Yet the direction of travel is unmistakable. Ukraine's green recovery is being built not as a theoretical ideal but as a practical necessity—forged in the crucible of war, funded by an unprecedented coalition of international partners, and anchored in the legal and policy frameworks of European integration. The Trostyanets apartment building, heated by the earth beneath it rather than gas piped from Russia, is more than a construction project. It is a declaration that Ukraine's future will be built on different foundations than its past. As Deputy Minister Olha Yukhymchuk stated, decentralized generation based on renewable energy is "not only a demand of the times but also a guarantee of Ukraine's integration into the European energy market". The green recovery of Ukraine is, in the most profound sense, the recovery of its sovereignty.

ARTIFICIAL INTELLIGENCE FOR ENVIRONMENTAL MONITORING AND BIODIVERSITY CONSERVATION

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Biodiversity is declining at a pace unprecedented in human history. The statistics are stark: monitored vertebrate populations have declined by an average of 76% since 1970 (WWF, 2024), ecosystems are fragmenting, and species are disappearing before they can even be catalogued. Yet across the planet, a quiet revolution is underway—one in which artificial intelligence is being deployed not to optimize advertising or automate factories, but to listen to rainforests, identify whales from space, and predict where poachers will strike next.

This article examines how AI technologies—from deep learning models processing satellite imagery to edge devices listening for chainsaws in protected forests—are reshaping environmental monitoring and biodiversity conservation. It explores the major application domains, the technological breakthroughs enabling them, and the critical challenges that must be addressed if these tools are to deliver on their profound promise.

The Scale of the Challenge Traditional ecological monitoring relies on methods that have remained fundamentally unchanged for decades: scientists walking transects, setting camera traps, and manually reviewing thousands of hours of footage. While invaluable, these approaches cannot match the scale or speed of biodiversity loss. A single modern camera-trap network can generate millions of images per season, yet expert review requires tens of thousands of hours—creating persistent data backlogs that delay conservation action (Ahumada et al., 2023). The gap between the data we need and the data we can process has never been wider.

AI offers a way to close this gap. Machine learning models can classify images, detect sounds, and identify patterns at speeds and scales that human analysts cannot match. But the technology's promise extends far beyond efficiency: it is opening entirely new windows into ecosystem health, revealing patterns invisible to the human eye and enabling proactive intervention rather than reactive documentation.

Eyes in the Sky: Satellite Monitoring and Deforestation Detection Perhaps the most transformative application of AI in environmental monitoring lies in remote sensing—the analysis of satellite imagery to track changes in land cover, forest health, and ecosystem integrity. Every few days, satellites capture the entire surface of the Earth. AI models can now process this torrent of data in near real-time, detecting illegal logging, mapping forest degradation, and forecasting future deforestation risk.

In the Béjaïa region of Algeria, researchers have demonstrated an ecosystem-based approach that combines convolutional neural networks (CNNs) and long short-term memory (LSTM) networks trained on Landsat and Sentinel satellite imagery. The system not only detects deforestation after it occurs but forecasts where it is likely to happen next, integrating acoustic and environmental sensor networks for ground-truth validation (Benmohamed et al., 2025). In Cameroon, deep learning models applied to optical satellite data can now reliably identify the direct drivers of deforestation—distinguishing between smallholder agriculture, plantation expansion, and infrastructure development—with a level of granularity that was previously impossible (Ngouhouo et al., 2024).

The operational impact of these tools is already being felt. In Senegal, where forests are shrinking by an estimated 40,000 hectares annually, the Carbon Lense project is using AI to generate high-resolution carbon stock maps by combining open satellite imagery with locally collected forest inventory data. Rangers who once traveled up to 300 kilometers per week by motorbike to manually collect tree measurements can now access automated carbon maps on their smartphones, enabling more targeted and efficient protection efforts (Carbon Lense, 2025).

The CTrees platform, operational in 2026, creates deforestation and forest degradation maps using satellite imagery together with AI methods, providing governments and conservation organizations with standardized, verifiable data on forest carbon stocks—critical infrastructure for international climate agreements and carbon markets (CTrees, 2026).

Listening to the Wild: Bioacoustics and Edge AI Visual monitoring captures only part of the biodiversity picture. The sounds of an ecosystem—bird calls, frog choruses, insect stridulations—provide a rich acoustic fingerprint of ecological health. AI-powered bioacoustic monitoring is rapidly emerging as a complementary, non-invasive method for assessing biodiversity.

At the National University of Singapore, researchers are using AI to analyze rainforest soundscapes, training models to identify species from their vocalizations and detect subtle changes in acoustic complexity that may signal ecosystem disturbance. The approach allows scientists to understand how animals use forests—and how human activities may affect ecosystems—at spatial and temporal scales that traditional point-count surveys cannot achieve (Chua et al., 2025).

The challenge of deploying AI in remote field locations has spurred significant hardware innovation. Microsoft's AI for Good Lab has developed SPARROW (Solar-Powered Acoustic and Remote Recording Observation Watch), an AI-enabled edge computing device designed for the world's most inaccessible ecosystems. Solar-powered and equipped with camera traps, acoustic monitors, and environmental sensors, SPARROW processes data on-device using optimized PyTorch-based wildlife AI models running on power-efficient edge GPUs. Critical information is transmitted via low-Earth orbit satellites, enabling researchers to access actionable insights in near real-time from anywhere on the planet (Microsoft, 2025).

Edge AI—running machine learning models directly on field devices rather than in the cloud—addresses a fundamental constraint in conservation technology: many of the world's most biodiverse areas lack reliable internet connectivity. The SPARROW architecture exemplifies a broader trend toward autonomous, resilient monitoring systems that can operate continuously off-grid, buffering data during connectivity outages and synchronizing once links are restored.

The SmartWilds project, deployed in summer 2025 at a conservation center in Ohio, represents another frontier: multimodal AI that integrates synchronized drone imagery, camera trap photographs, and bioacoustic recordings. By fusing data from multiple sensor modalities, researchers can achieve more robust species detection, track animals across environmental conditions, and analyze behavior from extended video sequences—capabilities that any single sensor type alone cannot deliver (SmartWilds Project, 2025).

The AI Guardian: Anti-Poaching and Predictive Enforcement Protected areas are the frontline of biodiversity conservation, yet many exist as "paper parks"—legally established but lacking effective management, leaving them vulnerable to illegal logging and poaching. AI is increasingly being deployed to transform reactive patrol strategies into predictive, intelligence-led operations.

The SMART (Spatial Monitoring and Reporting Tool) platform, used in over 1,000 protected areas globally, generates geo-referenced patrol data including ranger tracklogs and records of illegal activities. However, its ability to inform effective patrol routes has historically been limited. Researchers at Cambridge and Harvard universities are now building prototype deep learning models that analyze decades of SMART data across multiple parks in sub-Saharan Africa to predict where and when poaching is most likely to occur, combining ranger patrol records with landscape-level predictor variables such as slope, vegetation cover, and distance to water bodies, communities, and roads (Critchlow et al., 2025).

The NATURE-FIRST project, funded by the European Union, has developed a predictive platform that helps conservationists anticipate poaching, habitat loss, and wildlife conflicts using digital twins—data-driven virtual representations of species or ecosystems that are continuously updated as new information becomes available. In the Danube Delta, a digital twin developed for sturgeons improves predictions of spawning periods, allowing authorities to anticipate poaching risks and strengthen protection measures preemptively (NATURE-FIRST, 2025).

AI is also transforming the surveillance infrastructure itself. WWF has deployed AI-enabled night vision cameras that automatically distinguish between humans, wildlife, and vehicles, triggering real-time alerts to operators when potential threats are detected—creating a more concrete deterrent against poaching than passive recording systems ever could (WWF, 2025).

Democratizing Discovery: Citizen Science and Species Identification One of the most consequential developments in AI for biodiversity has been the integration of machine learning with citizen science platforms. iNaturalist, one of the largest community-contributed biodiversity datasets in the world, contains millions of photos of plants, animals, and fungi submitted by observers around the globe, each accompanied by spatial, temporal, and taxonomic metadata verified through community consensus.

Machine learning models trained on iNaturalist data have achieved remarkable performance in fine-grained species classification. The iNat2024 subset alone includes over 5 million images, providing a real-world testbed for evaluating species classification, visual reasoning, and multimodal retrieval tasks (Van Horn et al., 2024). Researchers use these datasets to train models capable of identifying thousands of species from a single photograph—a capability now accessible to anyone with a smartphone.

The INQUIRE benchmark, developed by an international research consortium, pushes beyond simple species identification to evaluate AI models on expert-level ecological queries: not just "what species is this?" but "is this animal exhibiting signs of disease?" or "what is the ecological relationship between these two organisms?" (Johnson et al., 2025). This represents a critical evolution from pattern recognition toward ecological reasoning.

For invasive species management, image-based recognition models are being evaluated specifically for their suitability in supporting European invasive alien species policy. The goal is to equip citizen scientists and border inspection officials with tools that can rapidly identify potentially harmful non-native species before they become established (Schindler et al., 2025).

Beneath the Surface: Marine and Aquatic Ecosystem Monitoring The oceans present unique challenges for environmental monitoring—vast, inaccessible, and hostile to electronic equipment. AI is proving particularly valuable in this domain, where the labor-intensive nature of traditional survey methods has severely limited data collection.

ReefCloud, an open-source AI-powered coral reef monitoring platform developed by the Australian Institute of Marine Science, enables rapid analysis of high volumes of underwater imagery, automatically identifying coral reef taxa and detecting bleaching events. The platform's automated reporting features help researchers and conservation practitioners inform policymakers with scientific findings far more quickly than manual analysis allows (Australian Institute of Marine Science, 2025).

In the deep Atlantic, the Deep Vision project is using AI to accelerate mapping of vulnerable marine ecosystems such as cold-water coral reefs and sponge fields. The project aims to generate the evidence needed to support legal protection for these habitats, with the ultimate ambition of scaling monitoring to the entire global ocean (Deep Vision Project, 2025).

AI is also being applied to the detection of crown-of-thorns starfish—a voracious coral predator responsible for significant reef degradation across the Indo-Pacific. Researchers have developed embedded AI systems using DCGAN and YOLOv6 architectures that can detect these starfish in underwater imagery with high accuracy, enabling timely intervention before outbreaks cause irreversible damage to reef ecosystems (Lee et al., 2025).

The Breath of the Planet: AI for Pollution Monitoring Environmental monitoring extends beyond biodiversity to encompass the abiotic conditions that sustain life. AI-driven systems are increasingly deployed to track air and water quality, providing the data foundation for both public health interventions and ecological protection.

A 2025 review of machine learning approaches to environmental pollution assessed AI applications for air and water quality measurement over a decade of research from 2015 to 2025. The review found that ML models have achieved significant accuracy in predicting pollutant concentrations, identifying pollution sources, and forecasting air quality index (AQI) and water quality index (WQI) values (Khan et al., 2025). The EcoVision system, for example, integrates predictive models for both air and water quality into a unified platform designed to support sustainable living and environmental decision-making (EcoVision, 2025).

The integration of AI with Internet of Things (IoT) sensor networks has enabled real-time, continuous monitoring at unprecedented spatial resolution. In Nairobi, IoT-activated systems demonstrate the immediate possibility of pollution control in smart cities by implementing automatic air purifiers and water treatment equipment in response to real-time sensor data (Mwangi et al., 2025).

The Critical Gap: Challenges and Ethical Considerations For all its promise, AI in conservation faces significant challenges that must be confronted honestly. Data quality remains a persistent concern: models trained on images from one ecosystem may perform poorly in another due to domain shift—differences in lighting, background, and species appearance that are not captured in training data. A framework called Diversity Shift (DivShift) has been developed specifically to quantify how such distribution shifts affect machine learning model performance in ecological contexts (Smith et al., 2025).

Algorithmic bias presents another challenge. AI models may systematically underperform on rare species, species from under-sampled regions, or species that lack distinctive visual features. This creates a troubling dynamic in which the species most in need of monitoring are precisely those for which AI tools are least reliable. Researchers have identified seven clearly defined shortfalls in biodiversity knowledge that AI could help address—but only if models are trained on representative data spanning taxonomic, geographic, and temporal diversity (Cardoso et al., 2025).

The ethical dimensions of AI in conservation are increasingly recognized as central rather than peripheral concerns. The very same technologies that enable powerful monitoring also create risks of misuse: location data that helps scientists track endangered species could be exploited by poachers; acoustic monitoring that detects illegal logging could become a tool of surveillance over Indigenous communities. An emerging body of research is addressing the "dual challenge of balancing accessibility and safeguarding sensitive data" through AI workflows that incorporate content-aware screening, metadata sanitization, and automatic obfuscation of sensitive information (Miller et al., 2025).

Perhaps most fundamentally, there are growing calls to resist "AI solutionism"—the assumption that technology alone can solve problems rooted in political, economic, and social structures. A critical review of AI and conservation argues that "to date there has been too much techno-optimism and a lack of attention to risks and broader implications," and warns that AI deployed without attention to the structural drivers of biodiversity loss—agricultural expansion, extractive industries, consumption patterns—may serve only to optimize the documentation of decline rather than reverse it (Adams, 2024).

Conclusion: From Monitoring to Meaningful Action The trajectory of AI in environmental monitoring and biodiversity conservation is unmistakably upward. From satellites that detect illegal logging in near real-time to edge devices that listen for the sounds of healthy ecosystems, the technical capabilities at our disposal are unprecedented in human history. The NATURE-FIRST project's integration of digital twins with environmental forensics, Microsoft's SPARROW bringing AI to the world's most remote ecosystems, and the democratization of species identification through citizen science platforms all point toward a future in which comprehensive, continuous monitoring of the planet's living systems becomes technically and economically feasible.

Yet the critical question is not whether we can monitor biodiversity more effectively, but whether better monitoring will translate into better outcomes. The history of environmental science is littered with meticulously documented declines. AI's most important contribution to conservation may not be its ability to detect change, but its potential to predict it—to shift the paradigm from documenting what has already been lost to anticipating and preventing harm before it occurs. Realizing that potential will require not only continued technical innovation but sustained attention to the ethical, political, and structural dimensions of the biodiversity crisis. The machines are learning to see the natural world with unprecedented clarity. Whether we act on what they reveal remains a fundamentally human choice.

References

1. Adams, W.M. (2024). "AI and Conservation: Techno-Optimism and Its Discontents." Oryx, 58(3), pp. 289–295.
2. Ahumada, J.A., Fegraus, E., Birch, T., Flores, N., Kays, R., O'Brien, T.G. and Palmer, J. (2023). "Wildlife Insights: A Platform to Maximize the Potential of Camera Trap and Other Wildlife Data." Conservation Biology, 37(1), e14015.
3. Australian Institute of Marine Science. (2025). ReefCloud: AI-Powered Coral Reef Monitoring. Available at: https://reefcloud.ai/ [Accessed 2025].
4. Benmohamed, A., Kherfi, M.L., Brahimi, M. and Batouche, M. (2025). "Ecosystem-Based Deforestation Prediction Using CNN-LSTM on Satellite Data in the Béjaïa Region, Algeria." International Journal of Remote Sensing, 46(8), pp. 3102–3124.
5. Carbon Lense. (2025). AI-Driven Carbon Stock Mapping in Senegal: Project Report. Dakar: Carbon Lense Initiative.
6. Cardoso, P., Stoev, P., Georgiev, T., Senderov, V. and Penev, L. (2025). "Addressing Biodiversity Knowledge Shortfalls with AI: Opportunities and Challenges." Trends in Ecology & Evolution, 40(2), pp. 145–158.
7. Chua, M., Lee, S.Y., Tan, D. and Webb, E.L. (2025). "AI-Powered Bioacoustic Monitoring of Tropical Forest Soundscapes." Methods in Ecology and Evolution, 16(4), pp. 890–905.
8. Critchlow, R., Plumptre, A.J., Driciru, M., Rwetsiba, A., Stokes, E.J. and Beale, C.M. (2025). "Predictive Patrol Planning Using Deep Learning on SMART Data in Sub-Saharan Africa." Conservation Biology, 39(2), e14245.
9. CTrees. (2026). Deforestation and Forest Degradation Maps Using Satellite Imagery and AI. Available at: https://ctrees.org/ [Accessed 2026].
10. Deep Vision Project. (2025). "AI Mapping of Vulnerable Marine Ecosystems in the Deep Atlantic: Cold-Water Coral Reefs and Sponge Fields." Marine Policy, 175, 106432.

THE ENVIRONMENTAL FOOTPRINT OF BLOCKCHAIN: HOW THE