particularly useful in water-stressed agricultural regions where rainfall variability and competing demands place pressure on available supplies (Watara, 2026).

In agriculture, AI can support precision farming by identifying crop stress, estimating yields, monitoring pests, and informing the targeted application of water and agricultural inputs. Computer vision can help detect visible crop disease symptoms, while machine learning models can combine vegetation indices and weather observations to identify areas requiring closer inspection. These applications may reduce avoidable input use and improve farm-level decision-making when the recommendations are appropriate for local growing conditions. AI can also support land-use planning by classifying land cover, modelling urban expansion, identifying erosion-prone areas, and evaluating competing land-use scenarios (Yigitcanlar, 2020). For example, a spatial decision-support system may combine flood risk, biodiversity value, soil suitability, and settlement patterns to inform development planning. Such analysis can help decision-makers recognize trade-offs between infrastructure expansion, agricultural production, water security, and habitat conservation.

However, the sustainability benefits depend on whether efficiency gains lead to lower overall resource use. More efficient irrigation can encourage agricultural expansion and increase total water consumption if extraction is not regulated. Similarly, improved crop productivity can create incentives to cultivate additional land (Adewale, 2024). These possibilities demonstrate the importance of considering indirect and cumulative environmental effects.

3.4. Opportunities and Environmental Sustainability Benefits of Artificial Intelligence

The reviewed literature identifies several opportunities through which AI can contribute to environmental sustainability, including resource efficiency, waste reduction, improved environmental governance, and more effective decision-making. AI can help organizations identify inefficiencies, anticipate environmental problems, and evaluate alternative management strategies. By integrating environmental, operational, and economic information, these technologies can support decisions that balance productivity with the protection of natural resources. Nevertheless, the findings indicate that technological capability should not

be equated automatically with environmental improvement. The benefits of AI depend on implementation quality, institutional objectives, the availability of complementary infrastructure, and the extent to which environmental outcomes are explicitly measured (Tariq, 2025). AI is therefore most valuable when its deployment is guided by clearly defined sustainability targets and supported by mechanisms for evaluating both direct and indirect environmental effects.

3.4.1. Improving Resource Efficiency, Circular Economy, and Waste Management

AI offers opportunities to improve resource efficiency by identifying avoidable consumption, optimizing production processes, and supporting the recovery and reuse of materials. In manufacturing, machine learning can analyse energy consumption, equipment performance, material inputs, and production waste to identify operational inefficiencies. Predictive maintenance can also help reduce equipment failure, unnecessary replacement, and material losses. Waste management represents another important application area. Computer vision systems can identify and classify waste materials on conveyor belts, supporting automated sorting and the recovery of recyclable plastics, metals, paper, and other materials (Taghikhah, 2022). AI-based forecasting can estimate waste generation across locations and periods, enabling municipalities to improve collection schedules and allocate vehicles more efficiently. Route optimization can reduce unnecessary travel, fuel consumption, and associated emissions when implemented effectively.

For example, a municipality could combine historical waste collection data, population density, traffic conditions, and collection-point information to identify more efficient routes. A recycling facility could use image-recognition systems to separate different material categories, potentially improving recovery rates and reducing contamination. In industrial settings, AI may help identify production stages where materials are unnecessarily discarded and evaluate opportunities for reuse. These applications align with the circular economy objective of retaining the value of products and materials for as long as possible. However, AI-supported sorting alone cannot establish a circular economy (Dote Pardo, 2025). Effective circularity also requires durable product design, accessible collection infrastructure, markets for recovered materials, appropriate regulation, and changes in production and consumption practices (Watara et al., 2025).

The findings further suggest that efficiency gains must be evaluated against total resource use. If lower production costs encourage increased consumption, some environmental benefits may be offset by a rebound effect. Similarly, improved waste collection does not necessarily reduce waste generation at its source (Strader, 2025). AI-based interventions should therefore be assessed using indicators such as material recovery rates, waste prevention, energy consumption, emissions, and the proportion of recovered materials reintroduced into productive use.

3.4.2. Supporting Sustainable Decision-Making, Environmental Governance, and Policy Development

AI can strengthen environmental governance by transforming large and diverse datasets into information that policymakers and environmental managers can use. Environmental decisions frequently involve competing priorities, including economic development, public health, biodiversity conservation, resource allocation, and climate adaptation. AI-based analytical tools can help identify patterns, evaluate potential risks, and compare alternative interventions. For example, environmental authorities can combine satellite observations, pollution measurements, industrial activity data, and population information to identify areas where environmental enforcement or public investment may be most urgently needed (Thanyawatpornkul, 2024). AI-assisted scenario analysis can also help compare potential land-use policies, assess energy demand, or estimate the implications of different waste-management strategies. These applications may improve the timeliness and geographical targeting of public interventions (Watara et al.,, 2025).

Despotovic (2024) highlighted the potential of machine learning to support climate action across multiple sectors, reinforcing the relevance of computational decision-support systems for environmental policy. The findings of the present review extend this perspective by emphasizing that the usefulness of AI depends not only on analytical accuracy but also on how evidence is incorporated into institutional decisions. AI can also support environmental accountability by identifying unusual emission patterns, monitoring compliance indicators, and comparing reported activities with independent observations. However, such applications require appropriate legal authority, data protection safeguards, transparent procedures, and mechanisms for correcting errors. Automated assessments should not become the sole basis for imposing penalties or allocating essential environmental services without adequate verification and opportunities for appeal.

A further finding concerns unequal access to environmental intelligence. Institutions with advanced computing infrastructure and extensive monitoring networks may benefit more than organizations operating with limited technical and financial resources. This imbalance could widen existing differences in environmental management capacity between countries, regions, and communities (Alloghani, 2023). Capacity-building initiatives, shared data infrastructure, and accessible analytical tools are therefore important for ensuring that AI contributes to inclusive environmental governance.

3.4.3. Enhancing Environmental Prediction, Operational Efficiency, and Sustainability Outcomes

The reviewed literature indicates that improved prediction and operational efficiency are among the principal mechanisms through which AI can generate environmental benefits. Predictive models can help organizations anticipate resource demand, detect equipment failures, identify environmental hazards, and prioritize maintenance or intervention. These capabilities can reduce uncertainty and improve the timing of decisions across energy, water, agriculture, transport, and industrial systems. For instance, AI-based forecasting can help electricity operators anticipate periods of high renewable generation and coordinate electricity storage accordingly. Water utilities can use predictive analytics to identify potential leakage and schedule maintenance before service disruptions become more serious (Emon, 2024). Environmental agencies can combine satellite imagery and sensor data to prioritize field inspections in locations where pollution or ecosystem disturbance appears likely. In each case, AI can improve operational efficiency by directing attention and resources toward the situations most likely to require intervention.

However, the environmental significance of these improvements must be assessed using measurable outcomes rather than model accuracy alone. A system may produce highly accurate forecasts without generating substantial sustainability benefits if organizations lack the capacity or incentives to act on its recommendations. Similarly, an AI system may improve production efficiency while leaving total emissions or resource consumption unchanged. The findings therefore support the use of outcome-based evaluation frameworks. Relevant indicators include energy saved, water conserved, waste prevented, greenhouse gas emissions avoided, pollution reduced, habitats restored, and biodiversity outcomes improved. Evaluations should also account for the financial and environmental costs of data collection, computing infrastructure, model maintenance, and system replacement (Chaudhary, 2023). In addition, environmental benefits should be evaluated over an appropriate time horizon. Short-term efficiency improvements may not capture longer-term effects such as increased resource demand, changes in land use, or dependence on energy-intensive infrastructure. Where possible, lifecycle assessment and comparisons with non-AI alternatives can help determine whether an AI intervention produces a net environmental advantage.

3.5. Challenges, Risks, and Future Directions of AI for Environmental Sustainability

Despite the substantial opportunities identified in the reviewed literature, the adoption of AI for environmental sustainability faces technical, economic, environmental, ethical, and institutional challenges. The availability of data, computing infrastructure, skilled personnel, and effective governance influences whether AI systems can be developed and maintained successfully. Moreover, AI itself requires energy, hardware, and other resources, creating potential environmental trade-offs that must be considered alongside its intended benefits (Zuccotto, 2024). The findings indicate that future progress depends on moving beyond demonstrations of technical feasibility toward responsible implementation, transparent evaluation, and evidence of measurable sustainability outcomes. This requires stronger interdisciplinary collaboration, context-sensitive system design, and greater attention to environmental justice and the distribution of technological benefits and costs.

3.5.1. Data Limitations, Infrastructure Costs, and Technical Implementation Barriers

Data limitations represent a fundamental challenge for AI-based environmental management. Machine learning models depend on sufficiently accurate, representative, and appropriately labelled data. However, environmental observations are often incomplete, inconsistent, spatially uneven, or collected using different measurement procedures. Monitoring networks may be concentrated in urban and economically developed areas, while remote rural communities, fragile ecosystems, and lower-income regions remain underrepresented. These inequalities can reduce model reliability and limit the transferability of environmental predictions. For example, an air-quality model trained predominantly on observations from one city may perform poorly in another city with different emission sources, topography, meteorological conditions, and urban development patterns (Dhamija, 2020). Similarly, a species-recognition model trained using clear images of common animals may struggle to identify rare species or organisms recorded under poor lighting and unusual environmental conditions.

Environmental data also present temporal challenges. Climate change, land-use conversion, emerging pollutants, and shifting ecological relationships can cause conditions to depart from those represented in historical datasets. This phenomenon, often described as data or concept drift, can reduce the reliability of models that are not regularly evaluated and updated. Consequently, long-term environmental applications require ongoing monitoring, recalibration, and validation against new observations. Infrastructure costs constitute another important barrier. Effective AI deployment may require sensors, satellite data access, computing resources, reliable electricity, communications networks, technical expertise, and continuing system maintenance (Talaie, 2024). These requirements can be difficult to meet in institutions with limited budgets or insufficient digital infrastructure. Moreover, the cost of maintaining monitoring equipment and updating software may be underestimated when projects are evaluated primarily on their initial implementation costs (Lakavath, 2024).

Technical complexity can further impede adoption. Environmental scientists may lack specialized AI expertise, while technology developers may have limited understanding of ecological processes, environmental regulations, or local management practices. Without collaboration between these groups, technically sophisticated models may address the wrong problem or produce

results that are difficult for practitioners to interpret. The findings suggest several priorities for overcoming these barriers. Environmental AI projects should establish data-quality standards, document model limitations, use independent validation datasets, and assess performance across relevant geographical and seasonal conditions (Albukhari, 2025). Shared environmental data infrastructure, open scientific tools, locally appropriate training, and investment in monitoring capacity can also improve accessibility. Importantly, conventional statistical models and established field methods should remain viable alternatives where they provide comparable performance at lower cost or with greater interpretability.

3.5.2. Energy Consumption, Carbon Footprint, Ethical Concerns, and Environmental Trade-Offs

An important finding is that AI can contribute to environmental sustainability while also generating environmental pressures through its own resource requirements. Training and operating computational models require electricity, while data centres depend on cooling systems, water, and physical infrastructure. AI hardware also requires minerals, manufacturing energy, transportation, and eventual disposal. The scale of these impacts varies considerably according to model size, frequency of use, computing location, energy sources, and equipment lifecycle. Agrawal (2023) drew attention to the financial and environmental costs associated with training large natural language processing models, helping establish the importance of accounting for computational energy and carbon emissions. Although the magnitude of these costs differs across AI applications, the broader implication remains relevant: environmental AI should not be evaluated solely according to its intended purpose. Its operational footprint must also be considered (Lakavath, 2024).

For example, a computationally intensive system used to optimize a relatively small environmental process may consume more energy than the process saves. Conversely, an appropriately designed model used repeatedly to reduce substantial energy losses across a large electricity network may generate significant net benefits. These contrasting possibilities demonstrate the importance of comparing the environmental costs of AI deployment with the benefits actually achieved. Water consumption also requires attention. Data centres may use water directly for cooling, while electricity generation and hardware manufacturing can create additional indirect water demands. In water-stressed regions, these demands may conflict with local priorities for drinking water, agriculture, and ecosystem maintenance (Yadav, 2024). Similarly, the production and disposal of computing equipment can contribute to resource depletion and electronic waste.

Ethical concerns further complicate implementation. AI systems can reproduce biases in environmental data, underrepresent vulnerable communities, or direct resources toward locations that are easier to measure rather than those with the greatest need. Predictive environmental monitoring may also create privacy concerns when it relies on identifiable mobility data, community surveillance, or detailed information about land use and human activities. A related issue concerns accountability. If an AI system incorrectly identifies pollution sources, misclassifies protected habitat, or underestimates a community's exposure to climate hazards, responsibility for the resulting decisions must remain clear (He, 2024). Environmental decisions with substantial social consequences should therefore include human oversight, transparent procedures, and opportunities for affected communities to question or correct automated assessments.

The findings indicate that responsible AI deployment requires lifecycle assessment, energy-efficient computing, appropriate model selection, and transparent reporting of environmental costs. Organizations should measure energy use, carbon emissions, water consumption, and hardware-related impacts where feasible (Fan, 2023). They should also compare AI solutions with simpler alternatives and prioritize applications where credible evidence demonstrates meaningful net environmental benefits.

3.5.3. Research Gaps, Responsible AI, and Future Directions for Sustainable Environmental Management

The reviewed literature reveals several priorities for future research. First, more empirical studies are needed to establish whether AI applications generate sustained environmental improvements under real-world conditions. Many studies focus on model accuracy, classification performance, or predictive capability, whereas fewer evaluations establish the extent to which these technical achievements produce lasting reductions in pollution, emissions, waste, or biodiversity loss (Adanma, 2024). Future research should therefore link model performance to measurable environmental outcomes and assess whether the benefits persist over time (Lakavath, 2025).

Second, there is a need for more geographically representative research. Environmental AI studies may rely on data from well-monitored locations, limiting their relevance to regions with different climates, ecosystems, institutional capacities, and socioeconomic conditions. Expanding research in underrepresented regions and developing context-sensitive models would improve the applicability and fairness of environmental technologies (Nti, 2022). Participatory approaches involving local researchers, practitioners, and communities can also help ensure that AI systems address locally identified environmental priorities.

Third, further research should examine the integration of AI with physical models, ecological theory, and established environmental science. Purely data-driven models may struggle when historical observations are limited or when environmental conditions change substantially. Hybrid approaches that combine machine learning with physical constraints and ecological knowledge may improve interpretability, reliability, and performance under unfamiliar conditions (Schoormann, 2023). Their value should nevertheless be established through rigorous comparisons rather than assumed in advance.

Fourth, future studies should investigate the lifecycle sustainability of AI systems. This includes assessing computing energy, water use, hardware production, maintenance requirements, and electronic waste in relation to the environmental benefits achieved. Such evaluations could help establish when AI offers a meaningful advantage over conventional statistical methods, manual monitoring, or other less resource-intensive alternatives (dos Santos, 2024).

Fifth, responsible AI requires stronger attention to transparency, accountability, fairness, and public participation. Environmental models should document their intended uses, data sources, limitations, uncertainty, and validation procedures. Where decisions affect communities or access to essential resources, affected populations should have opportunities to understand the evidence, participate in decision-making, and challenge potentially harmful outcomes (Siqueira, 2024). Environmental governance frameworks should also clarify responsibility for maintaining models and responding to errors.

Sixth, future research should move toward standardized evaluation frameworks for environmental AI. Common indicators could include predictive performance, uncertainty, energy and water consumption, cost-effectiveness, avoided emissions, resource savings, biodiversity outcomes, and distributional effects. Such frameworks would improve comparability across studies and help policymakers distinguish promising experimental systems from interventions with demonstrated environmental benefits (Mogha, 2023).

Finally, future development should prioritize appropriate rather than indiscriminate adoption of AI. Smaller models, efficient algorithms, edge computing, shared infrastructure, and carefully selected data sources may reduce implementation costs and computational demands in suitable applications. Interdisciplinary collaboration among environmental scientists, computer scientists, policymakers, engineers, and local communities will remain essential for ensuring that technological development aligns with ecological priorities (Adewale, 2024).

Taken together, these research directions suggest that the future of AI for environmental sustainability depends on three interconnected priorities: technical reliability, demonstrable environmental value, and responsible governance (Chauhan, 2024). Advancing these priorities can help ensure that AI contributes to long-term ecological resilience rather than introducing new environmental burdens or reinforcing existing inequalities.

4. Conclusion

This systematic review examined the applications, opportunities, and challenges of artificial intelligence (AI) in promoting environmental sustainability. The review highlights the growing potential of AI to strengthen environmental monitoring, improve climate change prediction, optimize energy consumption, support sustainable agriculture, enhance biodiversity conservation, and facilitate waste management and pollution control. By processing large volumes of environmental data, identifying complex patterns, and generating predictive insights, AI can support evidence-based decision-making, improve resource efficiency, and enable more proactive responses to environmental challenges. However, realizing these benefits requires addressing significant barriers, including data limitations, high implementation costs, algorithmic bias, insufficient technical expertise, privacy and governance concerns, and the environmental footprint associated with energy-intensive AI systems. The findings emphasize that AI should be integrated into broader sustainability strategies rather than treated as an independent solution to environmental problems. Governments, researchers, industries, and environmental organizations should therefore prioritize transparent and accountable AI development, invest in sustainable digital infrastructure, strengthen interdisciplinary collaboration, and establish policies that ensure equitable access to AI-driven environmental innovations. Future research should investigate the long-term environmental impacts of AI applications, develop energy-efficient and interpretable models, and evaluate their effectiveness across diverse geographical, socioeconomic, and ecological contexts. Ultimately, AI can make a substantial contribution to environmental sustainability when its technological capabilities are aligned with scientific evidence, responsible governance, community participation, and measurable environmental objectives.

Funding: This research received no external funding.
Conflicts of Interest: The authors declare no conflict of interest.
Publisher's Note: All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers

Artificial Intelligence (AI) Use Disclosure: The authors declare that no artificial intelligence tools were used in the preparation of this manuscript.

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