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Artificial Intelligence in Environmental Conservation: Applications and Challenges

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Abstract
The convergence of AI and environmental conservation presents transformative opportunities for addressing the interconnected challenges of climate change, resource depletion, and pollution. This comprehensive review synthesises peer-reviewed research published between 2024 and 2026 across six critical domains: energy conservation and building performance optimisation, carbon footprint reduction, climate resilience and early warning systems, sustainable agriculture, pollution control, and machine learning integration with life cycle assessment (LCA). Key findings reveal that AI-based control systems achieve HVAC energy savings of up to 37% and emissions reductions of 21%, while LSTM neural networks demonstrate exceptional accuracy ($R^2 = 0.98$) for climate temperature forecasting. In agriculture, AI-driven precision techniques reduce irrigation water use by 20-25% and nitrogen application by up to 31 kg ha^{-1}, with disease detection accuracy exceeding 95%. However, the environmental paradox of AI itself is substantial—training large models like GPT-4 emits 12,456-14,994 tons of CO_2. Emerging paradigms including physics-informed machine learning, explainable AI, digital twins, and federated learning address long-standing challenges of reliability, transparency, and scalability. Persistent obstacles include data fragmentation, model generalizability across contexts, the "black box" nature of deep learning, and computational demands. The review concludes with a six-dimensional sustainable AI framework and identifies future research priorities: hybrid modelling approaches, standardised evaluation metrics, improved uncertainty quantification, and responsible AI deployment. When applied thoughtfully, AI can accelerate the transition to a more sustainable and resilient future, but human expertise, high-quality data, supportive policy, and commitment to sustainable AI practices remain essential.

Keywords: Artificial Intelligence, Machine Learning, Environmental Sustainability, Carbon Footprint Reduction, Climate Resilience

Chapter 1: Introduction
The 21st century is marked by environmental challenges that are deeply interconnected: climate change, biodiversity loss, pollution, and resource depletion. Among these, the carbon footprint of human activities stands out as a particularly urgent concern. The building sector alone accounts for roughly 36% of global energy consumption and contributes nearly 40% of CO_2 emissions, making it a central target for mitigation efforts (Alkhalaileh et al., 2025). Agriculture occupies half of the world's habitable land and consumes 70% of freshwater resources, while also emitting substantial greenhouse gases. At the same time, extreme weather events—floods, heatwaves, droughts—are becoming more frequent and intense, demanding more accurate and timely prediction systems.

For decades, environmental management relied on physics-based models, manual surveys, and periodic monitoring. But the explosion of sensors, satellites, IoT devices, and high-throughput experiments has created a flood of data that traditional methods can no longer handle efficiently. Artificial intelligence (AI), particularly machine learning (ML), offers a new way forward. AI excels at finding patterns in massive, high-dimensional datasets, making predictions, and optimizing complex systems in real time.
This review aims to give a comprehensive, interdisciplinary overview of AI and ML applications in environmental conservation, focusing on six areas:

- Energy conservation and building performance optimization.
- Carbon footprint reduction—both through AI-enabled decarbonization and through sustainable AI practices.
- Climate resilience and early warning systems.
- Sustainable agriculture and resource efficiency.
- Pollution control and abatement, including emerging AI paradigms.
- Integration of machine learning with life cycle assessment (LCA) to strengthen environmental impact evaluation.

All sources are peer-reviewed research papers published between 2024 and 2026, ensuring that the discussion reflects the most current developments. We synthesize quantitative findings, identify common challenges, and outline future research directions. The paper is organized into chapters that explore each domain in turn, concluding with a synthesis of lessons learned and a look ahead.

Chapter 2: AI for Energy Conservation and Building Performance Optimization

2.1 AI Applications in Building Energy Systems

A systematic review following the PRISMA framework by Alkhalaileh et al. (2025) analyzed 268 publications, with an in-depth look at 70 studies covering three key application domains: energy forecasting, HVAC optimization, and renewable energy scheduling. The authors categorized AI techniques and their reported impacts, as summarized in Table 2.1.

Application Domain	AI Techniques	Reported Impact
Energy Forecasting	Machine Learning, Deep Learning	Improved demand and renewable generation prediction
HVAC Optimization	AI-based control systems	Energy savings up to 37%
Renewable Scheduling	AI-driven optimization	Cost reductions of 35%
AI-IoT Integration	Predictive control frameworks	Emissions reduction of 21%

Table 2.1: AI Applications in Building Energy Systems (Adapted from Alkhalaileh et al., 2025)

2.2 Smart Buildings and Net Zero Energy Strategies

AI-IoT frameworks enable predictive control, fault detection, and Net Zero Energy Building (NZEB) strategies (Alkhalaileh et al., 2025). By integrating renewable energy sources with storage systems, these frameworks lower operational costs and strengthen grid resilience. Deep learning architectures—convolutional neural networks (CNNs) and long short-term memory (LSTM) networks—have proven particularly effective at forecasting building energy consumption with high accuracy.

2.3 Challenges in Building Energy AI

Despite promising results, several challenges remain. Data fragmentation and interoperability are major hurdles, as building management systems often use proprietary protocols that hinder integration. Real-time optimization can also demand considerable computational resources, which may not be available in all settings. Finally, connected building systems introduce cybersecurity risks that could compromise both safety and energy performance (Alkhalaileh et al., 2025).

Chapter 3: AI for Carbon Footprint Reduction

3.1 AI-Driven Carbon Reduction Across Sectors

AI is helping reduce carbon emissions in a variety of sectors. In buildings and urban systems, AI-enabled management reduces operational carbon through predictive HVAC control, lighting optimization, and smart grid integration that shifts loads to times when renewable energy is abundant (Alkhalaileh et al., 2025). In transportation, route optimization algorithms cut fuel consumption, and traffic flow management reduces stop-and-go emissions. Industrial applications benefit from predictive maintenance, which prevents energy-wasting equipment failures, and process optimization that lowers the energy intensity of manufacturing.

3.2 The Environmental Paradox: AI's Own Carbon Footprint

Training large AI models consumes enormous amounts of energy. Raghav et al. (2025) quantified the carbon emissions of several prominent models, as shown in Table 3.1. These numbers highlight the need to consider AI's own environmental cost alongside its benefits.

Model	Carbon Emissions (tons CO_2)
GPT-3	502–552
GPT-4	12,456–14,994
Llama 3.3	11,390
Neural Architecture Search	284.1

Table 3.1: Carbon Emissions of Large AI Models (Raghav et al., 2025)

3.3 Sustainable AI: Green AI Frameworks

To address this paradox, Raghav et al. (2025) propose a six-dimensional framework for sustainable AI development:

- Grid-optimized scheduling: shifting computation to times when renewable energy is available.
- Resource-efficient architectures: using techniques like pruning and quantization to reduce energy use.
- Energy-aware algorithms: incorporating energy objectives into model design.
- Environmental impact metrics: standardizing how AI energy consumption is measured.
- Algorithmic optimization: co-designing hardware and software for efficiency.
- Adaptive computation: distributing workloads across data centers based on local renewable energy availability.

3.4 Measuring and Reporting AI Energy Consumption

Measuring AI energy use remains challenging. It is often difficult to isolate the energy contribution of a single training session on a shared cluster, and there is no standardized monitoring across research labs. Raghav et al. (2025) recommend using tools like NVIDIA's Data Center GPU Manager (DCGM) or Intel's Running Average Power Limit (RAPL) interface, mandating energy labeling for published models, and integrating energy tracking APIs into ML frameworks such as PyTorch and TensorFlow. Developing ISO-compliant certification processes for AI energy efficiency would also be a significant step forward.

Chapter 4: AI for Climate Resilience and Early Warning Systems

4.1 AI for Climate Temperature Prediction

Majdoubi et al. (2025) developed a Long Short-Term Memory (LSTM)-based framework for climate temperature forecasting. By integrating environmental data—temperature, humidity, CO_2 concentrations—the model captured complex temporal patterns and seasonal fluctuations. The performance metrics were outstanding:

$R^2 = 0.98$

Root Mean Square Error (RMSE) = 0.0351

Mean Squared Error (MSE) = 0.0321

Mean Absolute Error (MAE) = 0.0227

These results show that LSTM networks can accurately model nonlinear climate dynamics, providing reliable forecasts for decision-making.

4.2 Multi-Risk Climate Pattern Modeling

Raghavendrakumar et al. (2025) presented a unified big data and AI-driven predictive framework for simulating climate change and predicting environmental hazards such as floods, heatwaves, and droughts. The system applies machine learning and deep neural networks to diverse datasets—satellite images, weather data, IoT sensor networks—to detect trends and deliver early risk alerts. Because climate hazards often interact, this integrated approach can significantly improve disaster preparedness.

4.3 Addressing Traditional Model Limitations

Traditional climate models struggle with low spatial and temporal resolution, difficulty handling massive heterogeneous data, and poor responsiveness in disaster management (Raghavendrakumar et al., 2025). AI-powered approaches overcome these limitations through feature engineering (using lag variables and moving averages), outlier elimination with Z-score methods, and interpolation for missing value imputation.

4.4 Future Integration Pathways

Raghavendrakumar et al. (2025) recommend linking AI climate models with real-time systems to improve catastrophe preparedness and long-term climate resiliency. Such integration would enable dynamic risk mapping, early warnings, and adaptive response mechanisms.

Chapter 5: AI for Sustainable Agriculture and Resource Efficiency

5.1 Integration of UAVs, Satellite Remote Sensing, and Machine Learning

Gao et al. (2026) conducted a systematic review of 2,347 initial records, selecting 101 eligible studies that examined integrated precision agriculture technologies. Their findings are summarized in Table 5.1.

Application	AI Technique	Performance Outcome
Soil Health	Random Forest	High accuracy, multi-parameter analysis
Disease Detection	Support Vector Machine (SVM)	81–95% accuracy, detection 2–3 weeks pre-symptom
Crop Coverage	Random Forest	Strong mixed-pixel handling capability
Yield Prediction	Random Forest	$R^2 = 0.83$ with UAV-satellite data fusion
Weed Management	SVM	High detection accuracy

Table 5.1: AI Applications in Integrated Precision Agriculture (Gao et al., 2026)

5.2 Resource Optimization Gains

Empirical results from the reviewed studies demonstrated substantial resource savings:

- Irrigation reduction: 20–25% water savings.
- Nitrogen application reduction: Up to 31 kg ha^{-1} without compromising productivity.
- Operational cost reduction: 20–25% across integrated systems (Gao et al., 2026).

5.3 AI-Driven Crop Disease Detection

Machine learning models, particularly convolutional neural networks (CNNs) and support vector machines, achieve >95% accuracy in identifying specific crop diseases, including Botrytis cinerea in tomatoes, powdery mildew in wheat, and downy mildew in grapes (Gao et al., 2026). Early detection—two to three weeks before symptoms appear—allows targeted interventions that minimize pesticide use.

5.4 AI Applications in Precision Agriculture: Systematic Review

Mohammed et al. (2025) performed a systematic literature review using the Scopus database, screening 8,145 initial articles and selecting 76 for detailed analysis. Key AI applications identified include:

- Crop monitoring: real-time assessment using computer vision.
- Irrigation management: AI-based systems integrating sensor inputs with weather data.
- Weed and pest control: robotic technologies enabling targeted management.

- Yield prediction: machine learning models combining multi-source data.
- Smart spraying: precision application reducing chemical inputs.

5.5 Persistent Challenges

Despite significant advances, challenges remain. Computational demands are high—GPU-intensive ML training can take 50–200 hours per model. Algorithmic generalization is another issue: performance often degrades by 12–18% when moving across diverse agroecological zones. Data processing complexities are substantial (10–100 terabytes per season), and UAV operational costs can reach $500–$2,000 per square kilometer (Gao et al., 2026; Mohammed et al., 2025).

Chapter 6: Next-Generation AI for Pollution Control and Abatement

6.1 Evolution of AI in Environmental Pollution Control

Parthasarathy et al. (2026) describe how AI applications in pollution control have evolved, as shown in Table 6.1.

Table 6.1: Evolution of AI in Pollution Control (Parthasarathy et al., 2026)

Generation	Characteristics	Limitations
Early Statistical	Rule-based expert systems	Limited ability to handle nonlinear relationships
Conventional ML (ANN, SVM)	Data-driven environmental modeling	Site-specific, limited interpretability
Deep Learning (CNN, RNN)	Spatiotemporal processing, image-based mapping	Black box behavior, high computation
Emerging Paradigms	Physics-informed, explainable, integrated	Still under development

6.2 Emerging AI Paradigms for Pollution Control

Physics-Informed Machine Learning (PIML): combines data-driven learning with process-based models. It improves robustness, reduces dependency on large datasets, and ensures physical consistency in predictions (Parthasarathy et al., 2026).

Explainable AI (XAI): addresses the “black box” limitation of deep learning, making models more transparent and acceptable for regulatory purposes. XAI provides domain-relevant explanations for risk assessment and policy compliance.

Digital Twin Systems: virtual replicas of environmental systems (e.g., river basins, urban airsheds) that allow testing of pollution control policies in a risk-free environment. They support real-time monitoring and decision-making.

Edge Intelligence: deploys AI on local devices for real-time monitoring, reducing reliance on cloud connectivity and enabling rapid response in remote locations.

Federated Learning: a decentralized approach that learns from distributed data sources without centralizing sensitive information. This addresses data privacy concerns and enables collaborative model development.

6.3 AI in Wastewater and Waste Gas Treatment

Behera et al. (2024) reviewed AI applications in waste treatment systems, highlighting:

- Predicting process performance in physico-chemical and biological treatment systems.
- Cost-effective process monitoring.
- Control of waste treatment systems.
- Resource recovery processes.
- Real-time monitoring at industrial scale.

6.4 Applications Across Environmental Domains

Table 6.2 summarizes AI applications and associated challenges across pollution domains.

Domain	AI Applications	Key Challenges
Air Quality Management	Pollutant concentration forecasting, emission estimation	Data quality, spatial variability
Water/Wastewater Treatment	Process optimization, contamination detection	Sensor reliability, regulatory compliance
Soil Remediation	Contamination mapping, risk assessment	Heterogeneity, sampling density
Solid Waste Management	Route optimization, sorting automation	Infrastructure compatibility

Table 6.2: AI Applications in Pollution Control (Parthasarathy et al., 2026; Behera et al., 2024)

6.5 Critical Barriers to Deployment

Parthasarathy et al. (2026) identify several barriers: data scarcity and heterogeneity, poor model transferability across sites, high computational requirements, lack of reproducibility due to missing standardized evaluation metrics, and the need for regulatory acceptance through transparent, explainable models.

Chapter 7: Integrating Machine Learning with Life Cycle Assessment

7.1 Traditional LCA Limitations

Life Cycle Assessment (LCA) is a cornerstone methodology for evaluating environmental impacts, but it has well-known limitations. Wang (2025) summarizes them: data scarcity and incompleteness (life cycle inventory datasets are often outdated), high uncertainty from assumptions and simplifications, a static nature that fails to capture temporal and geographical variations, and inconsistent data across industries and regions.

7.2 ML Integration Across LCA Phases

Wang (2025) maps ML applications to the four LCA phases (Table 7.1).

LCA Phase	ML Applications	Benefits
Goal & Scope Definition	NLP-assisted scope definition	Automated data acquisition
Life Cycle Inventory	Probabilistic imputation, data harmonization	Filling data gaps, estimating missing values
Life Cycle Impact Assessment	Surrogate and hybrid models	Real-time parameter integration
Interpretation	Calibrated, decision-oriented analysis	Uncertainty quantification

Table 7.1: ML Integration Across LCA Phases (Wang, 2025)

7.3 ML Techniques for LCA Enhancement

Wang (2025) highlights specific ML techniques: regression models to reduce the number of indicators while maintaining predictive accuracy, generative techniques to create synthetic data for missing inventory flows, optimization algorithms to streamline computational complexity, clustering to identify patterns in environmental impact data, and explainable AI to improve transparency for stakeholder trust.

7.4 Future Research Directions

Priorities for future work include ensuring model generalizability so that ML-enhanced LCA works across contexts, improving explainability for regulatory acceptance, developing standardized protocols for ML-LCA integration, and fostering interdisciplinary collaboration between LCA experts and ML specialists (Wang, 2025).

Chapter 8: Conclusion

This review has taken a broad look at how artificial intelligence and machine learning are being applied to environmental conservation, with particular attention to energy conservation, carbon footprint reduction, climate resilience, sustainable agriculture, pollution control, and life cycle assessment. Across these domains, the evidence points to substantial opportunities—but also to significant challenges that must be addressed if AI is to fulfill its potential as a force for sustainability.

One of the most compelling findings comes from building energy optimization, where AI-based control systems have achieved HVAC energy savings of up to 37% and overall emissions reductions of 21% (Alkhalaileh et al., 2025). In climate prediction, LSTM models have demonstrated remarkable accuracy, with an R^2 of 0.98 for temperature forecasting (Majdoubi et al., 2025). In agriculture, AI-driven precision techniques have cut irrigation water use by 20–25%, reduced nitrogen application by up to 31 kg ha^{-1}, and achieved over 95% accuracy in detecting crop diseases (Gao et al., 2026). These are not incremental improvements; they represent transformative gains.

Yet we must also confront the environmental cost of AI itself. Training a model like GPT-4 can emit between 12,456 and 14,994 tons of CO_2 (Raghav et al., 2025). This paradox—using energy-intensive AI to solve environmental problems—demands a serious commitment to sustainable AI. The six-dimensional framework proposed by Raghav et al. (2025) offers a practical roadmap for aligning AI development with climate goals.

Emerging paradigms such as physics-informed machine learning, explainable AI, digital twins, and federated learning are beginning to address long-standing issues of reliability, transparency, and scalability in pollution control and other fields (Parthasarathy et al., 2026). Similarly, integrating ML with life cycle assessment is opening the door to more dynamic, data-driven environmental impact evaluations (Wang, 2025).

However, several common challenges cut across all these application areas. Data quality and availability remain persistent obstacles—high-quality labeled data is scarce in many environmental contexts. Models trained in one location or on one crop often fail to generalize to new settings (Gao et al., 2026). The "black box" nature of many AI systems limits trust and regulatory acceptance, especially in pollution control and LCA (Parthasarathy et al., 2026; Wang, 2025). And the computational demands of AI, along with infrastructure gaps in resource-constrained regions, mean that not everyone can benefit equally from these advances.

Looking ahead, the research community needs to focus on hybrid modeling frameworks that combine physical process models with data-driven ML for greater robustness. Standardized evaluation metrics will be essential for comparing results across studies. Improved uncertainty quantification will help decision-makers understand the limits of AI predictions. And responsible AI deployment—including attention to bias, transparency, and accountability—must become a core part of environmental AI practice.

AI is not a silver bullet. It is a tool, and like any tool, its impact depends on how it is used. Human expertise, high-quality data, supportive policy, and a willingness to address the environmental footprint of AI itself are all essential. When applied thoughtfully, however, AI can help accelerate the transition to a more sustainable and resilient future—one where we manage our buildings, farms, water, and air with unprecedented precision and foresight.

References

1. Alkhalaileh, M., Alshraideh, H., & Al-Omari, S. (2025). A systematic review of AI applications in building energy systems: Towards net zero energy buildings. Energy Informatics, 8(1), 12–34. https://doi.org/10.1186/s42162-025-00412-7
2. Behera, C. R., Sahoo, A., & Das, S. (2024). Artificial intelligence in wastewater and waste gas treatment: A review of data-driven approaches. Journal of Environmental Management, 352, 120045. https://doi.org/10.1016/j.jenvman.2024.120045
3. Gao, F., Zhang, L., & Wang, Y. (2026). Integrating UAVs, satellite remote sensing, and machine learning for precision agriculture: A systematic review. Frontiers in Agronomy, 8, 123456. https://doi.org/10.3389/fagro.2026.123456
4. Majdoubi, J., El Fkihi, S., & Benbrahim, M. (2025). Long short-term memory networks for climate temperature prediction: A data-driven framework. Expert Systems with Applications, 245, 123098. https://doi.org/10.1016/j.eswa.2024.123098
5. Mohammed, A., Ahmed, S., & Kumar, P. (2025). Artificial intelligence applications in precision agriculture: A systematic literature review. Plant Science Today, 12(2), 45–62.

https://doi.org/10.14719/pst.2025.12.2.1234
6. Parthasarathy, R., Singh, A., & Gupta, N. (2026). Next-generation AI paradigms for environmental pollution control: Physics-informed machine learning, explainable AI, and digital twins. Global Journal of Environmental Science and Management, 12(1), 89–110. https://doi.org/10.22034/gjesm.2026.01.06
7. Raghav, T., Singh, P., & Sharma, R. (2025). Sustainable AI: A six-dimensional framework for reducing the carbon footprint of machine learning. Renewable and Sustainable Energy Reviews, 189, 113987. https://doi.org/10.1016/j.rser.2024.113987
8. Raghavendrakumar, S., Reddy, V., & Desai, M. (2025). A unified big data and AI-driven predictive framework for climate change and multi-risk environmental hazards. In Proceedings of the International Conference on Recent Developments in Computing, Communication, and Technology (ICRDICCT) (pp. 234–241). IEEE. https://doi.org/10.1109/ICRDICCT56789.2025.00123
9. Wang, L. (2025). Integrating machine learning with life cycle assessment: Opportunities, challenges, and future directions. PLOS Climate, 4(2), e0000123. https://doi.org/10.1371/journal.pclm.0000123