

AI-DRIVEN ENVIRONMENTAL MONITORING SYSTEMS: A NEW FRONTIER IN CONSERVATION TECHNOLOGY

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Abstract:

The ongoing environmental degradation and climate crisis demand innovative solutions that are both scalable and precise. Artificial Intelligence (AI) is emerging as a transformative tool in ecological conservation, particularly in the field of environmental monitoring. This chapter explores the integration of AI into monitoring systems, detailing how machine learning, computer vision, remote sensing, and Internet of Things (IoT) technologies are revolutionising the way data is collected, analysed, and used to drive policy and conservation actions. From predicting forest fires and monitoring biodiversity to detecting pollution in real time, AI-driven monitoring systems are enabling smarter and faster environmental responses. This chapter presents current applications, case studies, benefits, and ethical concerns, and outlines future directions for AI in ecological stewardship.

Keywords: AI, Environmental Monitoring, Conservation, Machine Learning, Biodiversity

Introduction:

Environmental monitoring plays a vital role in understanding and protecting ecosystems. It involves collecting and analysing data on air and water quality, biodiversity, and land use to assess ecosystem health and inform decision-making (Lovett *et al.*, 2007). With increasing environmental pressures from human activity, the need for efficient, real-time monitoring has never been greater. Traditional methods like field surveys and lab analysis are essential but often slow, expensive, and limited in scale. They struggle to keep pace with rapidly evolving threats like wildfires or deforestation (Porter *et al.*, 2005). This has driven demand for more scalable and timely solutions. Artificial Intelligence (AI) offers a transformative alternative. Through machine learning and computer vision, AI systems can rapidly process massive datasets—from satellite imagery to sensor networks—with high accuracy (Reichstein *et al.*, 2019). They detect patterns and changes that would take years to identify manually.

AI's strength lies in automation. It enables continuous monitoring and early detection of issues such as pollution, algal blooms, or habitat loss. Predictive models help forecast air quality, wildfires, and ecological disruptions, allowing for proactive intervention (Rolnick *et al.*, 2019). AI-powered drones and robots can monitor remote environments with minimal human input, delivering frequent, high-resolution data (Tuia *et al.*, 2022). When combined with IoT, cloud computing, and GIS, AI enables real-time environmental dashboards that guide smarter decisions (Singh *et al.*, 2021). These innovations also support global goals like the UN SDGs (Goals 13, 14, 15) (Vinuesa *et al.*, 2020). Yet challenges persist, including data gaps, lack of model transparency, and ethical issues around privacy and community rights (Sendak *et al.*, 2020; Cath *et al.*, 2018).

Despite these concerns, platforms like Google Earth Engine and Global Fishing Watch showcase AI's real-world impact. Future advancements in explainable AI and edge computing will further enhance performance and trust. Ultimately, interdisciplinary collaboration and ethical deployment are key to maximising AI's potential in environmental conservation.

2. Foundations of AI in Environmental Monitoring

Artificial Intelligence (AI) refers to computational methods that replicate human intelligence for tasks like learning, reasoning, and decision-making. In environmental monitoring, AI addresses key challenges of traditional data collection, such as handling large, complex, and varied datasets across time and space. Through machine learning, deep learning, neural networks, computer vision, and natural language processing, AI enables scalable, adaptive, and continuous monitoring of environmental conditions (Reichstein *et al.*, 2019; Rolnick *et al.*, 2019).

2.1 Key Technologies in AI

AI is not a monolithic concept but rather a collection of subfields, each offering unique tools for environmental monitoring:

Machine Learning (ML) involves algorithms that can learn patterns from historical data and make predictions or decisions without being explicitly programmed. ML is used extensively in environmental science to detect trends, classify land cover, or assess ecological health (LeCun *et al.*, 2015).

Deep Learning, a subfield of ML, employs neural networks with multiple layers to model complex, non-linear relationships in large datasets. Deep learning is particularly effective in image recognition tasks, such as identifying wildlife in camera trap images or detecting deforestation from satellite imagery (Tuia *et al.*, 2022).

Computer Vision allows AI systems to "see" and interpret visual information from images or video feeds. It has revolutionised biodiversity monitoring, enabling automated species identification, behaviour analysis, and habitat mapping (Beery *et al.*, 2018).

Natural Language Processing (NLP) is useful for analysing unstructured text data, such as environmental reports, citizen science records, or social media posts about environmental conditions (Young *et al.*, 2018).

2.2 Applications of AI in Environmental Monitoring

AI technologies support several key functions in environmental monitoring:

Pattern Recognition

AI excels in identifying patterns, correlations, and anomalies in complex datasets. This capability is crucial for monitoring dynamic environmental systems, such as forests, oceans, and urban landscapes. For instance, AI can detect sudden changes in vegetation health, unusual wildlife movements, or unexpected pollution events that may indicate ecological stress (Xie *et al.*, 2018). Such insights allow for early warnings and prompt responses to emerging threats.

Predictive Modeling

Predictive modelling is one of the most valuable applications of AI in conservation. By training algorithms on historical environmental data, AI can forecast events such as droughts, floods, wildfires, or algal blooms (Rolnick *et al.*, 2019). For example, convolutional neural networks (CNNs) have been employed to predict coral bleaching events by analysing sea surface temperature anomalies and underwater images (Kumar *et al.*, 2021). These forecasts enable more proactive management strategies, potentially minimising the impact of ecological disruptions.

Decision Support Systems

AI is also increasingly used in decision support tools that guide policymakers and conservationists. These systems can simulate different environmental scenarios, optimise resource allocation, and prioritise conservation actions based on risk assessments and predictive analytics. For example, AI-based tools are helping conservation planners decide where to establish new protected areas or how to manage species migration corridors under climate change scenarios (Chadès *et al.*, 2012).

2.3 Integration with Remote Sensing, GIS, and IoT

AI does not function in isolation; its true strength lies in its integration with other technological systems:

Remote Sensing technologies, including satellites and drones, generate vast amounts of spatial data. AI algorithms process this data to classify land use, detect illegal mining, assess vegetation cover, and monitor glacier retreat, among other applications (Reichstein *et al.*, 2019).

Geographic Information Systems (GIS) provide the spatial framework within which environmental data are stored, analysed, and visualised. AI enhances GIS by enabling automatic feature extraction and spatial-temporal trend analysis, turning raw geospatial data into actionable intelligence (Singh *et al.*, 2021).

Internet of Things (IoT) devices, such as wireless environmental sensors, offer continuous streams of real-time data on temperature, humidity, air and water quality, or soil conditions. When combined with AI, these sensors enable intelligent monitoring systems that can detect anomalies, trigger alerts, and even suggest corrective actions (Zhou *et al.*, 2020).

2.4 Benefits and Emerging Trends

Emerging trends include the use of edge AI, where data is processed locally on devices such as drones or sensors, reducing reliance on cloud infrastructure and enabling faster decision-making (Wearn *et al.*, 2019). Another trend is explainable AI (XAI), which seeks to make AI outputs more interpretable, thereby increasing trust and adoption among stakeholders. The convergence of AI with monitoring technologies offers multiple benefits:

- **Scalability:** AI models can be trained to work across various ecosystems and geographical regions, facilitating large-scale monitoring.
- **Cost-efficiency:** Once developed, AI models can automate tasks previously requiring extensive human labour, such as image analysis or data interpretation.
- **Timeliness:** Real-time analytics powered by AI enable quicker responses to ecological threats, reducing the time lag between data collection and action.

3. Applications of AI-Driven Monitoring Systems

Artificial Intelligence (AI)-driven monitoring systems are revolutionising environmental science by fundamentally transforming how data is collected, processed, and applied across diverse ecosystems. From tropical forests to urban environments and marine ecosystems, AI offers rapid, precise, and cost-effective tools that significantly enhance the management of natural resources.

3.1 Forest and Deforestation Monitoring

Forests are vital ecosystems essential for biodiversity, carbon storage, and climate regulation. Traditional forest monitoring methods, like manual surveys and aerial photography, are often slow and limited. AI has revolutionised this process by enabling near-real-time analysis of satellite imagery and remote sensing data. Platforms like Global Forest Watch use machine learning to track forest loss, degradation, and regeneration by detecting patterns from high-resolution satellite images (Hansen *et al.*, 2013). These tools provide timely alerts and

visualisations for governments, NGOs, and local communities to act against threats such as logging and fires. Google Earth Engine is another powerful example, combining satellite data with AI to detect deforestation, map vegetation, and monitor forest health globally (Gorelick *et al.*, 2017). This supports informed, data-driven conservation efforts.

3.2 Wildlife and Biodiversity Surveillance

Wildlife monitoring is vital for assessing ecosystem health and protecting biodiversity. Traditional methods are labour-intensive and often miss elusive species. AI has revolutionised this field by automating species identification and behaviour analysis using camera traps, acoustic sensors, GPS, and drones. Deep learning models can rapidly identify species, count individuals, and detect rare animals (Norouzzadeh *et al.*, 2018). Initiatives like Microsoft's AI for Earth apply CNNs to analyse millions of wildlife images (Beery *et al.*, 2019). AI also processes acoustic data to track animal calls, with networks in the Amazon and Australia monitoring birds, bats, and frogs—key indicators of ecological health (Stowell *et al.*, 2019).

3.3 Air and Water Quality Monitoring

Clean air and water are crucial for human and ecosystem health, yet traditional monitoring systems often lack real-time responsiveness. AI bridges this gap by analysing data from sensors, satellites, and weather feeds to predict pollution trends. In cities, AI uses IoT sensor data to track air quality, identify pollution sources, and forecast spread, exemplified by the EU's AIRSENSE project (Bourtsalas *et al.*, 2019). For water quality, AI interprets sensor data on pH, turbidity, and contaminants to predict algal blooms and detect spills. In India, AI helps the Central Pollution Control Board monitor river pollution (Bhatia *et al.*, 2022). Satellite imagery, processed with deep learning, also enables large-scale monitoring of eutrophication and watershed health (Feng *et al.*, 2020).

3.4 Climate Change and Weather Forecasting

As climate change intensifies, accurate weather forecasting is critical for disaster management, agriculture, and urban planning. Traditional models like numerical weather prediction (NWP) are powerful but computationally demanding and limited in capturing local climate dynamics. AI, particularly deep learning models like LSTMs and GANs, helps uncover complex patterns in vast climate datasets. IBM's The Weather Company uses AI to combine radar, satellite, and historical data, producing hyper-local, hourly forecasts that aid sectors like aviation and agriculture in managing extreme weather events (Chantry *et al.*, 2021). AI also enhances climate modelling by downscaling global models for regional planning, helping simulate temperature, rainfall, and sea-level rise under different scenarios (Reichstein *et al.*, 2019). Additionally, AI improves early warning systems by analysing seismic and cyclone data

to better predict aftershocks and storm paths, boosting preparedness and response (Tompson *et al.*, 2017).

3.5 Ocean and Marine Ecosystem Monitoring

Oceans, covering over 70% of Earth's surface, are crucial for biodiversity, climate regulation, and food security. Monitoring marine environments is challenging due to their vastness and inaccessibility, but AI has become a key tool for tracking ocean health, predicting threats, and managing fisheries. AI helps monitor coral reefs through programs like NOAA's Coral Reef Watch, which uses satellite data to detect temperature anomalies linked to bleaching (Liu *et al.*, 2014). Autonomous drones and underwater vehicles also use AI to survey coral cover, marine species, and plastic pollution efficiently (Krause *et al.*, 2021). In fisheries, AI analyses catch data and ocean conditions to predict stock changes and enforce quotas. Platforms like Global Fishing Watch use AI and satellite data to detect illegal fishing by identifying suspicious vessel activity (Kroodsmas *et al.*, 2018). AI also supports coastal conservation by mapping habitats like mangroves and wetlands through satellite imagery, helping monitor erosion and plan protective measures.

4. Benefits of AI-Driven Monitoring Systems

The integration of Artificial Intelligence (AI) into environmental monitoring marks a transformative shift in conservation. As environmental challenges grow more complex, AI offers powerful tools to manage large-scale, real-time, and diverse data. With benefits like scalability, speed, accuracy, cost-efficiency, and seamless data integration, AI significantly improves our capacity to monitor, understand, and protect ecosystems. This chapter outlines these key advantages in detail.

4.1 Scalability

A major advantage of AI-based monitoring is its scalability across large and remote areas. Unlike traditional methods limited by labour and geography, AI uses satellite imagery, sensors, and drones to collect and analyse environmental data consistently and efficiently. Platforms like Google Earth Engine and Global Forest Watch use AI and satellite data to track forest cover and deforestation globally, including in hard-to-reach regions like the Amazon and Siberia (Hansen *et al.*, 2013; Gorelick *et al.*, 2017). AI also enables continuous monitoring, capturing seasonal shifts, long-term trends, and sudden events like wildfires or floods, enhancing early response and environmental management (Reichstein *et al.*, 2019).

4.2 Real-time Data Processing

AI-driven monitoring offers the key advantage of real-time data analysis, reducing delays between data collection and action. Traditional methods often lag, but AI enables rapid

processing through automated pipelines. Machine learning models can instantly detect air pollution spikes or water contaminants from IoT sensors, allowing swift responses to urban health risks (Bourtsalas *et al.*, 2019). In biodiversity monitoring, AI analyses images and sounds in real time to detect endangered species or poaching threats, enabling fast intervention (Norouzzadeh *et al.*, 2018). AI also forecasts events like hurricanes or coral bleaching, enhancing disaster preparedness and reducing environmental and human impacts (Liu *et al.*, 2014; Tompson *et al.*, 2017).

4.3 Cost-effectiveness

While AI-based monitoring requires upfront investment, it greatly reduces long-term costs. Traditional methods involve labour-intensive fieldwork, lab analysis, and logistics, which are expensive and often unfeasible in remote areas. AI automates data collection and analysis, handling vast datasets like satellite imagery or sensor inputs with minimal human oversight, lowering costs per data unit (Chantry *et al.*, 2021). In marine conservation, AI-powered drones replace costly expeditions by autonomously surveying reefs (Krause *et al.*, 2021). In agriculture, AI helps monitor soil, water, and pests, boosting productivity while cutting inputs (Kamilaris & Prenafeta-Boldú, 2018). Early detection enabled by AI also prevents costly environmental crises, such as forest loss or invasive species outbreaks.

4.4 Improved Accuracy

AI systems often outperform traditional methods in precision and consistency, detecting subtle environmental changes that humans might miss. Machine learning can uncover complex patterns in large datasets. In wildlife studies, AI surpasses human accuracy in identifying species from images and audio, even for rare or overlapping calls (Beery *et al.*, 2019; Norouzzadeh *et al.*, 2018). In weather forecasting, deep learning enhances predictions by modelling non-linear climate relationships (Reichstein *et al.*, 2019). For water quality, AI detects pollutants more sensitively than conventional methods, improving environmental management and public health decisions (Bhatia *et al.*, 2022).

4.5 Integration of Multiple Data Sources

AI-driven monitoring systems excel at integrating diverse data streams to deliver comprehensive environmental insights. Unlike traditional methods that analyse systems in isolation, AI combines data from atmospheric, terrestrial, aquatic, and socioeconomic sources to capture ecosystem interconnections. For instance, AI-enhanced climate models integrate satellite data, soil moisture, and economic indicators to forecast droughts or crop yields (Reichstein *et al.*, 2019). In cities, AI merges traffic, energy, and air quality data to guide sustainable planning (Zhou *et al.*, 2020). In marine contexts, AI links ocean temperatures, chlorophyll levels, and

vessel tracking to manage fisheries and habitats. This holistic approach supports more informed, system-level environmental decision-making.

5. Challenges and Limitations

Artificial Intelligence (AI) is revolutionising environmental monitoring by enabling real-time tracking, large-scale analysis, and data integration. However, its implementation faces challenges such as data scarcity, algorithmic bias, infrastructure gaps, and ethical concerns. Addressing these issues is essential to promote responsible innovation and ensure sustainable, equitable conservation outcomes.

5.1 Data Limitations

AI systems depend heavily on high-quality, extensive datasets for effective training and prediction. Environmental data—from satellites, sensors, or camera traps—is often limited, especially in remote or biodiverse regions like tropical rainforests and deep-sea habitats (Rolnick *et al.*, 2019). This scarcity can lead to biased or unreliable AI outputs (Beery *et al.*, 2018). Moreover, data fragmentation across institutions and inconsistent standards further hinder interoperability and large-scale model development (Stephenson *et al.*, 2022), limiting the potential of AI in global environmental monitoring.

5.2 Algorithm Bias

AI systems are only as accurate as the data they learn from. Incomplete or biased datasets can lead to unreliable outputs, especially in biodiversity monitoring, where rare species and under-studied areas are often underrepresented (Norouzzadeh *et al.*, 2018). Models may misidentify species in unfamiliar conditions or overlook vulnerable communities lacking sufficient data (Willi *et al.*, 2019). Bias also affects climate and pollution models, which often rely on data from well-monitored, industrialised regions, widening global environmental disparities (Vinuesa *et al.*, 2020). Reducing bias requires diverse datasets, transparent modelling, and collaboration with local experts and communities.

5.3 Technical Barriers

AI-based monitoring systems require robust infrastructure—high-speed internet, cloud services, and GPUs, which are often lacking in developing regions (Tsamados *et al.*, 2022). A shortage of skilled personnel with expertise in ecology and data science further limits adoption (Reichstein *et al.*, 2019). High costs and the need for continual updates pose challenges for underfunded conservation efforts. Additionally, many AI models lack generalizability, performing poorly outside their training environments without retraining (Tuia *et al.*, 2022). Addressing these issues calls for investment in capacity building, open-access tools, and scalable solutions.

5.4 Ethical and Privacy Concerns

AI in environmental monitoring raises ethical concerns around privacy, consent, and indigenous rights. Technologies like drones and sensors may unintentionally capture sensitive data, intruding on local communities or sacred lands (Sandbrook *et al.*, 2021). Without proper consultation, such surveillance can erode trust and provoke resistance. Wildlife tracking tools, while useful, risk misuse by poachers if data security is weak (Garcia *et al.*, 2020). Automated decisions in conservation also raise accountability issues if AI misclassifies data, leading to flawed interventions. Moreover, overreliance on AI may marginalise local knowledge and participatory governance. Ethical AI must ensure inclusivity, transparency, and respect for environmental justice (Cave *et al.*, 2019).

6. Future Directions

Artificial Intelligence (AI) is transforming environmental monitoring through real-time analysis, predictive modelling, and data integration. Looking ahead, emerging trends such as edge AI, explainable AI (XAI), citizen science, and cross-disciplinary collaboration will further enhance system efficiency, accessibility, and ethical use. These innovations are set to boost performance while promoting trust, inclusivity, and impact in global conservation efforts.

6.1 Edge AI: Reducing Latency and Enhancing Autonomy

A major advancement in environmental AI is the rise of edge AI, which processes data locally on devices like drones or sensors instead of relying on cloud servers (Zhao *et al.*, 2021). This allows faster decisions, reduces data transmission, and enhances privacy. Edge AI is ideal for remote areas with limited connectivity, enabling real-time detection of issues like illegal logging or wildfires without internet access (PremSankar *et al.*, 2018). It also lowers energy use and supports the development of sustainable, low-carbon monitoring systems (Rolnick *et al.*, 2019).

6.2 Explainable AI (XAI): Building Trust and Transparency

An important advancement in conservation AI is explainable AI (XAI), which addresses the "black box" problem in complex models by making their decisions understandable (Guidotti *et al.*, 2018). This transparency is crucial for building trust and ensuring accountability in high-stakes areas like deforestation alerts or wildlife protection (Arrieta *et al.*, 2020). XAI clarifies which factors influenced a prediction, helping stakeholders make informed decisions and collaborate effectively. It also aids in identifying and correcting biases, promoting more ethical and inclusive environmental monitoring.

6.3 Citizen Science and Participatory AI

With growing access to AI, combining it with citizen science is enhancing data collection and public engagement. Non-experts—like students or birdwatchers—contribute ecological data through platforms such as iNaturalist and eBird, where AI helps identify species from images or sounds (Van Horn *et al.*, 2018). AI also validates and filters this crowdsourced data, increasing its scientific value. These tools boost environmental awareness and empower public participation in conservation. Future platforms may further expand access in underserved regions through localised, interactive features.

6.4 Cross-disciplinary Collaboration: Bridging Silos for Greater Impact

Solving complex environmental challenges requires cross-disciplinary collaboration. AI must be integrated with ecological knowledge, policy, and community input to be effective (Reichstein *et al.*, 2019). Developing tools for tasks like species monitoring involves understanding ecosystems, legal frameworks, and local customs. Partnerships among ecologists, data scientists, and policymakers promote responsible innovation and ensure AI aligns with conservation goals. Initiatives like AI for Earth and Data Science for Conservation support this collaboration through funding, open datasets, and shared training platforms (Vinuesa *et al.*, 2020).

6.5 Toward a Responsible and Inclusive AI Future

As AI plays a larger role in environmental monitoring, it must prioritise ethical design, transparency, and inclusion of marginalised communities. Future systems should support adaptive management and integrate local and indigenous knowledge to enhance relevance and impact (Stephenson *et al.*, 2022). With climate change accelerating, AI tools must be built for resilience and sustainability, not only in environmental outcomes but also in energy efficiency and community involvement.

Conclusion:

Artificial Intelligence is transforming environmental conservation by delivering fast, accurate, and scalable insights into ecosystems. From detecting deforestation to monitoring wildlife and forecasting climate impacts, AI enables real-time analysis and informed decision-making. Its benefits—scalability, cost-efficiency, and predictive power—are revolutionising how we manage and protect the planet. Yet challenges remain, including data gaps, ethical concerns, and limited infrastructure, especially in the Global South. Future progress depends on ethical design, interdisciplinary collaboration, and inclusive governance. Emerging tools like edge computing, explainable AI, and citizen science will further strengthen conservation efforts. Used

responsibly, AI is not just a technological advancement but a vital ally in safeguarding biodiversity and building a resilient, sustainable future.

References:

1. Arrieta, A. B., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., ... & Herrera, F. (2020). Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. *Information Fusion*, 58, 82–115.
2. Beery, S., Morris, D., & Yang, S. (2019). Efficient pipeline for camera trap image classification. *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops*, 254–262.
3. Beery, S., Van Horn, G., & Perona, P. (2018). Recognition in terra incognita. *Proceedings of the European Conference on Computer Vision (ECCV)*, 456–473.
4. Bhatia, S., Gupta, R., & Chhabra, P. (2022). Water quality monitoring using AI: A review of emerging technologies and trends in India. *Journal of Environmental Management*, 309, 114703. <https://doi.org/10.1016/j.jenvman.2022.114703>
5. Bourtsalas, A. C., Themelis, N. J., & Castaldi, M. J. (2019). Real-time air pollution monitoring using AI and IoT: The AIRSENSE case study. *Environmental Science & Policy*, 101, 77–87. <https://doi.org/10.1016/j.envsci.2019.07.006>
6. Cath, C., Wachter, S., Mittelstadt, B., Taddeo, M., & Floridi, L. (2018). Artificial intelligence and the ‘good society’: the US, EU, and UK approach. *Science and Engineering Ethics*, 24(2), 505–528. <https://doi.org/10.1007/s11948-017-9901-7>
7. Cave, S., Coughlan, K., & Dihal, K. (2019). Scary robots: Examining public responses to AI. *Nature Machine Intelligence*, 1(11), 404–406.
8. Chadès, I., Martin, T. G., Nicol, S., Burgman, M. A., Possingham, H. P., & Buckley, Y. M. (2012). General rules for managing and surveying networks of pests, diseases, and endangered species. *Proceedings of the National Academy of Sciences*, 109(20), 8323–8328. <https://doi.org/10.1073/pnas.1118765109>
9. Chantry, M., Dueben, P. D., Wedi, N., & Palmer, T. N. (2021). Machine learning for data assimilation and weather prediction. *Philosophical Transactions of the Royal Society A*, 379(2194), 20200086. <https://doi.org/10.1098/rsta.2020.0086>
10. Feng, L., Li, X., & Du, Y. (2020). Remote sensing of inland water quality: A review on advances and perspectives. *Remote Sensing of Environment*, 239, 111654.
11. Garcia, J. A., Van der Wal, R., & Gill, N. (2020). Conservation surveillance: Animal tracking, data infrastructures, and the politics of ecology. *Journal of Environmental Policy & Planning*, 22(6), 757–769. <https://doi.org/10.1080/1523908X.2020.1797161>

12. Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*, 202, 18–27. <https://doi.org/10.1016/j.rse.2017.06.031>
13. Guidotti, R., Monreale, A., Ruggieri, S., Turini, F., Giannotti, F., & Pedreschi, D. (2018). A survey of methods for explaining black box models. *ACM Computing Surveys (CSUR)*, 51(5), 1–42. <https://doi.org/10.1145/3236009>
14. Hansen, M. C., Potapov, P. V., Moore, R., Hancher, M., Turubanova, S. A., Tyukavina, A., ... & Townshend, J. R. G. (2013). High-resolution global maps of 21st-century forest cover change. *Science*, 342(6160), 850–853. <https://doi.org/10.1126/science.1244693>
15. Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. *Computers and Electronics in Agriculture*, 147, 70–90.
16. Krause, J., Arik, S. O., Chang, C., & Pham, H. (2021). AI-powered autonomous underwater drones for marine environment mapping. *Nature Machine Intelligence*, 3(6), 474–483.
17. Kroodsma, D. A., Mayorga, J., Hochberg, T., Miller, N. A., Boerder, K., Ferretti, F., ... & Worm, B. (2018). Tracking the global footprint of fisheries. *Science*, 359(6378), 904–908.
18. Kumar, R., Vyas, A., & Sharma, R. (2021). Deep learning model for coral reef bleaching prediction using sea surface temperature data. *Environmental Monitoring and Assessment*, 193(2), 1–14. <https://doi.org/10.1007/s10661-021-08860-w>
19. LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, 521(7553), 436–444.
20. Liu, G., Strong, A. E., Skirving, W., & Arzayus, L. F. (2014). Overview of NOAA Coral Reef Watch program's near-real-time satellite global coral bleaching monitoring activities. *Proceedings of the 10th International Coral Reef Symposium*, 178–182.
21. Lovett, G. M., Burns, D. A., Driscoll, C. T., Jenkins, J. C., Mitchell, M. J., Rustad, L., ... & Weathers, K. C. (2007). Who needs environmental monitoring? *Frontiers in Ecology and the Environment*, 5(5), 253–260.
22. Norouzzadeh, M. S., Nguyen, A., Kosmala, M., Swanson, A., Palmer, M. S., Packer, C., & Clune, J. (2018). Automatically identifying, counting, and describing wild animals in camera-trap images with deep learning. *Proceedings of the National Academy of Sciences*, 115(25), E5716–E5725. <https://doi.org/10.1073/pnas.1719367115>
23. Porter, J. H., Nagy, E., Kratz, T. K., Hanson, P., Collins, S. L., & Arzberger, P. (2005). New eyes on the world: advanced sensors for ecology. *BioScience*, 55(9), 735–746.
24. Premsankar, G., Di Francesco, M., & Taleb, T. (2018). Edge computing for the Internet of Things: A case study. *IEEE Internet of Things Journal*, 5(2), 1275–1284.

25. Reichstein, M., Camps-Valls, G., Stevens, B., Jung, M., Denzler, J., Carvalhais, N., & Prabhat. (2019). Deep learning and process understanding for data-driven Earth system science. *Nature*, 566(7743), 195–204. <https://doi.org/10.1038/s41586-019-0912-1>
26. Rolnick, D., Donti, P. L., Kaack, L. H., Kochanski, K., Lacoste, A., Sankaran, K., ... & Bengio, Y. (2019). Tackling climate change with machine learning. arXiv preprint arXiv:1906.05433. <https://arxiv.org/abs/1906.05433>
27. Sandbrook, C., Luque-Lora, R., & Adams, W. M. (2021). Human bycatch: Conservation surveillance and the social implications of camera traps. *Conservation and Society*, 19(3), 235–246. https://doi.org/10.4103/cs.cs_20_61
28. Sendak, M., D’Arcy, J., Kashyap, S., Gao, M., Nichols, M., Corey, K., ... & Balu, S. (2020). A path for translation of machine learning products into healthcare delivery. *NPJ Digital Medicine*, 3(1), 1–10. <https://doi.org/10.1038/s41746-020-00314-2>
29. Singh, R., Garg, P., & Kumar, M. (2021). AI-based environmental monitoring using IoT and big data: a comprehensive review. *Environmental Monitoring and Assessment*, 193(9), 1–19. <https://doi.org/10.1007/s10661-021-09352-6>
30. Stephenson, P. J., Burgess, N. D., Jungmann, L., Loh, J., Outhwaite, C. L., & Walpole, M. J. (2022). Overcoming barriers to data sharing in biodiversity monitoring. *Biological Conservation*, 266, 109440. <https://doi.org/10.1016/j.biocon.2021.109440>
31. Stowell, D., Seki, H., & Noda, K. (2019). Acoustic monitoring of biodiversity using machine learning. *Current Opinion in Environmental Sustainability*, 36, 86–95.
32. Tompson, J., Schlachter, K., Sohl-Dickstein, J., & Sutskever, I. (2017). Accelerating weather prediction with deep learning. arXiv preprint arXiv:1702.05174
33. Tsamados, A., Aggarwal, N., Cowls, J., Morley, J., Roberts, H., Taddeo, M., & Floridi, L. (2022). The ethical AI governance framework: A practical tool for policymakers. *AI and Ethics*, 2, 1–14. <https://doi.org/10.1007/s43681-021-00107-6>
34. Tuia, D., Kellenberger, B., Beery, S., Costelloe, B. R., Zuffi, S., Risse, B., ... & Gomes, C. P. (2022). Seeing biodiversity: Using computer vision to monitor biodiversity. *Science*, 375(6582), eabf8671. <https://doi.org/10.1126/science.abf8671>
35. Tuia, D., Kellenberger, B., Beery, S., Costelloe, B. R., Zuffi, S., Risse, B., ... & Kays, R. (2022). Perspectives in machine learning for wildlife conservation. *Nature Communications*, 13(1), 792. <https://doi.org/10.1038/s41467-022-28388-7>
36. Van Horn, G., Mac Aodha, O., Song, Y., Cui, Y., Sun, C., Shepard, A., ... & Perona, P. (2018). The iNaturalist species classification and detection dataset. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 8769–8778.

37. Vinuesa, R., Azizpour, H., Leite, I., Balaam, M., Dignum, V., Domisch, S., ... & Fuso Nerini, F. (2020). The role of artificial intelligence in achieving the Sustainable Development Goals. *Nature Communications*, 11(1), 1–10. <https://doi.org/10.1038/s41467-019-14108-y>
38. Wearn, O. R., Freeman, R., & Jacoby, D. M. P. (2019). Responsible AI for conservation. *Nature Sustainability*, 2(7), 476–478. <https://doi.org/10.1038/s41893-019-0387-8>
39. Willi, M., Pitman, R. T., Cardoso, A. W., Locke, C., Swanson, A., Boyer, A., ... & Fortson, L. (2019). Identifying animal species in camera trap images using deep learning and citizen science. *Methods in Ecology and Evolution*, 10(1), 80–91.
40. Xie, C., Shao, Z., & Shen, L. (2018). Remote sensing image classification using deep learning and cloud model. *International Journal of Remote Sensing*, 39(15-16), 5490–5513.
41. Young, T., Hazarika, D., Poria, S., & Cambria, E. (2018). Recent trends in deep learning based natural language processing. *IEEE Computational Intelligence Magazine*, 13(3), 55–75.
42. Zhao, Z., Wang, L., Liu, Q., Sun, H., Liu, Z., & Xie, Y. (2021). Edge AI: On-demand accelerating deep neural network inference via edge computing. *IEEE Transactions on Industrial Informatics*, 17(9), 6302–6311. <https://doi.org/10.1109/TII.2020.3008693>
43. Zhou, Y., Xu, Y., & Zhang, Q. (2020). Smart city and artificial intelligence: Applications and research agenda. *Sustainable Cities and Society*, 61, 102373.