Applications of artificial intelligence in environmental monitoring and conservation: an exploratory review

Aplicaciones de la inteligencia artificial en el monitoreo y conservación ambiental: una revisión exploratoria

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Abstract

This paper explores the utilization of artificial intelligence (AI) in the surveillance and preservation of water, air, and soil. The analysis examined peer-reviewed studies published between 2020 and 2024, with a specific focus on the contribution of AI to the improvement of environmental management techniques. The selection procedure was limited down to thirty-three pertinent research, which were classified into three primary domains: Soil Quality and Management, Air Pollution and Environmental Monitoring, and AI Applications. Artificial intelligence techniques, including machine learning and deep learning, show great promise in enhancing the accuracy of predictions and optimizing the allocation of resources in several environmental fields. The primary uses of this technology are to evaluate the quality of soil, predict air pollution levels, and manage water resources. Integrating AI with conventional monitoring methods improves the accuracy and effectiveness of environmental management. Nevertheless, there are ongoing difficulties in ensuring the accuracy and reliability of data, the capacity of models to apply to different scenarios, and the successful integration of these models in various situations. Artificial intelligence demonstrates the ability to bring about significant changes in the fields of environmental monitoring and conservation. Subsequent investigations should prioritize the enlargement of datasets, the incorporation of AI with developing technologies, and the resolution of socio-economic consequences to fully connect the potential of AI in addressing intricate environmental concerns.

Keywords: Artificial Intelligence, Environmental Monitoring, Machine Learning, Sustainable Management

Resumen

Este artículo explora el uso de la inteligencia artificial (IA) en la vigilancia y preservación del agua, el aire y el suelo. El análisis examinó estudios revisados por pares publicados entre 2020 y 2024, con un enfoque específico en la contribución de la inteligencia artificial a la mejora de las técnicas de gestión ambiental. El procedimiento de selección se limitó a treinta y tres investigaciones pertinentes, que se clasificaron en tres dominios principales: calidad y gestión del suelo, contaminación del aire y monitoreo ambiental, y aplicaciones de IA. Las técnicas de inteligencia artificial, incluido el aprendizaje automático y el aprendizaje profundo, muestran un gran potencial para mejorar la precisión de las predicciones y optimizar la asignación de recursos en varios campos ambientales. Los usos principales de esta tecnología son evaluar la calidad del suelo, predecir los niveles de contaminación del aire y gestionar los recursos hídricos. La integración de la IA con los métodos de monitoreo convencionales mejora la precisión y la eficacia de la gestión ambiental. Sin embargo, existen dificultades continuas para garantizar la precisión y confiabilidad de los datos, la capacidad de los modelos para aplicarse a diferentes escenarios y la integración exitosa de estos modelos en diversas situaciones. La inteligencia artificial ha demostrado su capacidad para generar cambios significativos en los campos de la vigilancia y la conservación del medio ambiente. Las investigaciones posteriores deberían dar prioridad a la ampliación de los conjuntos de datos, la incorporación de la IA a las tecnologías en desarrollo y la resolución de las consecuencias socioeconómicas, a fin de aprovechar al máximo el potencial de la IA para abordar cuestiones ambientales complejas.

Palabras clave: Inteligencia artificial, Monitoreo ambiental, Aprendizaje automático, Gestión sostenible.

1. INTRODUCTION

The process of urbanization and the phenomenon of climate change have resulted in a rise in the monitoring and conservation of environmental resources. It is worth noting that air pollution alone is responsible for causing around seven million premature deaths per year (Organization, 2014) (Alghieth *et al.,* 2021). Metropolises such as Beijing and New Delhi have implemented air quality prediction systems that utilize artificial intelligence to offer public health advisories and inform policy decisions. The degradation of soil resulting from unsustainable farming methods and mining activities (Lima *et al.,* 2024) presents substantial threats to the stability of ecosystems and the security of food production. Water supplies are under substantial strain as a result of both saline and business's pollution (Krishnan *et al.,* 2022). The use of AI technology into environmental monitoring has the potential to enhance the accuracy of data and the effectiveness of management.

Artificial intelligence has greatly enhanced the monitoring of the environment by utilizing machine learning models to predict changes in air quality (B. Karthikeyan *et al.,* 2023), analyzing soil quality for conservation purposes (Liu *et al.,* 2024), and improving water resource management through hydrology (Chang *et al.,* 2023). Nevertheless, there is a need of extensive research that integrates AI approaches across diverse environmental domains, frequently concentrating on specific applications and geographical areas, so impeding the generalizability of findings. Subsequent investigations should explore the synergistic application of artificial intelligence across diverse environmental domains.

Preliminary analysis indicates a deficiency in the organized incorporation of AI technologies in the three primary environmental areas of water, air, and soil. Although there have been separate studies on the application of AI in monitoring air quality (Alghieth *et al.,* 2021), assessing soil quality (El Behairy *et al.,* 2024), and managing water resources (Chang *et al.,* 2023), there is a noticeable lack of comprehensive reviews that combine these findings to identify overall patterns, methodologies, and difficulties.

The objective of this study is to comprehensively analyze existing literature on the use of artificial intelligence in environmental monitoring and conservation to gain a unified understanding of technological advancements and their impact on sustainable management methods. Although the domain is broad, the idea is to identify clues about advances in technology, methodologies employed, observed advantages, and challenges encountered in environmental management. We have defined the following research question to guide the analysis conducted:

• *What are the current uses and effects of artificial intelligence technologies in water, air, and soil monitoring and preservation?*

Answering this question contributes to the field of environmental science by offering insight into the applications of artificial intelligence in monitoring and conservation of natural resources, as well as identifying effective approaches and highlighting best practices that can improve environmental management strategies.

The methodological approach for this exploratory review consisted of a meticulous selection process. A set of thirty-three research that met specific inclusion and exclusion criteria were included. The search equation employed broad keywords such as: *Artificial Intelligence*, *Machine Learning*, *Deep Learning*, *Air Quality Monitoring*, *Atmospheric Monitoring*, *Air Pollution*, *Soil Quality*, *Soil Conservation*, *Soil Monitoring*, and *Land Degradation*.

The review specifically examined peer-reviewed articles published from 2020 to 2024 on Scopus database. The exclusion criteria encompassed non-English publications, conference abstracts, and studies without empirical data, so guaranteeing the inclusion of only pertinent and high-quality research. The analysis techniques utilized encompassed detect trends and patterns in AI applications across the three environmental domains, ensuring a thorough and methodical examination of the literature.

This document is structured as follows: Section II describes the methodology employed in this study. Section III describe the results, which are systematically organized according to the categories identified during the clustering of works. Section IV presents a comprehensive discussion of the findings, while Section V elucidates the conclusions drawn from this research.

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2. METHODOLOGY

This review employs a systematic approach to assess the utilization of artificial intelligence in the surveillance and preservation of water, air, and soil. The process systematically selects, evaluates, and combines pertinent studies, offering a clear framework for analyzing data. This technique is in line with the study objectives as it allows for the discovery of technological advancements, methodologies, benefits, and issues in environmental management.

2.1 Search Strategy

The literature review employed Scopus database to ensure thorough inclusion of peer-reviewed research in the fields of environmental science and AI applications. Scopus index highly influential academic articles. In addition to doing database searches, we employed physical examination and followed citation trails to locate pertinent information. The search was restricted to the timeframe from January 2020 to July 2024 to focus on the most recent developments and uses of AI technology. This was done to reduce any biases in the selection process and ensure a thorough evaluation

2.2 Equation Development

The search equation was defined to encapsulate the core themes of the review. The final search equation is as follows:

all= (('artificial AND intelligence' OR 'ai' OR 'machine AND learning' OR 'deep AND learning') AND (('air AND quality AND monitoring' OR 'atmospheric AND monitoring' OR 'air AND pollution') OR ('soil AND quality' OR 'soil AND conservation' OR 'soil AND monitoring' OR 'land AND degradation'))) AND PUBYEAR > 2019 AND PUBYEAR < 2025 AND (LIMIT-TO (SUBJAREA , "ENVI") OR LIMIT-TO (SUBJAREA , "COMP") OR LIMIT-TO (SUBJAREA , "ENGI") OR LIMIT-TO (SUBJAREA , "EART")) AND (LIMIT-TO (DOCTYPE , "ar") OR LIMIT-TO (DOCTYPE , "cp") OR LIMIT-TO (DOCTYPE , "re")) AND (LIMIT-TO (LANGUAGE , "English")) AND (LIMIT-TO (EXACTKEYWORD , "Machine Learning") OR LIMIT-TO (EXACTKEYWORD , "Forecasting") OR LIMIT-TO (EXACTKEYWORD , "Artificial Intelligence") OR LIMIT-TO (EXACTKEYWORD , "Deep Learning") OR LIMIT-TO (EXACTKEYWORD , "Machine-learning") OR LIMIT-TO (EXACTKEYWORD , "Learning Systems") OR LIMIT-TO (EXACTKEYWORD , "Artificial Neural Network") OR LIMIT-TO (EXACTKEYWORD , "Environmental Monitoring"))

The basis of this equation involves the deliberate utilization of boolean operators to guarantee the retrieval of research that concentrate on AI applications in both air and soil contexts. The phrases Artificial Intelligence, Machine Learning, and Deep Learning were chosen based on their significance and frequency in the literature. Additionally, terms pertaining to air and soil monitoring were picked to specifically address the environmental contexts of interest.

2.3 Selection Criteria

Inclusion criteria for this review comprised: (1) articles published within the specified temporal range, (2) peer-reviewed publications, and (3) studies that explicitly focus on AI applications in environmental monitoring and conservation. Exclusion criteria contained: (1) duplicated articles (2) non-English papers, (3) conference abstracts, and (4) studies lacking empirical data. The emphasis on peer-reviewed articles ensures the reliability and academic rigor of the included studies, while the focus on empirical data is vital for assessing the practical implications of AI technologies.

2.4 Screening and Selection Process

The screening process was conducted in a multi-stage manner, beginning with an initial review of titles and abstracts to eliminate irrelevant studies. This was followed by a full-text review to confirm eligibility based on the inclusion and exclusion criteria.

2.5 Data Extraction

Data extraction was performed using a standardized form. Key variables extracted included study characteristics (e.g., authors, year of publication), AI methodologies employed, environmental contexts (air, water, soil), observed benefits, and challenges reported.

2.6 Quality Assessment

This assessment focused on the methodological rigor, validity, and reliability of the findings reported in each study. The results of the quality assessment were integrated into the analysis, influencing the interpretation of findings and conclusions drawn from the review. This process also allows for the identification of gaps in the literature and areas for future research.

2.7 Data Synthesis and Analysis

Data synthesis was approached through a narrative synthesis, allowing for a comprehensive integration of findings across diverse studies. This exploratory approach to data synthesis ensures that the review captures the complexity of the findings while providing a clear narrative of the current state of AI applications in environmental monitoring and conservation.

2.8 Bias Consideration

We detected potential biases such as publication and selection bias and employed a thorough search strategy to encompass a broad spectrum of papers. Strictly peer-reviewed articles were selected to guarantee credibility. Nevertheless, the review technique does have certain limitations, such as the exclusion of non-English studies and the potential biases in the selected databases. However, these constraints are acknowledged and implemented to provide transparency in the research process.

3. RESULTS

The result of the exploratory process after applied the methodology is described in Table 1. This analysis permitted to establish a global taxonomy consistent of three primary categories, and three subcategories by each one main category (see Figure 1.). The papers distribution by category and the works distribution by subcategory was estimated (see Figure 2 and Figure 3).

3.1 Soil Quality and Management

Works in this group focuses on the implementation of methods that evaluate, preserve, and enhance soil well-being, guaranteeing sustainable agricultural methods, environmental preservation, and land restoration. The integration of several scientific methodology, such as soil quality assessment techniques, the utilization of AI in soil management, and the assessment of soil quality in agricultural systems, is employed. Important topics in this category involve the creation and verification of soil quality indices, the influence of various land use and management practices on soil characteristics, and the incorporation of advanced technologies like machine learning for forecasting and mapping soil attributes. Studies have shown that ANN and decision trees are highly accurate in forecasting soil quality indicators, as indicated by (dos Santos *et al.,* 2024; El Behairy *et al.,* 2024; Lima *et al.,* 2024; Pacci *et al.,* 2024; Thabit *et al.,* 2024). Additionally, studies demonstrate the significance of mapping SOC and the influence of cropping patterns on the distribution of SOC and soil (Ou et al., 2024). The consequences of irrigation techniques, reclamation initiatives, and the influence of invasive species on soil quality are topic in this category (Cao *et al.*, 2024; Fadl *et al.*, 2024; Paliwal *et al.*, 2024). Soil Quality and Management is essential for enhancing our comprehension of soil ecosystems and formulating strategies for sustainable land use and agricultural output.

Table 1. *Study selection process, results for exploratory review.*

Stage	Number of Papers
Records identified through database searching (Scopus)	674
Additional records identified through other sources (citation trails, physical examination)	2
Total records identified	676
Records after duplicates removed	550
Records screened (titles and abstracts reviewed)	550
Records excluded (irrelevant titles and abstracts)	462
Full-text articles assessed for eligibility	88
Full-text articles excluded (with reasons)	55
Studies included in qualitative synthesis	33

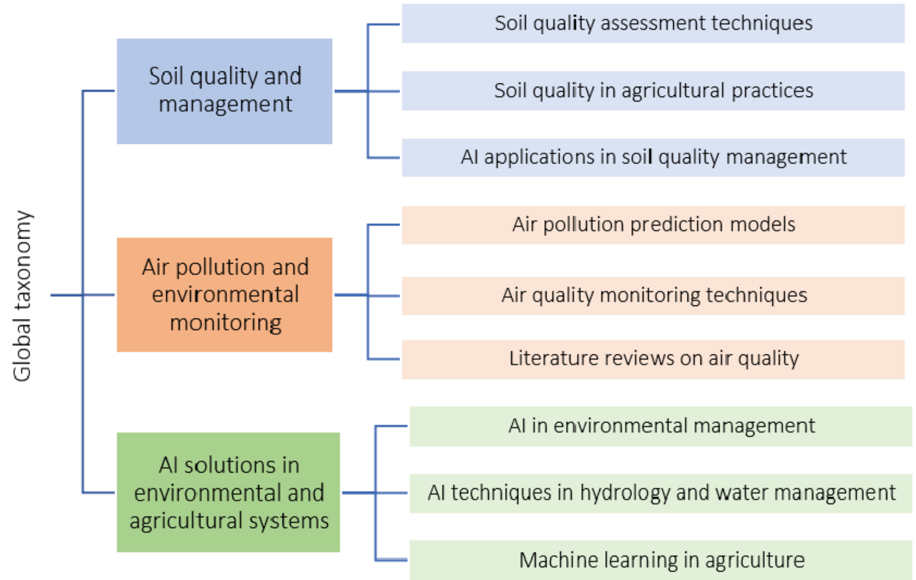

Figure 1. *Concept map of research areas in soil quality, environmental monitoring, and artificial intelligence applications.*

3.2 Soil Quality Assessment Techniques

Soil Quality Assessment Techniques encompass a range of methodologies and tools used to evaluate the health and productivity of soil. This subcategory provides insights into soil's physical, chemical, and biological properties, which are essential for sustainable agricultural practices and environmental conservation. Key themes include the use of machine learning models, soil quality indices,

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and advanced spectroscopic methods for precise and efficient soil quality evaluation.

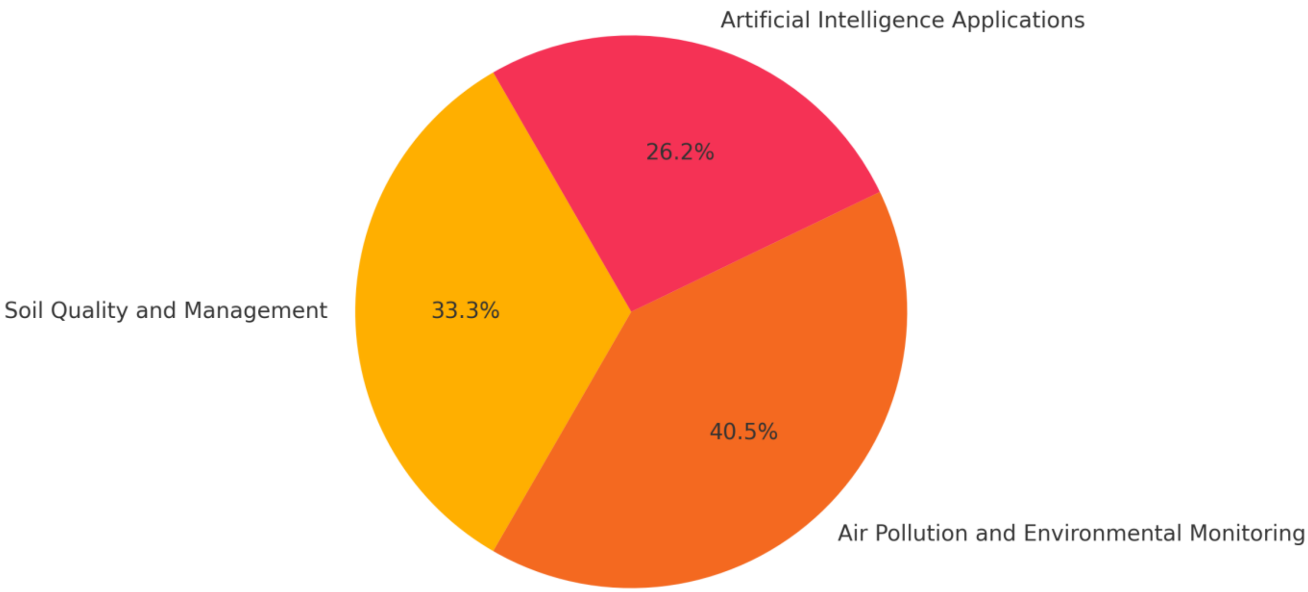

Figure 2. *Distribution of articles by main categories.*

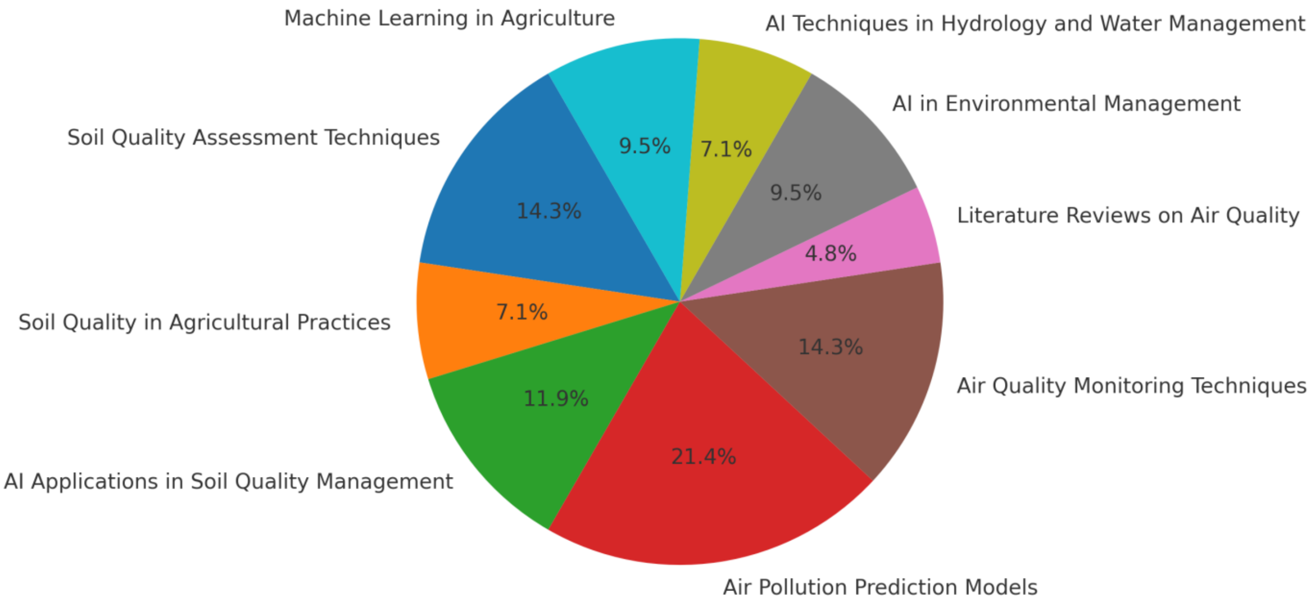

Figure 3. *Distribution of articles by subcategories.*

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This category encompasses the integration of machine learning models, soil quality indices, and spectroscopic methods to enhance soil quality evaluation. Several papers emphasize the use of ANN and other machine learning models for soil quality prediction. For instance, (Pacci *et al.,* 2024) investigates the application of ANN in predicting soil quality in tea cultivation areas, demonstrating high accuracy with significant properties such as organic matter and microbial biomass carbon. Similarly, (El Behairy *et al.,* 2024) employs ANN to predict soil quality in drylands, achieving high accuracy and efficiency, thus underscoring the potential of machine learning in soil quality assessment.

The use of decision trees and other machine learning models is also evident in (Lima *et al.,* 2024), which focuses on the recovery of mining-impacted ecosystems. This study identifies critical soil quality indicators, such as Cation Exchange Capacity (CEC) and Microbial Biomass Carbon (MBC), using decision trees, achieving high accuracy in distinguishing between affected and unaffected soils. This approach provides a practical framework for monitoring soil recovery post-mining activities.

The integration of soil quality indices (SQI) is another common theme. In (Zhu *et al.,* 2024) utilizes SQI to evaluate artificial soil quality in rehabilitation areas, highlighting the importance of SOC and moisture content. It demonstrates that prolonged restoration enhances soil quality, providing a robust framework for ecological restoration practices. Similarly, (Ou et al., 2024) focuses on SOC mapping in farmlands using the Cubist model, identifying key factors influencing SOC dynamics under different cropping systems. It indicates the need for tailored agricultural practices to enhance SOC sequestration.

Spectroscopic methods combined with machine learning models are explored in (Thabit *et al.,* 2024), which investigates the use of DRIFT-FTIR spectroscopy and various regression models for SOC estimation. It finds that Partial Least Squares Regression (PLSR) outperforms other models, highlighting its robustness for SOC prediction and its potential for sustainable land management.

The works advance knowledge in Soil Quality Assessment Techniques by showing the effectiveness of machine learning models and soil quality indices in various contexts. They highlight the importance of integrating advanced technologies for accurate and efficient soil quality evaluation, which is essential for sustainable agricultural practices and environmental conservation. However, contradictions and debates are evident, particularly regarding the generalizability of findings across different regions and soil types. For example, (Pacci *et al.,* 2024) and (El Behairy *et al.,* 2024) acknowledge the need for further validation of ANN models in diverse environmental conditions. Additionally, (Thabit *et al.,* 2024) notes the limitations of small sample sizes and the potential for overfitting in machine learning models.

Future research in this topic should focus on expanding datasets to include multiple regions, exploring the long-term effects of various soil amendments, and integrating additional environmental variables to improve the robustness of predictive models for soil quality. This will enhance the applicability and accuracy of soil quality assessment techniques, contributing to more effective soil management practices.

3.3 Soil Quality in Agricultural Practices

Research on assessment and enhancement of soil health using different agricultural methods is a crucial field of study. The importance of this topic lies in its crucial role in advancing sustainable agriculture, as the quality of soil has a direct impact on agricultural productivity, environmental well-being, and the long-term sustainability of land. The main areas of emphasis are the dynamics of SOC, the capacity of the soil to retain nutrients, the activity of soil microorganisms, and the impacts of irrigation and land reclamation.

Recent research has utilized several approaches, such as meta-analyses, geomatics, and machine learning algorithms, to assess and forecast soil quality in different agricultural systems. (Cao *et al.,* 2024) performed a meta-analysis to investigate the effects of different reclamation methods on soil quality in open-pit mines located on the Chinese Loess Plateau. Their research highlighted the efficacy of land rehabilitation in promoting soil quality, specifically through forestland reclamation which has shown significant benefits in increasing soil organic matter and microbial carbon. Significantly, they observed a delay in the microbial reaction to alterations in the environment, emphasizing the intricate nature of soil ecosystem restoration.

(Fadl *et al.,* 2024) conducted a study to investigate the lasting impacts of irrigation on soil quality in Egypt's dry plains using geomatic analysis. Their study unveiled substantial enhancements in SOC and nitrogen reserves because of extended irrigation, particularly in alluvial soils. The authors highlighted the beneficial effects of soil fertility and structure, but also warned about potential drawbacks such as heightened salinity. This underscores the importance of adopting sustainable irrigation methods.

(Ou et al., 2024) made progress in the field of methodology by utilizing machine learning models to enhance the process of mapping soil organic carbon (SOC) in agricultural fields. They achieved this by integrating intricate information on cropping systems. Their research highlighted farming systems, climate conditions, soil characteristics, and vegetation indices as crucial elements that affect the dynamics of SOC. The Cubist model was found to be the most accurate predictor of SOC spatial distribution, making it a valuable tool for future research and agricultural planning.

The literature shows the importance of customized agricultural practices for enhancing soil quality, the essential function of SOC in maintaining soil health, and the usefulness of modern analytical techniques in evaluating soil quality. Nevertheless, there are still other areas of research that have not been addressed. Future research should focus on examining the long-term viability of irrigation methods (Fadl *et al.,* 2024), the individual contributions of different plant species to soil restoration (Cao et al., 2024), and the intricate effects of human activities on soil organic carbon dynamics (Ou et al., 2024).

Advancing our efforts in developing increasingly sophisticated and efficient ways for managing soil quality continues to be a significant challenge. It is essential to incorporate knowledge from these many methods to develop comprehensive solutions that effectively combine agricultural productivity with long-term environmental sustainability.

3.4 AI Applications in Soil Quality Management

AI applications in soil quality management utilize machine learning techniques, remote sensing technologies, and multi-model simulations to optimize monitoring, analysis, and administration of soil quality. These applications highlight the impact of environmental stresses on land use and ecosystem services over a forty-year period, emphasizing the need for sustainable environmental management. The use of advanced GIS and machine learning technology provides a structure for forecasting ecological hazards and guiding policy formulation.

In (Liu *et al.,* 2024) examines the effects of environmental stresses on land use and ecosystem services over a period of forty years. The system uses multi-model land use simulations and artificial intelligence to identify key ecological nodes essential for landscape connectivity. The study emphasizes the impact of climate change and inefficient land management on land use patterns, offering valuable insights for sustainable environmental stewardship.

In (Paliwal *et al.,* 2024) evaluate the efficacy of AI and remote sensing in tracking the spread of Prosopis juliflora, identifying key environmental factors such as NDVI, precipitation, and land cover type. The Decision Tree/Random Forest classifier achieved a 95% accuracy rate, demonstrating the potential of technology innovations in creating sustainable management strategies tailored to specific ecological and social obstacles.

In (Sow *et al.,* 2024) examines the application of artificial intelligence to enhance the utilization of agricultural inputs. By analyzing 180 papers, researchers discovered that the implementation of artificial intelligence can enhance farmers' ability to manage nutrients, water, and weeds. This, in turn, results in enhanced soil quality and increased agricultural productivity. The study also examines the influence of environmental pressures on land utilization and the provision of ecosystem services over a span of 40 years. The system utilizes sophisticated land use models and artificial intelligence to pinpoint crucial ecological nodes for enhancing landscape connectivity. It emphasizes the impact of climate change and insufficient land management on land consumption patterns, providing valuable insights for the promotion of sustainable environmental stewardship. GIS and machine learning technology are utilized to predict ecological threats and inform policy development.

In (Bammou *et al.,* 2024) machine learning techniques were employed to evaluate the vulnerability of gully erosion in the Tensift catchment area in Morocco. The study employed seven machine learning algorithms, including SVM, KNN, RF, XGBoost, ANN, DT, and LR, to accurately identify 28.18% of the catchment area that is most susceptible to erosion. The XGBoost and KNN models exhibited superior performance, showcasing the promise of artificial intelligence in accurately forecasting and effectively managing soil erosion risks. (El-Rawy *et al.,* 2024) investigated soil salinity in the Siwa Oasis, Egypt, by employing remote sensing and a modified deep learning U-NET convolutional neural network (MU-NET) to identify and separate areas with salinity and vegetation. The MU-NET model, as presented, obtained a remarkable accuracy of 91.27% for salinity detection and 90.83% for vegetation detection. This demonstrates the efficacy of artificial intelligence in monitoring and assessing soil salinity problems. Both studies showcase the utilization of sophisticated machine learning techniques for accurate evaluation of soil quality.

Machine learning algorithms and remote sensing technologies are frequently employed to manage and control soil quality and ecosystem services, effectively tackling environmental and agricultural difficulties. The main contributions consist of identifying the environmental factors that influence the identification of invasive species and incorporating multi-model simulations to get insights into the dynamics of land use. Nevertheless, the assessment process recognizes several constraints and identifies potential areas for further investigation, including reliance on correlation analysis, the requirement for data spanning multiple years, the significant initial expenses associated with integrating AI technology, and the necessity for consistent ways of data gathering. Additional investigation is required to surmount these obstacles.

3.5 Air Pollution and Environmental Monitoring

The field of air quality management focuses on assessing, predicting, and managing air quality to mitigate the negative effects of air pollution on human health and the environment. It addresses the issue of air pollution, exacerbated by urbanization, industrialization, and human activities. Key topics include developing and applying air pollution prediction models, implementing advanced monitoring techniques, and synthesizing research findings. Artificial intelligence and machine learning have become prominent in this field, enabling more accurate and efficient prediction models and monitoring systems. Deep learning models like Long Short-Term Memory (LSTM) and hybrid approaches combining convolutional and recurrent neural networks (RNN) have shown exceptional performance in forecasting pollutant concentrations and managing air quality (Alghieth *et al.,* 2021; B. Karthikeyan *et al.,* 2023; Neo *et al.,* 2023; Omri *et al.,* 2024). The integration of AI/ML in environmental monitoring enhances the precision of exposure assessments and public health studies (Krupnova *et al.,* 2022; Vidnerová & Neruda, 2021).. The field also explores environmental justice, emphasizing the need for equitable access to advanced monitoring technologies and mitigation of environmental health disparities. These interdisciplinary approaches aim to foster sustainable urban development and inform policymaking for improved environmental governance.

1. Air Pollution Prediction Models

Air pollution prediction models play a crucial role in soil quality and management by accurately predicting pollutants and effectively reducing their environmental effects. Notable methodologies encompass machine learning (ML), deep learning (DL), and the integration of data from several sensors.

In (Zareba *et al.,* 2023) and(Alghieth *et al.,* 2021) has shown that deep learning models, specifically LSTM, are highly effective in accurately predicting pollutants such as PM10. These models have demonstrated their efficacy particularly in regions such as Saudi Arabia and Malaysia, as highlighted by (Neo *et al.,* 2023). Hybrid models, which integrate multiple machine learning algorithms, have been shown to improve prediction accuracy. This has been demonstrated in studies conducted by (Omri *et al.,* 2024) and (Subramaniam *et al.,* 2022).

Novel approaches such as Oppositional Shark Shell Optimization and Graph Convolutional Networks (GCN) have been proposed to enhance predictive accuracy, as demonstrated in the studies conducted by (Dutta *et al.,* 2022) and (B. Karthikeyan *et al.,* 2023). The incorporation of artificial intelligence and machine learning in the field of environmental justice is of utmost importance, as emphasized by (Krupnova *et al.,* 2022), who have raised issues regarding the fair and impartial execution of these technologies.

There are still obstacles to overcome, such as the need to clean the data and the risk of overfitting. Future study should concentrate on broadening the geographical coverage, integrating real-time data, and adopting standardized procedures, as recommended by (Vidnerová & Neruda, 2021).

3.6 Air Quality Monitoring Techniques

Air Quality Monitoring Techniques in Soil Quality and Management primarily involve the observation and analysis of air contaminants and their interactions with soil ecosystems. The main objective is to comprehend their influence on soil health, agricultural production, and environmental sustainability. Primary techniques employed are remote sensing, machine learning, and artificial intelligence to observe and forecast air pollution and its impact on soil.

Artificial intelligence has demonstrated its worth in the field of environmental monitoring, specifically in hydrology, as emphasized (Chang *et al.,* 2023; Latif & Ahmed, 2023). AI methods are utilized to handle intricate procedures by utilizing a variety of data sources such as remote sensing and Internet of Things (IoT) devices. This improves the accuracy of modeling and forecasting and has the potential to be used for monitoring air quality.

Deep learning methods demonstrate higher accuracy than conventional machine learning models in capturing environmental processes (Latif & Ahmed, 2023). These techniques enhance the accuracy of forecasting environmental phenomena, such as air pollution, and allow for the development of monitoring systems that can adjust to changing conditions using real-time data.

The integration of satellite data, machine learning algorithms, and multi-criteria evaluation has enabled the automation of environmental risk assessment. This approach has been successfully applied to tasks such as flood monitoring and soil erosion assessment and has the potential to be adopted for air quality research as well (Prakash *et al.,* 2024). This method enables the monitoring of the spread of pollutants and the evaluation of their effects on soil quality.

Integrating various data sources and analytical methods is essential for improving the accuracy of predictions in different environmental areas (Chang *et al.,* 2023; Latif & Ahmed, 2023; Prakash *et al.,* 2024). The integration of artificial intelligence, remote sensing, and real-time data presents a viable framework for enhancing environmental modeling and management tactics.

Nevertheless, there are still obstacles that need to be addressed. The transferability of AI models across diverse environmental contexts is a matter of concern (Chang *et al.,* 2023), and the dependability of these models may be influenced by variations in data quality and model implementation (Latif & Ahmed, 2023). Future research should prioritize the development of hybrid models that combine the advantages of various AI techniques. Additionally, it should investigate the socio-economic consequences of AI-powered environmental solutions.

3.7 Literature Reviews on Air Quality

This group of works assesses the influence of air pollutants on the condition of soil, the productivity of agriculture, and the well-being of ecosystems. It highlights the significance of artificial intelligence in monitoring the environment, specifically in the areas of air pollution and wastewater treatment.

Two studies, (Guo *et al.,* 2022; Yu *et al.,* 2023), employ bibliometric analysis to delineate research patterns, revealing a substantial surge in the utilization of artificial intelligence since 2017, particularly in China and USA. Both studies emphasize the significance of global collaboration and examine crucial factors and cooperative networks.

The study conducted by (Guo *et al.,* 2022) primarily examines the application of artificial intelligence in the context of air pollution. The authors highlight the significance of accurately predicting PM2.5 levels and propose that AI has the capability to improve air quality monitoring and contribute valuable insights for public health policy. In (Yu *et al.,* 2023) emphasizes the significance of artificial neural networks and deep learning in the field of wastewater treatment. The authors acknowledge that AI has the capability to enhance operational efficiency and facilitate the automated identification of defects. Both studies emphasize the importance of enhanced collaboration and multidisciplinary methods, but they also recognize certain limitations. These limitations include the use of the Web of Science database as the primary source of information and the exclusion of publications not written in English, which could potentially introduce bias.

Future research should prioritize the integration of AI with other technologies in environmental monitoring, investigate the socio-economic consequences of AI, develop multidisciplinary approaches, and adopt more comprehensive search strategies.

3.8 AI Solutions in Environmental and Agricultural Systems

This category focuses on the application of AI technologies to address intricate real-world issues, improving decision-making, resource allocation, and effectiveness in many fields. The main topics covered include machine learning, deep learning, and AI techniques, which are used to analyze massive datasets, model complicated systems, and make predictions.

AI has a wide-ranging impact, as it is used in several fields such as environmental management, hydrology, and agriculture. AI-driven models, such as those described by (Liu *et al.,* 2024), have been utilized to observe and track alterations in land use and ecosystem services, thereby aiding in the promotion of environmental sustainability. AI has played a crucial role in identifying invasive species and overseeing rangeland ecosystems (Paliwal *et al.,* 2024). Additionally, in the field of agriculture, AI improves the effectiveness of resource utilization and boosts agricultural production (Sow *et al.,* 2024).

In the context of hydrological modeling and water resources management, artificial intelligence is used to assist in predicting and reducing the impact of disasters (Chang *et al.,* 2023). This category highlights the transdisciplinary nature of AI applications in tackling global concerns.

In general, this group of works specifically examines the contribution of AI in the monitoring, prediction, and management of environmental changes. This includes areas such as land use dynamics, ecosystem services, and the identification of invasive species.

3.9 AI in Environmental Management

This category specifically examines the utilization of artificial intelligence technologies in the field of Soil Quality and Management. It highlights the importance of these technologies in improving land utilization, agriculture, and mitigating ecological risks.

The study conducted by (Liu *et al.,* 2024) examines the alterations in land use within the Loess Hilly-Gully region by employing artificial intelligence. The analysis identifies climate change and inadequate land management as significant factors contributing to these changes. The study emphasizes the necessity of adopting sustainable practices to address these issues. (Paliwal *et al.,* 2024) employs artificial intelligence and remote sensing techniques to accurately identify Prosopis Juliflora in Kenyan rangelands, achieving a 95% accuracy rate. Their study highlights the significance of incorporating ecological and socio-economic variables into management practices.

In the ground of agriculture, in (Sow *et al.,* 2024) demonstrates the potential of artificial intelligence to enhance the efficient utilization of resources and enhance crop yields. The study emphasizes the importance of uniform data collecting and improved internet infrastructure. In this study, (Yu *et al.,* 2023) perform a bibliometric analysis on the application of artificial intelligence in wastewater treatment. They observe a significant increase in research activity, particularly in China and USA. The authors emphasize the crucial role of international collaboration and the integration of AI with developing technologies in this field.

Some notorious gaps and future directions, including the need for advanced methodologies to establish causal relationships, training programs for farmers, improved rural internet infrastructure, and understanding the socio-economic impacts of AI-driven solutions in various contexts.

3.10 AI Techniques in Hydrology and Water Management

This section focuses on the application of artificial intelligence technology in hydrological processes and water resource management. The main goal is to increase the precision of forecasts and better the process of making decisions.

(Verjans & Robel, 2024) highlight the effectiveness of deep learning in replicating subglacial hydrology. They provide evidence that DL attains extraordinary accuracy and efficiency, hence highlighting the potential of artificial intelligence to enhance ice sheet models. Two more studies investigate the significance of AI in addressing uncertainties associated with hydro-geo-meteorological variables and improving the precision of forecasting reservoir inflow. These research employ machine learning and deep learning techniques, such as LSTM networks. (Chang *et al.,* 2023) emphasizes the effectiveness of AI in hydrological modeling, specifically in the long and medium term. This enhances water management and helps to accomplish global sustainability goals. (Latif & Ahmed, 2023) did a literature assessment on artificial intelligence methodologies used to forecast reservoir inflow. Deep learning models are popular because of their superior accuracy. The researchers also highlighted the importance of rainfall data in this forecasting procedure.

The research provide evidence that AI has the potential to significantly enhance hydrological models and procedures used in water management. Their recommendation is to give priority to future research on hybrid models that integrate DL with traditional ML techniques. In addition, they suggest incorporating real-time data to improve the precision of forecasts. The recognition of challenges such as the adaptability of AI models to various situations and the necessity for comprehensive comprehension in GeoAI is also acknowledged.

3.11 Machine Learning in Agriculture

Machine Learning in Agriculture refers to the application of machine learning and deep learning techniques to optimize various agricultural processes, including soil quality and management. Key themes include soil nutrient prediction, hydroponic and soil compound dynamics, and efficient management of agricultural inputs such as water and fertilizers. The use of deep learning models to predict soil and hydroponic compound dynamics (Abidi *et al.,* 2024), spectral-based soil nutrient prediction (Jain *et al.,* 2024), and AI-driven strategies for optimizing nutrient, water, and weed management (Sow *et al.,* 2024) are recurrent themes.

In (Abidi *et al.,* 2024) introduces an innovative approach that leverages a multi-scale feature fusion-based Convolution Autoencoder with a

Gated Recurrent Unit (MS-CAGRU) network. This model enhances the understanding of plant-environment interactions and aids in making informed agricultural decisions. Main contribution lies in its novel predictive framework that integrates multiple deep learning techniques, addressing a critical gap in soil and agricultural research. The exploratory review on (Jain *et al.*, 2024) provides a comprehensive assessment of 155 papers, highlighting the potential of hyperspectral and multispectral sensors in precise nutrient identification.

(Oriol *et al.,* 2024) contribute to the field by applying deep learning techniques to the automatic identification of Collembola, soil-dwelling organisms that serve as indicators of soil quality. Their study addresses a critical challenge in soil biodiversity assessment by developing a novel approach to species identification using microscope slide images. The authors evaluate various state-of-the-art deep learning models on a newly created, manually annotated dataset of Collembola images.

In (Sow *et al.,* 2024), it explores the potential of AI technologies in optimizing nutrient, water, and weed management. By providing a detailed overview of AI applications in agriculture, this study contributes to the field by demonstrating how AI can revolutionize agricultural practices and improve resource efficiency.

While the works align on the potential of ML and DL in agriculture, there are noted limitations and challenges. For instance, the variability in study quality and the limited availability of open datasets, as well as the high initial costs and the need for large datasets for AI training, are significant barriers to widespread adoption. These challenges suggest a need for further refinement and validation of predictive models and the development of standardized data collection methods.

Future research should focus on expanding datasets, exploring additional environmental variables, and refining predictive models to enhance their applicability in real-world settings. Additionally, developing hybrid models that combine ML and DL techniques and creating new spectral indices for improved prediction accuracy are essential. Enhancing internet infrastructure in rural areas and creating training programs for farmers to effectively utilize AI technologies are also critical areas for future research.

In summary, Table 2 shows main techniques used in environmental monitoring and conservation. Machine Learning and models and ANN are the most used techniques in general. Furthermore, Table 3 shows main limitations in the application of AI-related techniques, quality and live data is the most recurrent limitations in general.

4. DISCUSSION

An in-depth examination of AI applications in monitoring and conserving water, air, and soil has provided valuable insights into the status and promise of these technologies in environmental management. The results of our research indicate that AI technologies, including machine learning and deep learning, have been widely used in many environmental situations. These technologies have shown significant advantages in terms of accurately predicting outcomes, optimizing resource usage, and promoting sustainable management practices.

4.1 Soil Quality and Management

AI applications have demonstrated extraordinary effectiveness in the field of soil quality and management. Research has shown that AI models, such as Artificial Neural Networks and decision trees, can accurately forecast soil quality indicators. These models have proven to be highly effective in integrating intricate datasets to deliver accurate estimates of soil quality. For example, the application of ANN in forecasting soil quality in tea production and drylands has resulted in a high level of accuracy, demonstrating the promise of ML in many agricultural settings. Nevertheless, it is crucial to conduct additional validation of these models in other geographies and soil types.

4.2 Air Pollution and Environmental Monitoring

AI approaches, such as LSTM networks and hybrid models that combine CNN with RNN, have demonstrated outstanding performance in predicting and monitoring air pollution. These models have proven to be successful in predicting levels of pollutants, which is essential for proactive environmental management and safeguarding public health. An example of the application of LSTM networks in predicting PM_{10} concentrations in Saudi Arabia and Malaysian cities has shown exceptional precision. Nevertheless, there are ongoing difficulties with regards to data cleansing and the incorporation of real-time data, which could potentially impact the dependability of these models.

Table 2. Main techniques used in environmental monitoring and conservation.

Category	Subcategory	Techniques Used with References
Soil Quality and Management	Soil Quality Assessment Techniques	- Machine Learning Models, ANN, Decision Trees [Pacci et al., 2024; El Behairy et al., 2024; Lima et al., 2024] - Soil Quality Indices [Zhu et al., 2024; Ou et al., 2024] - Spectroscopic Methods [Thabit et al., 2024]
	Soil Quality in Agricultural Practices	- Meta-analysis [Cao et al., 2024] - Geomatic Analysis [Fadl et al., 2024] - Machine Learning Models - Cubist Model [Ou et al., 2024]
	AI Applications in Soil Quality Management	- Machine Learning Techniques, SVM, KNN, RF, ANN, DT, LR, Decision Trees, Random Forest, XGBoost [Paliwal et al., 2024; Bammou et al., 2024] - Remote Sensing, MU-NET [El-Rawy et al., 2024] - Multi-model Simulations [Liu et al., 2024]
Air Pollution and Environmental Monitoring	Air Pollution Prediction Models	- Deep Learning Models - LSTM, Hybrid Models, GCN [Alghieth et al., 2021; Neo et al., 2023; Dutta et al., 2022]
	Air Quality Monitoring Techniques	- Remote Sensing [Latif & Ahmed, 2023; Prakash et al., 2024] - Machine Learning Models [Latif & Ahmed, 2023] - AI Techniques [Chang et al., 2023]
	Literature Reviews on Air Quality	- Bibliometric Analysis [Guo et al., 2022; Yu et al., 2023] - AI Models - ANN, Deep Learning [Guo et al., 2022; Yu et al., 2023]
AI Solutions in Environmental and Agricultural Systems	AI in Environmental Management	- Machine Learning [Sow et al., 2024] - Remote Sensing [Paliwal et al., 2024] - AI Techniques [Liu et al., 2024]

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	AI Techniques in Hydrology and Water Management	- Deep Learning - LSTM Networks [Latif & Ahmed, 2023] - Hybrid Models [Chang et al., 2023] - Real-time Data Integration [Latif & Ahmed, 2023]
	Machine Learning in Agriculture	- Deep Learning Models - MS-CAGRU [Abidi *et al.*, 2024] - Spectral-based Prediction [Jain et al., 2024] - AI-driven Strategies [Sow et al., 2024]

Table 3. Identified Limitations in the application of AI-related techniques.

Category	Subcategory	Limitations
Soil Quality and Management	Soil Quality Assessment Techniques	- Generalizability issues across different regions and soil types. - Overfitting risks due to small sample sizes
	Soil Quality in Agricultural Practices	- Potential for sensitive salinity with prolonged irrigation. - Delay in microbial reaction to environmental changes
	AI Applications in Soil Quality Management	- High initial costs associated with AI technology; dependency on correlation analysis and multi-year data
Air Pollution and Environmental Monitoring	Air Pollution Prediction Models	- Need for real-time data integration. - Risk of overfitting; challenges in cleaning data
	Air Quality Monitoring Techniques	- Transferability issues of AI models across diverse environmental contexts. - Dependency on data quality
	Literature Reviews on Air Quality	- Bias due to reliance on specific databases - Web of Science. - Exclusion of non-English publications
AI Solutions in Environmental and Agricultural Systems	AI in Environmental Management	- Necessity for consistent data gathering methods; High initial implementation costs. - Adaptability of models to various contexts
	AI Techniques in Hydrology and Water Management	- Challenges in integrating real-time data for improved predictions. - Transferability issues across different environmental contexts
	Machine Learning in Agriculture	- Variability in study quality. - High initial costs. - Need for large datasets for effective AI training

4.3 Water Management

AI has demonstrated encouraging outcomes in the fields of hydrology and water management, namely in the areas of remote sensing and

Internet of Things (IoT) devices. Deep learning models have demonstrated superior efficacy compared to conventional methods in predicting reservoir inflow, hence improving the precision of forecasts in water management. Nevertheless, the work of integrating these models in different hydrological scenarios continues to be a difficult endeavor. The demonstrated efficacy of AI in monitoring soil, air, and water suggests its capacity to profoundly influence sustainable management practices. By combining AI with traditional environmental monitoring techniques, the precision and efficiency of resource management may be enhanced, leading to the advancement of environmental conservation and sustainability. The utilization of AI in environmental monitoring can also enhance policymaking by delivering accurate and timely data, which is essential for effective environmental governance. Nevertheless, there are constraints in this domain, including the reliance on existing literature, the adaptability of AI models to different environmental settings and geographical locations, and the necessity for additional research to enhance datasets and investigate the incorporation of AI with other technologies such as blockchain and edge computing.

5. CONCLUSIONS

This review has presented a thorough examination of the current uses and effects of artificial intelligence technology in monitoring and preserving water, air, and soil. The major findings emphasize the substantial potential of AI in improving predictive precision, optimizing resource allocation, and advancing sustainable environmental practices. Artificial intelligence models, such as ANN, Long Short-Term Memory, and hybrid methods, have shown outstanding performance in many environmental scenarios. They have significantly improved soil quality evaluations, air pollution predictions, and water resource management.

The results directly tackle the research question and aims by emphasizing the revolutionary capacity of artificial intelligence in environmental management. This work makes significant contributions by identifying the crucial applications and methodology of AI, examining the observed advantages and difficulties, and discussing the consequences for future research and practice. This research highlights the significance of combining AI with conventional environmental monitoring methods to improve accuracy and effectiveness in resource management. On the other hand, the lack of available data presents a significant challenge in these fields. Datasets are crucial not only for training AI models but also for testing and validating their accuracy and effectiveness. The incorporation of artificial intelligence into the field of environmental monitoring and conservation shows great potential for promoting and enhancing sustainable management methods. To fully harness the potential of AI in tackling intricate environmental concerns, it is crucial to continue conducting research and development, as well as fostering interdisciplinary collaboration. This study emphasizes the significance of utilizing sophisticated technologies to increase environmental sustainability and facilitate informed decisions.

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