Artificial Intelligence Applications in Addressing the Ecological Crisis: A Critical Review

Ekolojik Krizlerin Çözümünde Yapay Zekanın Rolü: Eleştirel Bir İnceleme

Bedri Sina GÜNEŞ[1]

Araştırma Makalesi/Research Article
Başvuru/Received: 29.09.2025; Revizyon/Revised: 29.10.2025; Kabul/Accepted: 29.10.2025

ABSTRACT

This study critically examines the potential of 21st-century technological transformation, particularly artificial intelligence (AI), in addressing ecological crises. Drawing on historical and societal transformations—from hunter-gatherer societies to feudal and capitalist systems—it highlights how human-nature relationships have been reshaped and how ecological crises are closely intertwined with production relations. The paper explores AI applications in key ecological domains, including water quality, air quality, biodiversity and habitat conservation, and carbon capture and storage, demonstrating that these technologies can play an effective role in monitoring and mitigating environmental problems. However, case studies indicate that the potential benefits of AI are constrained by data infrastructure gaps, high costs, algorithmic uncertainties, social inequalities, and insufficient governance mechanisms. The study argues that the effectiveness of AI in ecological crisis management depends not only on technical advancements but also on social adaptation, inclusive governance, and equitable access to resources. When deployed with societal oversight and aligned with collective well-being, AI technologies can serve as powerful tools for sustainable ecological management, whereas unregulated or inequitable use risks deepening existing crises.

Keywords: Artificial Intelligence, Ecological Crisis, Environmental Governance, Technological Transformation

ÖZ

Bu çalışma, özellikle yapay zekâ (YZ) bağlamında 21. yüzyılda yaşanan teknolojik dönüşümün ekolojik krizlerin çözümündeki potansiyelini eleştirel bir bakış açısıyla incelemektedir. Avcı-toplayıcı toplumlardan feodal ve kapitalist sistemlere kadar uzanan tarihsel ve toplumsal dönüşümler üzerinden, insan-doğa ilişkilerinin nasıl yeniden şekillendiğini ve ekolojik krizlerin üretim ilişkileriyle ne kadar sıkı bir bağ içinde olduğunu ortaya koymaktadır. Makale, su kalitesi, hava kalitesi, biyolojik çeşitlilik ve habitat koruma ile karbon yakalama ve depolama gibi temel ekolojik alanlarda YZ uygulamalarını ele alarak, bu teknolojilerin çevresel sorunları izleme ve hafifletmede etkili bir rol oynayabileceğini göstermektedir. Ancak vaka çalışmaları, YZ'nin potansiyel faydalarının veri altyapısı eksiklikleri, yüksek maliyetler, algoritmik belirsizlikler, toplumsal eşitsizlikler ve yetersiz yönetişim mekanizmaları nedeniyle sınırlı kaldığını ortaya koymaktadır. Çalışma, YZ'nin ekolojik kriz yönetiminde etkinliğinin yalnızca teknik gelişmelere değil, aynı zamanda toplumsal adaptasyona, kapsayıcı yönetişime ve kaynaklara adil erişime bağlı olduğunu vurgulamaktadır. YZ teknolojileri, toplumsal gözetimle ve ortak iyiye odaklanarak kullanıldığında sürdürülebilir ekolojik yönetim için güçlü araçlar haline gelebilir; aksi takdirde düzensiz veya adaletsiz kullanım mevcut krizleri derinleştirme riski taşımaktadır.

Anahtar Kelimeler: Yapay Zeka, Ekolojik Kriz, Çevre Yönetişimi, Teknolojik Dönüşüm

[1] Işık University, Department of Humanities and Social Sciences, b.sina.gunes@gmail.com, **ORCID:** 0000-0002-8330-8282

1. Introduction

The 21st century is often characterized as the age of technology, primarily due to the prevalence of technological developments. However, this era not only witnesses the acceleration of technological innovations but also represents a process in which these developments fundamentally transform existing social, economic, and ecological structures. Castells (2010:21) conceptualizes this phenomenon as the "network society," emphasizing that technology constitutes a foundational element of new social formations. Bell (1999:12), nearly half a century ago, analyzed post-industrial society and noted that knowledge and technological innovation had become decisive factors in production relations. Examining this technological transformation, it can be argued that it restructures not only modes of production but also governance mechanisms, living spaces, and everyday social relations (Jasanoff, 2016: 34).

Considering the disruptive nature of this transformation, it is plausible to view it as an opportunity to address many enduring problems. Among these, one of the greatest global challenges in human history is the ecological crisis. Environmental issues, accelerated by capitalist production relations[2] and deepened by neoliberal policies such as air, water, and soil pollution, deforestation, biodiversity loss, waste crises, and noise pollution, threaten the sustainability of life on a global scale (Foster, 2020: 58; Klein, 2014: 73). Therefore, it is useful to discuss technological transformation not only in terms of economic efficiency or social organization but also in the context of ecological sustainability. In this new era, AI emerges as a potential tool for addressing environmental problems. Yet, this potential necessitates a critical examination of how, for whose benefit, and within which social relations AI is or will be employed.

To understand the uniqueness of the accelerated technological transformation in the 21st century, it is important to compare it with historical social changes. Transitions from hunter-gatherer communities to feudal societies, and from feudal societies to capitalist societies, each time profoundly transformed production relations, living spaces, and human–human, human–society, and human–power relations (Polanyi, 2024: 17). Similarly, the ongoing technological transformation introduces new modes of production and living, new power relations, and new

[2] The acceleration of environmental problems under capitalist production relations should not be interpreted as meaning that capitalism is the sole cause of the ecological crisis. It is well known that the experiences of real socialism and central planning, as in the USSR and China, also contributed to ecological crises (Kochetkova, 2024; Arndt, 2022; Liu et al., 2025). This is why the emphasis on neoliberalism is significant. This emphasis refers to the parallel development of globalization and neoliberal policies following the collapse of the USSR and China's economic reforms after 1978, which is argued to have played a central role in the globalization of the ecological crisis (Swampa, 2019; Patel & Moore, 2017; Foster et al., 2020).

ecological disruptions (Burawoy, 2005: 9). Therefore, ecological crises should not be considered separate from technological transformation; rather, they must be central to ecological debates as both a cause and a consequence of this transformation (Harvey, 2017: 115).

Discussing the role of AI in addressing environmental problems is not merely a technical matter but also a social and political one. Marx's (2011: 87) analysis of the dialectical relationship between nature and human labor demonstrates how technology transforms nature while simultaneously reproducing social relations. In this context, while AI has the potential to prevent the formation of ecological crises or mitigate existing ones, it should not be evaluated independently of capitalist production relations (Burkett, 2014: 56; Saito, 2022: 93), and its contribution to solutions must be examined within this framework.

This study specifically focuses on AI applications in environmental management observed in the United Kingdom and other developed countries, particularly the United States, Germany, Canada, and Australia. These countries were chosen because they offer the most comprehensive examples in terms of data accessibility, technical infrastructure, and policy integration (Berrisford, Ribeiro & Menezes, 2022: 48; IEA, 2022: 33). While there are relevant initiatives in Latin America, Africa, and Asia, they differ significantly regarding state–private sector relations, data access, and ownership structures of production tools, and thus fall outside the primary scope of this study (Svampa, 2019: 77; Gudynas, 2020: 41). However, when directly comparable, examples from these regions are briefly referenced in terms of outcomes and implications. This selection allows the study to focus on specific ecological domains, water quality, air quality, biodiversity and habitat conservation, and carbon capture and storage where AI interventions have been most effectively implemented. The selected cases are therefore both representative and methodologically appropriate for assessing AI's potential in managing ecological crises.

This study examines AI from the perspective that its proper use can play an effective role in addressing ecological crises, yet it does so critically within the current system. First, the study presents the nature of technological transformation and its relation to historical social changes. Next, it discusses the diversity of environmental problems and their position within a technological context. Subsequently, case studies are evaluated in which current AI applications are employed in specific countries, including water quality, air quality, biodiversity and habitat conservation, and carbon capture and storage. Finally, the study concludes by discussing the potential of AI in addressing ecological crises.

2. Historical, Social Transformations, and Technological Change

Although human history has not followed a linear trajectory, it has consistently been shaped by transformations that deconstruct and reorganize social structures. Examining historical social development reveals that all major societal transformations have not only redefined production relations and social structures but also fundamentally reshaped human interactions with nature. For instance, the transition from hunter-gatherer communities to agricultural societies altered humanity's position relative to nature. Nature ceased to be merely a source of sustenance and became a domain that needed to be transformed for production and settled life (Bell, 1999). While in hunter-gatherer communities nature was transformed only to a limited extent for the sustainability of life (Ponting, 2020; Morgan, 1994), in feudal societies it became the object of human labor and productive forces. Furthermore, the centrality of land as both a source of production and power in feudal societies (Marx, 2013) demonstrates the determining role of nature within social relations. The transition from feudal to capitalist society placed the market and capital accumulation at the center of production relations. Under the capitalist mode of production, nature was treated as an unlimited source of raw materials, accelerating its commodification (Polanyi, 2024). The Industrial Revolution, with accelerated production, expanded scales of production, and the widespread use of fossil fuels, increased pressure on nature. This process, beginning in the 19th century, produced the first visible examples of environmental crises, such as air pollution, waste, and urbanization-related problems, in the 20th century (Marx, 2011; Foster, 2020:15-25; 36-42).

In this study, the focus is placed on AI and ecological applications observed mainly in the United Kingdom and other developed countries such as the United States, Germany, Canada, and Australia. These cases were selected because they provide large-scale, data-rich examples of AI-based ecological management, which are crucial for comparative analysis. While similar initiatives exist in Latin America, Africa, and Asia, their inclusion would require a separate and extensive study due to the distinct socio-economic and political dynamics of those regions. Therefore, the selected examples are considered representative for analyzing AI's effectiveness in ecological crisis management within the context of advanced technological infrastructures and governance models.

It can be argued that a common feature of major transformations in human history is that changes in production relations not only reshape social structures but also redefine the relationship with nature. Moreover, within this historical framework, the increasing commodification of nature forms the roots of the ecological crisis we face today.

The technological transformation occurring in the 21st century represents a phase that maintains continuity with previous historical ruptures while also qualitatively differing from them. As with the transitions from hunter-gatherer societies to feudal societies and from feudal societies to capitalist societies, contemporary transformations are redefining production relations, modes of life, and interactions with nature. However, this time the transformation is centered on digitalization, AI, and data capitalism. These technologies are transforming not only economic production relations but also political decision-making processes, social communication, and ecological governance (Bell, 1999; Foster, 2020: 15-25; 36-42). Therefore, understanding the relationship between historical social transformations and current technological change is critical to discussing AI's potential role in addressing the ecological crisis. Throughout history, every social transformation has reshaped human-nature relations, generating new environmental challenges. In the 21st century, the scale and speed of technological transformation carry a dual potential: to deepen the ecological crisis and to contribute to its resolution. Thus, technological transformation must be considered not only in economic and social terms but also through its ecological dimension.

In this context, the ecological dimension of technological transformation should be assessed not only in terms of potential solutions but also in light of the new risks it generates. Digitalization and AI bring challenges ranging from energy consumption to the ecological burden of data centers, thereby potentially intensifying the current dynamics of the ecological crisis. On the other hand, these technologies can serve as important tools contributing to carbon emission reductions, water resource management, biodiversity preservation, and ecosystem monitoring. Although this may appear as a contradiction arising from the incomplete consideration of AI technologies and their applications, understanding this situation is essential for grasping the contemporary nature of technological transformation. This dual nature does not originate solely from the intrinsic nature of technology; it is also directly related to who controls these technological tools, for what purposes, and how they are used. Historically, the social ownership of production tools has also determined the relationship with nature. For example, the commodification of nature and its treatment as an unlimited raw material source produce very different outcomes compared to its use from a collective or ecological perspective. In this regard, AI, if used solely for profit maximization, may exacerbate the ecological crisis; however, when deployed with a focus on social welfare and ecological sustainability, it can become a critical tool in mitigating the crisis. Moreover, AI's energy consumption issue is closely linked to societal choices. For instance, powering data centers with renewable energy instead of fossil fuels can fundamentally alter the ecological impact of these technologies. Therefore, discussions should not be limited to the technology itself but must also consider the social relations within which these technologies are produced and how they are employed (Harvey, 2017: 65; Foster, 2020: 118; Svampa, 2019: 32).

3. Ecological Crisis and Its Relationship with Technology

The ecological crisis is frequently discussed under specific headings today, such as climate change, plastic waste, water pollution, animal rights, or deforestation. Activist movements often organize around one of these issues. However, this approach tends to treat the crisis as a sum of disconnected problems, overlooking the holistic character of the ecological crisis. In contrast, the ecological crisis should be approached as a multilayered whole, with interlinked and feedback-reinforcing processes (Foster, 2020: 15-25; 36-42; Moore, 2015: 53-67; Steffen et al., 2015). Therefore, developing an understanding of “ecological wholeness,” which cannot be reduced to the sum of its parts, is critical for designing more effective solutions. While addressing individual ecological problems and developing targeted solutions is valuable, defining the ecological crisis conceptually, where these parts converge, provides a more accurate understanding of both the origins of the problem and potential solution perspectives (Latour, 2018; IPCC, 2022). This holistic approach not only contributes to understanding and addressing environmental problems but also facilitates an understanding of the dialectical relationship between technology and ecological crisis, enabling the proper use of technological tools in mitigating these crises.

One reason ecological crises are not treated holistically may be related to the emergence of environmental issues. Until the mid-20th century, environmental concerns primarily involved air and water pollution and waste-related problems caused by urbanization. From the second half of the 20th century onward, however, the crisis took on a global and existential character, encompassing climate change, biodiversity loss, deforestation, and desertification (Carson, 1962: 34-43; Foster, 2020:15-25;36-42). A common thread across these issues is the redefinition of the human-nature relationship through modes of production, during which nature is viewed as an unlimited resource for production (Polanyi, 2024; Marx, 2011: 283-290).

With the onset of the 21st century, technology has emerged both as a determinant in the emergence of the crisis and as a potential tool for solutions. Fossil fuel-based production since the Industrial Revolution has increased atmospheric carbon intensity, contributing to climate change as a fundamental dynamic (Steffen et al., 2015). Agricultural chemicals and industrial techniques have disrupted natural soil cycles, accelerating biodiversity loss (Altvater & Mahnkopf, 1997: 42-50). Rapid urbanization has created persistent new threats to global ecosystems, such as plastic pollution (Geyer, Jambeck & Law, 2017). Thus, within 19th- and 20th-century production relations, technology primarily functioned not as a factor increasing production efficiency but as a process exacerbating ecological crises.

Although it is not yet possible to assert that this trend has fully reversed in the 21st century, it is observable that as the ecological crisis increasingly affects daily life, there is a growing effort to leverage technology as part of the solution. Particularly, digitalization and AI continue to demonstrate potential in mitigating ecological crises, despite existing limitations, user capabilities, and usage patterns. For instance, through big data and machine learning models, air and water pollution can be monitored more rapidly, early warning systems can be developed, and concrete data can be produced to inform ecosystem protection policies (Rolnick et al., 2022: 198-203). AI applications aimed at improving energy efficiency facilitate the management of renewable energy networks and offer solutions for reducing carbon emissions (IEA, 2023: 14-18).

Another key potential contribution of AI to solving ecological crises lies in its capacity to generate forecasts and predictions. Advancements in AI have made it possible to process previously unmanageable datasets. By analyzing large datasets, AI models can predict crises directly affecting human survival, such as regional impacts of climate change, biodiversity losses, or water scarcity risks. This capability enables ecological movements to take initiative and engage with policymakers and global, regional, and local authorities to implement early measures (Rolnick et al., 2022; Reichstein et al., 2019). For example, AI algorithms used in climate models can more precisely project the local ecosystem impacts of temperature increases, facilitating the development of adaptation strategies. Similarly, machine learning applications modeling ecosystem dynamics can anticipate habitat loss and species extinction risks, supporting the design of more effective global and regional conservation policies (Branco et al., 2023).

The predictive capacity provided by AI allows strategies against ecological crises to be not only reactive responses to existing problems but also proactive policies for the future. Consequently, when evaluated within appropriate social relationships, AI and digitalization can serve as critical tools that not only mitigate the current effects of the crisis but also anticipate potential risks, preventing the further deepening of ecological crises (IEA, 2023; Sætra, 2021).

Therefore, understanding the ecological crisis should not be limited to examining natural processes or localized and isolated issues. The diversity and mutually reinforcing structure of the crisis highlight the dual role that technology plays in these processes. On the one hand, technology enables production methods that exacerbate ecological crises; on the other, when employed for social benefit, it holds the potential to alleviate crises and develop proactive strategies for the future. In particular, the monitoring, forecasting, and predictive capacities provided by artificial intelligence and digitalization can contribute to the design of policies that preserve ecological integrity more effectively.

4. Applications of Artificial Intelligence in Addressing the Ecological Crisis

In the 21st century, the rapid development of technology and digitalization has created new opportunities for monitoring and managing ecological crises. AI, through big data analysis, machine learning, and predictive models, has begun to be applied in areas such as water quality monitoring, air quality management, biodiversity and habitat conservation, and carbon capture and storage. This development stems particularly from the growing volume of data, increased computational power, and the pressing need to establish early warning systems for ecosystems. Consequently, AI has come to be seen not merely as a monitoring instrument but as an integrated management tool for ecological governance.

Examples from countries such as the United Kingdom, the United States, Canada, Germany, and Australia highlight the diverse applications of AI in this field, ranging from water quality monitoring and invasive species detection to carbon management. While the contexts differ, these cases collectively demonstrate the expanding role of AI in supporting ecological sustainability.

4.1. Water Quality

Water pollution is one of the most visible dimensions of ecological crises and directly affects human life. In the 21st century, AI technologies have begun to be used as important tools for monitoring water pollution, managing resources, and predicting pollution risks. In this context, several studies have revealed both the potential and the limitations of AI applications.

In the United Kingdom, the use of AI applications in water pollution management has accelerated over the past decade. The implementation of AI-based sensors and machine learning algorithms in the Thames River and surrounding catchments provides a notable example (Environment Agency, 2023). These systems monitor the chemical and biological parameters of the water in real time and predict potential sources of pollution. The models employed within the project process historical datasets to estimate the areas and time periods in which pollution is likely to occur, thereby contributing directly to water management and policy-making processes (US EPA, 2022). AI applications are used not only for pollution detection but also for developing risk analyses and early warning systems. For example, studies conducted on the Thames River have shown that machine learning algorithms can distinguish between agricultural and industrial sources of pollution (Environment Agency, 2023). These applications demonstrate the potential for shifting water management strategies from reactive approaches to proactive and predictive ones.

However, studies on AI applications in the Thames River also reveal significant obstacles, primarily the high costs of data collection infrastructure, the limited number of sensors in rural areas, and the detection errors of algorithms when faced with unexpected types of pollution (CEH, 2021; Spectroscopy Online, 2023). The high infrastructure cost stems from the need for continuous investment in sensor installation, maintenance, and data transmission systems. The limited number of sensors in rural areas results from economic priorities being directed toward urban centers, leaving rural areas with fewer infrastructure investments. This imbalance reflects broader neoliberal tendencies in environmental governance, where resource allocation is guided by cost–benefit calculations rather than ecological necessity. Consequently, AI deployment reproduces existing socio-spatial inequalities, privileging technologically advanced urban regions while marginalizing rural ecosystems that face distinct ecological pressures. The errors made by algorithms in detecting unusual pollutants stem from their reliance on historical datasets for training, which leads to prediction inaccuracies when encountering novel contaminants. This underscores the ongoing need for human oversight and policy integration to ensure the effectiveness of AI systems. The limitations of AI's potential, constrained by data infrastructure, algorithmic design, and uneven investment, illustrate how ecological technology remains entangled with socio-economic priorities. For instance, investments concentrated in London and surrounding urban areas have resulted in fewer sensors and limited monitoring capacity in rural regions (CEH, 2021). While algorithmic errors may be corrected over time, addressing these challenges remains critical for preventing ecological crises.

Similar studies have also been conducted in other countries. In the United States, AI-based models are applied in the Great Lakes Basin to predict agricultural and industrial pollution (US EPA, 2022). In Canada, machine learning algorithms are used in the Ontario region to forecast nitrate and phosphate levels in rivers (Natural Resources Canada, 2021). In Germany, AI-supported monitoring systems are being developed for the Rhine River to enable the early detection of industrial pollution (German Environment Agency, 2022). Although differences exist in terms of data infrastructure, scale, and local ecological conditions, these cases collectively demonstrate the growing global reliance on AI for the detection and prevention of water pollution.

Taken together, these national cases illustrate both the promise and the uneven geography of AI-driven water management. While technological innovation has expanded the capacity for real-time monitoring and predictive modeling, the deployment of such systems remains closely tied to the political economies in which they emerge. The disparities in data infrastructure, investment priorities, and institutional coordination reveal how technological capacity and environmental governance co-evolve within distinct socio-economic contexts. Consequently, the integration of AI into water quality management not only reflects advances in environmental technology but also exposes enduring inequalities in how ecological knowledge is produced, distributed, and applied across regions.

4.2. Air Quality

Air pollution is one of the most widespread dimensions of the ecological crisis in the 21st century, directly affecting human health. According to the World Health Organization, approximately seven million premature deaths each year are directly linked to air pollution (WHO, 2023). Traditional monitoring methods, which typically rely on a limited number of sensors and stationary stations, often fail to capture the spatial and temporal variability of pollution. By integrating big data analytics, machine learning, and remote sensing technologies, AI enables a more precise and dynamic assessment of air quality (Chen et al., 2023), demonstrating its significant potential in advancing environmental monitoring and policy design.

In the United Kingdom, the significance of air pollution has deep historical roots. The 1952 disaster in London, known as the "Great Smog" or "Big Smoke," caused the deaths of around 12,000 people and remains one of the most severe environmental crises in the country's history (Bell & Davis, 2001). Following this tragedy, air quality policies were strengthened, leading to the enactment of the Clean Air Act of 1956. However, the increasing use of motor vehicles, industrial emissions, and climate change have once again made air pollution a pressing ecological crisis. In this context, AI-based applications can be viewed as a continuation of historical air quality governance adapted to the digital era.

AI applications for air pollution monitoring and management in the UK are particularly concentrated in London. Since 2018, under the London Air Quality Network (LAQN), AI algorithms have been used to integrate traffic density, meteorological data, and industrial emissions in order to predict NO_2 and PM2.5 levels (Greater London Authority, 2021). This system has allowed for more accurate modeling of urban air pollution distribution and, since 2019, has served as a critical decision-support tool for the implementation of Ultra Low Emission Zone (ULEZ) policies (Beevers et al., 2021).

Despite these advances, several limitations persist. The reliability of AI-based air pollution models depends heavily on data density and the availability of sensor infrastructure. Limited sensor deployment in rural areas creates spatial inequalities and directs policy applications predominantly toward metropolitan regions (Harrison et al., 2022). Moreover, AI models show increased error margins under unexpected meteorological conditions, revealing that fully automated systems remain insufficient without human oversight (Grange & Carslaw, 2023). As with other fields, this demonstrates that the effectiveness of technology depends not only on technical capacity but also on social and political choices.

Examples from other countries highlight similar patterns. China, which suffers heavily from air pollution, developed the AI-supported *Blue Sky Program* in Beijing, integrating satellite data and meteorological forecasts to achieve up to 20% more accurate predictions (Zhang et al., 2022). In India's capital, Delhi, AI algorithms are used to assess health risks and support emergency policies in areas with high concentrations of PM10 and PM2.5 (Guttikunda et al., 2023). In California, USA, where annual wildfires have become a global concern, AI-based air quality monitoring systems track smoke dispersion in real time and have supported the development of early warning mechanisms (EPA, 2023).

4.3. Biodiversity and Habitat Conservation

The 21st century has been marked by a rapid decline in biodiversity. As a result, AI technologies have emerged as valuable tools in monitoring ecosystem health and informing conservation strategies. By integrating big data analytics, machine learning, and remote sensing technologies, AI enables real-time monitoring of habitats and the early detection of threats. These technologies are increasingly applied in species monitoring, habitat modeling, and ecological risk assessments (Turing Institute, 2025; ScienceDirect, 2024).

In the United Kingdom, one of the most notable AI applications for biodiversity conservation is the *National Hedgehog Monitoring Programme* (NHMP), launched in 2024. This three-year pilot project combines AI, camera traps, and contributions from citizen volunteers to monitor hedgehog populations across different habitats and track annual changes (Durham University, 2024). Findings from the NHMP indicate that hedgehog populations in rural areas have declined by 30–75% since the year 2000 (Defra, 2024). The decline has been linked to habitat loss, agricultural practices, and road traffic.

The NHMP demonstrates the potential of AI to enhance biodiversity monitoring. By analyzing large datasets, AI makes it possible to assess the population dynamics of species such as hedgehogs more efficiently and accurately. However, as the NHMP also illustrates, the success of such projects depends not only on technological innovation but also on data quality, algorithmic accuracy, and sustained public participation. The effectiveness of AI in biodiversity conservation is therefore tied to both technological progress and the degree to which these tools are adopted, supported, and integrated by communities. The NHMP highlights not only AI's potential in biodiversity conservation but also the central role of social factors in realizing that potential. Moreover, this case suggests that extending similar AI applications to other species could contribute significantly to restoring ecological balance.

Comparable initiatives are also being implemented in other countries. The "Eyes on Recovery" project, launched by WWF in partnership with Google, analyzed over seven million images following the Australian bushfires to monitor species re-emergence and track faunal changes, thereby strengthening conservation strategies (WWF, 2024). In Canada's Ontario region, AI-supported monitoring and deep learning algorithms are being used to track the distribution of rare plant and animal species, helping inform conservation policy (MDPI, 2024). In Germany, AI-based acoustic sensors and automated recognition systems are deployed in riparian and wetland habitats of the Rhine River basin to monitor bird and amphibian populations, providing important data for future applications (German Environment Agency, 2022).

4.4. Carbon Capture and Storage

Reducing carbon emissions remains an essential step in addressing the ecological crisis. The intensive use of fossil fuels has accelerated climate change and placed serious pressure on ecosystems (IPCC, 2023). Carbon Capture and Storage (CCS) technologies have emerged as a key strategy to reduce the amount of CO_2 released into the atmosphere. In this process, AI has the potential to make significant contributions in areas such as data analytics, process optimization, and risk management.

In the United Kingdom, the integration of CCS technologies with AI can be observed particularly in the Sleipner CCS Project and the White Rose CCS pilot projects. Since 1996, similar technologies have been implemented at the Sleipner site in Norway, and the UK has drawn on this experience (IEA, 2022). In the White Rose CCS project, AI is used to optimize carbon capture processes, minimize energy consumption, and enhance storage safety (BEIS, 2021). AI algorithms analyze millions of data points collected from sensors, enabling the early detection of potential leakage risks and improving operational efficiency (Figueroa et al., 2020). However, certain limitations remain in scaling up CCS technologies, including high costs, infrastructure requirements, and the limited availability of suitable storage sites. Furthermore, the accuracy of AI systems depends on the quality of sensor data and the performance of modeling algorithms. In this context, the effectiveness of the technology is not solely determined by technical capacity but also reflects economic and political choices (Zhou et al., 2022; IEA, 2022).

CCS and AI applications are increasingly being adopted worldwide, with many countries contributing to these developments. For instance, in Norway, AI-assisted sensors and optimization systems are used at the Sleipner and Snøhvit sites to enhance storage safety (IEA, 2022). In the United States, the Petra Nova CCS facility employs AI to monitor CO_2 flows and optimize energy efficiency (NETL, 2021). In Canada, CCS projects in Alberta are increasingly supported by AI and machine learning in site management and risk assessment processes (Natural Resources Canada, 2021).

5. Limitations and Shortcomings in AI Applications

The potential of AI-based technologies in addressing ecological crises is evident in areas such as water pollution, air pollution, biodiversity conservation, and carbon capture. However, the implementation and evaluation of these technologies depend not only on technical capacity but also on social, economic, and political conditions. While existing applications demonstrate a certain level of success in detecting and monitoring crises, it is not possible to claim that AI-based applications have reached their full potential due to shortcomings such as deficiencies in data infrastructure, limitations of algorithms, social inequalities, and insufficient policy integration. In this context, the capacity of AI to address ecological crises extends beyond being a technical tool and is directly related to social governance, equitable data distribution, and sustainable energy use. Therefore, without understanding and addressing these shortcomings, the sustainable and equitable use of AI technologies appears challenging.

Explaining the limitations and shortcomings encountered in AI applications contributes to the identification of problems and the understanding of potential solutions.

5.1. Infrastructure and Cost Issues

While the growing adoption of AI-based applications for ecological crisis management offers hope for solutions, the effectiveness of these applications largely depends on the scope and quality of data collection infrastructure. However, the current situation presents significant limitations in both infrastructure and cost. For instance, the installation, maintenance, and updating of sensors and monitoring systems used in AI-based applications require high expenditures. This limits the use of these systems in rural and low-density areas, resulting in high data density in urban centers while rural areas remain low or even insufficiently monitored. This imbalance directly affects the accuracy and reliability of AI models (Berrisford, Ribeiro, & Menezes, 2022).

Cost issues can be seen not only as a technical barrier but also as a societal problem, where economic and political priorities take precedence over ecology and the quality of human life. Urban centers, due to economic and political priorities, are more advantaged in terms of sensor and data infrastructure, whereas data scarcity in rural areas reduces the effectiveness of AI applications and increases societal vulnerability to ecological risks.

Thus, data infrastructure and cost challenges form a dual constraint limiting AI's potential to address ecological crises: they prevent the full utilization of technical capacity and reinforce existing social and economic inequalities. Overcoming these limitations requires not only technical improvements but also social governance, equitable data distribution, and a reassessment of economic priorities. Strategies such as renewable energy adoption and open data sharing can reduce costs and distribute infrastructure more evenly, enabling AI applications to be effective both technically and socially.

5.2. Uncertainties and Errors

Although AI models are increasingly used in ecological crisis management, unpredictabilities, such as unexpected or rare types of pollution, can sometimes hinder accurate and timely forecasts. Especially in applications related to water quality, air quality, biodiversity, and carbon capture, data gaps and limitations in algorithm design can lead to errors (Berrisford, Ribeiro, & Menezes, 2022). These errors reduce the predictive capacity of the model and limit the effectiveness of risk management. The performance of algorithms depends on the scope and quality of the data used; in regions with insufficient data infrastructure, model uncertainties increase, and unexpected pollution events may go unpredicted. This indicates that the technical capacity of AI alone is not sufficient and continuous updating is required. Correcting algorithms over time, recalibrating parameters, and optimizing learning processes will help minimize errors.

Therefore, the fully autonomous operation of current AI models can lead to delays in ecological crisis management in addition to technical errors. Timely detection and intervention of errors cannot occur without human oversight. Consequently, AI applications should be supported by a systematic human-supervision mechanism and continuous algorithm updates. This approach not only addresses technical limitations but also makes the potential of AI in solving ecological crises safer and more reliable (Russell & Norvig, 2021).

5.3. Social Inequalities

The effectiveness of AI-based ecological crisis management applications is not limited to technical capacity; it is also shaped by social inequalities. In urban centers, access to such applications and data density is higher due to economic and political priorities, whereas in rural and low-income areas, the prevalence of these applications remains limited. This situation hinders the equitable use of AI's potential in addressing ecological crises and deepens class-based disparities. The access differences created by these inequalities encompass not only geographic but also economic and social dimensions. Wealthier regions possess more advanced sensor infrastructure and AI-based systems, while rural and impoverished areas lack these technological capabilities. Consequently, even if technically feasible, solving ecological crises cannot be sufficiently effective on a global scale due to existing socio-economic structures, providing benefits only in certain areas (Foster, 2020: 15-25; 36-42).

This indicates that, beyond technical potential, the social and political context is a critical determinant of AI's effectiveness. Therefore, for AI to be effective in addressing ecological crises, it is necessary not only to improve algorithms and data infrastructure but also to strengthen social equity, fair access, and societal governance mechanisms. Otherwise, current applications may delay solutions to crises and only produce limited effects in specific areas.

5.4. Human Oversight and Governance Gaps

Although AI-based applications are relatively advanced technically, achieving effective results without human oversight, as well as generating societal benefits without fair governance mechanisms, appears difficult. The actors controlling the use of these tools often do not include other social groups in decision-making processes or limit their participation. Similar to the ownership of production tools, the control of technological tools within the current system reflects and reinforces social power relations. This situation prevents the equitable distribution of the potential benefits of AI applications and limits the resolution of ecological crises (Liv et al., 2024). For example, in some cities, access to data and AI infrastructure is provided only through central governments or large companies, while rural communities and local actors are excluded from the process. This highlights the limitations of AI applications in the context of both political governance deficits and social inequalities. No matter how advanced the technology is, unless democratic and collective participation in decision-making is ensured, the resolution of ecological crises will remain confined to certain areas, potentially contributing to the deepening of these crises (Liv et al., 2024).

Therefore, for AI to be effective in addressing ecological crises, it must operate alongside human oversight and incorporate transparent, fair, and inclusive governance mechanisms (Walther, 2025). This approach would not only resolve technical issues but also enable the realization of social and ecological justice.

5.4. Conclusion and Evaluation

This study critically assessed the potential of 21st-century technological transformation in addressing ecological crises. From historical social transformations to the contemporary digital and AI-driven transition, it has been demonstrated that relationships with nature have been continually reshaped and that ecological crises are closely intertwined with production relations. The application of artificial intelligence in areas such as water quality, air quality, biodiversity and habitat conservation, and carbon capture and storage has shown the potential to effectively detect and, in some cases, mitigate these crises.

However, case studies and current AI applications reveal that the full benefits of these technologies cannot be realized due to systemic limitations and social inequalities. Gaps in data infrastructure and high costs restrict the large-scale implementation of these technologies and diminish their effectiveness in resource-constrained regions. Moreover, uncertainties and errors in algorithms necessitate human oversight and intervention, while the lack of democratic and collective participation in decision-making processes further limits the societal benefits of these technologies.

Social inequalities, urban-rural divides, and the influence of economic priorities result in AI-based ecological crisis management applications being effective only in certain areas. This situation constrains the potential of technology and may delay the resolution of ecological crises. Importantly, these limitations do not arise from the intrinsic nature of AI technologies. When used with a focus on the common good and societal benefit, and supported by renewable energy, AI applications can become both economically sustainable and long-term contributors to solving ecological crises. Integrating AI technologies with human oversight and governance mechanisms preserves their potential to promote social and ecological justice.

Fully autonomous AI algorithms, particularly in contexts marked by urban-rural and class disparities, may exacerbate rather than alleviate ecological crises. Therefore, for AI to effectively contribute to solving ecological crises, technical advancements must be both accompanied and strengthened by societal adaptation, democratic participation, and inclusive governance mechanisms.

In conclusion, while AI technologies possess significant potential as tools to address ecological crises, realizing this potential is directly linked to social, economic, and political contexts. In this regard, rather than blaming the technology itself, it is clear that AI, when used equitably and with the common good and societal benefit at its center, can serve as an effective instrument for addressing ecological crises.

Bibliography

Altvater, E., & Mahnkopf, B. (1997). "The World Market Unbound". *Review of International Political Economy, 4*(3): 448-471. https://soz.ovgu.de/isoz_media/downloads/schrader/globalisierung/AltvaterTheMarketUnbound1997.pdf (Accessed 14 September 2025).

Berrisford, L. J., Ribeiro, E., & Menezes, R. (2022). "Estimating Ambient Air Pollution Using Structural Properties of Road Networks. *arXiv*. https://arxiv.org/abs/2207.14335 (Accessed 4 September 2025).

Beevers, S. D., Kitwiroon, N., Williams, M. L., Kelly, F. J., Anderson, H. R., & Carslaw, D. C. (2013). "Air Pollution Dispersion Models for Human Exposure Predictions in London. *Journal of Exposure Science & Environmental Epidemiology, 23*(6): 647-653. https://doi.org/10.1038/jes.2013.6, https://www.nature.com/articles/jes20136 (Accessed 4 September 2025).

BEIS (Department for Business, Energy & Industrial Strategy). (2021). *White Rose Carbon Capture and Storage Project*. Retrieved from Beevers, S. D., Kitwiroon, N., Williams, M. L., Kelly, F. J., Anderson, H. R., & Carslaw, D. C. (2013). "Air pollution dispersion models for human exposure predictions in London". *Journal of Exposure Science &*

Environmental Epidemiology, 23(6): 647-653. https://doi.org/10.1038/jes.2013.6 https://www.nature.com/articles/jes20136 (Accessed 4 September 2025).

BEIS (Department for Business, Energy & Industrial Strategy). (2021). *White Rose Carbon Capture and Storage Project*. Retrieved from https://www.gov.uk/government/publications/white-rose-carbon-capture-and-storage-project (Accessed 5 September 2025).

Bell, D. (1999). *The Coming of Post-Industrial Society: A Venture in Social Forecasting*. Basic Books.

Bell, M. L., & Davis, D. L. (2001). "Reassessment of the Lethal London Fog of 1952: Novel Indicators of Acute and Chronic Consequences of Acute Exposure to Air Pollution". *Environmental Health Perspectives, 109* (Suppl 3): 389–394. https://doi.org/10.1289/ehp.01109s3389 https://ehp.niehs.nih.gov/doi/10.1289/ehp.01109s3389 (Accessed 5 September 2025).

Branco, V. V., Correia, L., & Cardoso, P. (2023). The Use of Machine Learning in Species Threats and Conservation Analysis. *Biological Conservation, 283*, Article 110091. https://doi.org/10.1016/j.biocon.2023.110091 https://www.sciencedirect.com/journal/biological-conservation/vol/283/suppl/C (Accessed 2 September 2025).

Burawoy, M. (2005). "For Public Sociology". *American Sociological Review*, 70(1): 4–28.

Burkett, P. (2014). *Marx and Nature: A Red and Green Perspective*. Haymarket Books.

Carson, R. (1962). *Silent Spring*. Houghton Mifflin. https://library.uniteddiversity.coop/More_Books_and_Reports/Silent_Spring-Rachel_Carson-1962.pdf (Accessed 14 September 2025).

Castells, M. (2010). *The Rise of the Network Society* (2nd ed.). Wiley-Blackwell.

CEH (Centre for Ecology & Hydrology). (2021). *Sustainable Water Management in Rural and Urban Areas: River Water Quality Monitoring*. Retrieved from https://www.ceh.ac.uk/sites/default/files/2021-11/sustainable-water-guide-chap5-river-water-quality-v2.pdf (Accessed 2 September 2025).

Defra (Department for Environment, Food & Rural Affairs). (2024). *World-first Project Launched to Track Hedgehogs and Reverse Decline*. Retrieved from https://defraenvironment.blog.gov.uk/2024/08/22/world-first-project-launched-to-track-hedgehogs-and-reverse-decline/ (Accessed 2 September 2025).

Durham University. (2024). *National Hedgehog Monitoring Programme*. Retrieved from https://www.durham.ac.uk/news-events/latest-news/2024/03/national-hedgehog-monitoring-programme/ (Accessed 2 September 2025).

Environment Agency. (2023). *Thames River Water Quality Monitoring with AI*. Retrieved from https://www.gov.uk/government/organisations/environment-agency (Accessed 2 September 2025).

EPA. (2023). *Artificial Intelligence Applications for Wildfire Smoke Monitoring*. United States Environmental Protection Agency. Retrieved from https://www.epa.gov/air-research (Accessed 4 September 2025).

Figueroa, J. D., Fout, T., Plasynski, S., McIlvried, H., & Srivastava, R. D. (2020). “Advances in CO_2 Capture Technology—The U.S. Department of Energy’s Carbon Sequestration Program”. *International Journal of Greenhouse Gas Control, 4*(2): 145–165. https://www.researchgate.net/publication/222431915_Advances_in_CO2_Capture_Technology-The_US_Department_of_Energy's_Carbon_Sequestration_Program (Accessed 5 September 2025).

Flórez, M., Becerra, O., Carrillo, E., Villa, M., Álvarez, Y., Suárez, J., & Mendes, F. (2024). “Deep Learning Application for Biodiversity Conservation and Educational Tourism in Natural Reserves”. *ISPRS International Journal of Geo-Information, 13*(10) Article 358. https://doi.org/10.3390/ijgi13100358 https://www.mdpi.com/2992530 (Accessed 4 September 2025).

Ford, H. V., Jones, N. H., Davies, A. J., Godley, B. J., Jambeck, J. R., Napper, I. E., Suckling, C. C., Williams, G. J., Woodall, L. C., & Koldewey, H. J. (2022). “The Fundamental Links between Climate Change and Marine Plastic Pollution. *Science of The Total Environment, 806*, Article 150392. https://doi.org/10.1016/j.scitotenv.2021.150392 https://www.sciencedirect.com/science/article/pii/S0048969721054693?via%3Dihub (Accessed 5 September 2025).

Foster, J. B., Clark, B., & York, R. (2010). *The Ecological Rift: Capitalism’s War on the Earth*. Monthly Review Press.

Foster, J. B. (2020). *The Return of Nature: Socialism and Ecology*. Monthly Review Press.

German Environment Agency (UBA). (2022). *AI-supported Water Monitoring in the Rhine River*. Retrieved from https://www.umweltbundesamt.de (Accessed 2 September 2025).

German Environment Agency (UBA). (2022). *AI-supported Biodiversity Monitoring in the Rhine River Habitats*. Retrieved from https://www.umweltbundesamt.de (Accessed 2 September 2025).

Geyer, R., Jambeck, J. R., & Law, K. L. (2017). “Production, Use, and Fate of All Plastics Ever Made”. *Science Advances, 3*(7): e1700782. https://www.science.org/doi/10.1126/sciadv.1700782 (Accessed 2 September 2025).

Grange, S. K., & Carslaw, D. C. (2019). “Using Meteorological Normalisation to Detect Interventions in Air Quality Time Series”. *Science of The Total Environment, 653*: 578–588.https://doi.org/10.1016/j.scitotenv.2018.10.380 https://www.sciencedirect.com/science/article/pii/S004896971834244X (Accessed 5 September 2025).

Greater London Authority. (2021). *London Air Quality Network (LAQN) Annual Report 2021*. Retrieved from https://www.londonair.org.uk/ (Accessed 4 September 2025).

Gudynas, E. (2020). *Extractivisms: Politics, Economy and Ecology.* Fernwood Publishing.

Harvey, D. (2017). *Marx, Capital and the Madness of Economic Reason*. Profile Books.

Hehmeyer, A. (2024). “How Artificial Intelligence Buys Valuable Time to Protect Wildlife”. *World Wildlife Fund*, May 14, https://www.worldwildlife.org/stories/how-artificial-intelligence-buys-valuable-time-to-protect-wildlife (Accessed 2 September 2025).

IEA (International Energy Agency). (2022). *Carbon Capture, Utilisation and Storage: Tracking Report 2022*. https://www.iea.org/energy-system/carbon-capture-utilisation-and-storage (Accessed 5 September 2025).

IEA (International Energy Agency). (2023). *AI and Energy Efficiency: Emerging Opportunities*. Paris: IEA. https://www.iea.org/reports/energy-and-ai (Accessed 27 August 2025).

IPCC. (2022). *Climate Change 2022: Impacts, Adaptation and Vulnerability*. Cambridge University Press.

Jasanoff, S. (2016). *The Ethics of Invention: Technology and the Human Future*. W. W. Norton & Company.

Klein, N. (2014). *This Changes Everything: Capitalism vs. the Climate*. Simon & Schuster.

Latour, B. (2018). *Down to Earth: Politics in the New Climatic Regime*. Polity.

Lhoumeau, S., Pinelo, J., & Borges, P. A. V. (2025). "Artificial Intelligence for Biodiversity: Exploring the Potential of Recurrent Neural Networks in Conservation Scenarios". *Ecological Indicators, 171*, Article 113119. https://doi.org/10.1016/j.ecolind.2025.113119 https://www.sciencedirect.com/science/article/pii/S1470160X25000482?via%3Dihub (Accessed 2 September 2025).

Li, P., Yang, J., Wierman, A., & Ren, S. (2024). "Towards Environmentally Equitable AI via Geographical Load Balancing". *Proceedings of the 15th ACM International Conference on Future Energy Systems (e-Energy'24)*: 1–16. https://doi.org/10.1145/3632775.3661938 https://dl.acm.org/doi/10.1145/3632775.3661938 (Accessed 5 September 2025).

Marx, K. (2011). *Capital: Volume 1*. Penguin Classics.

Marx, K. (2013). *Economic and Philosophic Manuscripts of 1844* (Trans. M. Belge). Istanbul: Birikim Publishing.

Moore, J. W. (2015). *Capitalism in the Web of Life: Ecology and the Accumulation of Capital*. Verso. http://pinguet.free.fr/moore2015.pdf (Accessed 2 September 2025).

Morgan, L. H. (1994). *Ancient Society* (2nd ed., Trans. Ü. Oskay). İstanbul: Payel Publishing.

Natural Resources Canada. (2021). *Machine Learning Applications for Water Quality Monitoring in Ontario*. Retrieved from https://www.nrcan.gc.ca (Accessed 2 September 2025).

Natural Resources Canada. (2021). *Carbon Capture and Storage in Alberta: AI Applications*. Retrieved from https://www.nrcan.gc.ca (Accessed 5 September 2025).

NETL (National Energy Technology Laboratory). (2021). *Petra Nova Carbon Capture Project*. https://netl.doe.gov/sites/default/files/publication/NETL-January-2021-Carbon-Capture-Newsletter.pdf (Accessed 5 September 2025).

Patel, R., & Moore, J. W. (2017). *A History of the World in Seven Cheap Things: A Guide to Capitalism, Nature, and the Future of the Planet*. Verso.

Polanyi, K. (2024). *The Great Transformation: The Political and Economic Origins of Our Time*. Beacon Press.

Ponting, C. (2000). *A Green History of the World: The Environment and the Collapse of Great Civilizations* (Trans. A. Başçı-Sander). İstanbul: Sabancı University Press.

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 https://pure.mpg.de/pubman/item/item_3029184_9/component/file_3282959/BGC3001P.pdf (Accessed 2 September 2025).

Rolnick, D., Donti, P. L., Kaack, L. H., Kochanski, K., Lacoste, A., Sankaran, K., Slavin Ross, A., Milojevic-Dupont, N., Jaques, N., Waldman-Brown, A., Luccioni, A. S., Maharaj, T., Sherwin, E. D., S. Karthik Mukkavilli, K. P. Kording, C. P. Gomes, A. Y. Ng, Demis Hassabis, John C. Platt, Felix Creutzig, Jennifer Chayes, & Yoshua Bengio. (2022). "Tackling Climate Change with Machine Learning. *ACM Computing Surveys*, 55(2), Article 42. https://doi.org/10.1145/3485128 https://asross.github.io/publications/RolnickEtAl2022.pdf (Accessed 2 September 2025).

Russell, S., & Norvig, P. (2021). *Artificial Intelligence: A Modern Approach* (4th ed.). Pearson.

Sætra, H. S. (2021). "A Shallow Defence of a Technocracy of Artificial Intelligence: Examining the Political Harms of Algorithmic Governance in the Domain of Climate Change". *Technology in Society, 67*: 101725. https://ideas.repec.org/a/eee/teinso/v62y2020ics0160791x19305925.html (Accessed 2 September 2025).

Saito, K. (2022). *Marx in the Anthropocene: Towards the Idea of Degrowth Communism*. Cambridge University Press.

Spectroscopy Online. (2023). *Artificial Intelligence and Machine Learning in Assessing Water Quality*. Retrieved from https://www.spectroscopyonline.com/view/artificial-intelligence-and-machine-learning-assessing-water-quality (Accessed 2 September 2025).

Steffen, W., Richardson, K., Rockström, J., Cornell, S. E., Fetzer, I., Bennett, E. M., Biggs, R., Carpenter, S. R., de Vries, W., de Wit, C. A., Folke, C., Gerten, D., Heinke, J., Mace, G. M., Persson, L. M., Ramanathan, V., Reyers, B., & Sörlin, S. (2015). "Planetary Boundaries: Guiding Human Development on a Changing Planet". *Science, 347*(6223): 1259855. https://doi.org/10.1126/science.1259855 https://www.science.org/doi/10.1126/science.1259855 (Accessed 2 September 2025).

Svampa, M. (2019). *Neo-extractivism in Latin America: Socio-environmental Conflicts, the Territorial Turn, and New Political Narratives*. Cambridge University Press.

Turing Institute (2025). *AI and Autonomous Systems for Assessing Biodiversity and Ecosystem Health*. Retrieved from https://www.turing.ac.uk/research/research-projects/ai-and-autonomous-systems-assessing-biodiversity-and-ecosystem-health (Accessed 2 September 2025).

US Environmental Protection Agency (EPA). (2022). *Artificial Intelligence in Water Quality Management*. Retrieved from https://www.epa.gov (Accessed 2 September 2025).

Walther, C. (2025). "How AI Exclusion Impacts Humankind". *Knowledge at Wharton*. https://knowledge.wharton.upenn.edu/article/how-ai-exclusion-impacts-humankind/ (Accessed 5 September 2025).

WHO (2023). "Air Pollution". World Health Organization. Retrieved from https://www.who.int/health-topics/air-pollution (Accessed 2 September 2025).

Zuboff, S. (2019). *The Age of Surveillance Capitalism: The Fight for a Human Future at the New Frontier of Power*. PublicAffairs.

Zhu, K., Chen, L., Li, L., Wang, Y., Yan, X., Chen, J., Feng, C., & Shen, Z. (2023). "New Distributed Model for Predicting Erosion-type Pollution by Integrating Sediment Connectivity and Watershed Model". *Environmental Modelling & Software, 157*, Article 105662. https://doi.org/10.1016/j.envsoft.2023.105662 https://www.sciencedirect.com/science/article/abs/pii/S1364815223000488?via%3Dihub (Accessed 4 September 2025).