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Review

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Integrating Artificial Intelligence Agents with the Internet of Things for Enhanced Environmental Monitoring: Applications in Water Quality and Climate Data

Tymoteusz Miller [1,2,*], Irmina Durlik [3], Ewelina Kostecka [4], Polina Kozlovska [5], Adrianna Łobodzińska [6,7], Sylwia Sokołowska [8] and Agnieszka Nowy [3]

[1] Institute of Marine and Environmental Sciences, University of Szczecin, 71-141 Szczecin, Poland
[2] Faculty of Data Science and Information, INTI International University, Nilai 71800, Negeri Sembilan, Malaysia
[3] Faculty of Navigation, Maritime University of Szczecin, 71-650 Szczecin, Poland
[4] Faculty of Mechatronics and Electrical Engineering, Maritime University of Szczecin, 71-650 Szczecin, Poland
[5] Faculty of Economics, Finance and Management, University of Szczecin, 71-101 Szczecin, Poland
[6] Institute of Biology, University of Szczecin, 71-415 Szczecin, Poland
[7] Doctoral School of the University of Szczecin, 71-412 Szczecin, Poland
[8] Polish Society of Bioinformatics and Data Science BioData, 71-214 Szczecin, Poland
* Correspondence: tymoteusz.miller@usz.edu.pl

Abstract: The integration of artificial intelligence (AI) agents with the Internet of Things (IoT) has marked a transformative shift in environmental monitoring and management, enabling advanced data gathering, in-depth analysis, and more effective decision making. This comprehensive literature review explores the integration of AI and IoT technologies within environmental sciences, with a particular focus on applications related to water quality and climate data. The methodology involves a systematic search and selection of relevant studies, followed by thematic, meta-, and comparative analyses to synthesize current research trends, benefits, challenges, and gaps. The review highlights how AI enhances IoT's data collection capabilities through advanced predictive modeling, real-time analytics, and automated decision making, thereby improving the accuracy, timeliness, and efficiency of environmental monitoring systems. Key benefits identified include enhanced data precision, cost efficiency, scalability, and the facilitation of proactive environmental management. Nevertheless, this integration encounters substantial obstacles, including issues related to data quality, interoperability, security, technical constraints, and ethical concerns. Future developments point toward enhancements in AI and IoT technologies, the incorporation of innovations like blockchain and edge computing, the potential formation of global environmental monitoring systems, and greater public involvement through citizen science initiatives. Overcoming these challenges and embracing new technological trends could enable AI and IoT to play a pivotal role in strengthening environmental sustainability and resilience.

Keywords: artificial intelligence (AI) agents; Internet of Things (IoT); environmental monitoring; water quality; climate data; predictive analytics; real-time decision making; sustainable environmental management; AI–IoT integration; smart environmental systems

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1. Introduction

1.1. Background

The modern world is confronted with numerous environmental issues [1–3], which present serious risks to ecosystems [4,5], public health [6,7], and the global economy [8–10].

Issues such as climate change [11–13], water pollution [14–16], deforestation [17–19], and loss of biodiversity [20,21] are escalating at an unprecedented rate, driven by industrialization [22–24], urbanization [25–27], and unsustainable resource exploitation [28,29]. For instance, rising global temperatures [30–33] are altering weather patterns, leading to extreme events like hurricanes, droughts, and floods, which in turn disrupt agricultural productivity and compromise water security. Likewise, the pollution of water bodies [34,35] due to agricultural runoff, industrial discharges, and untreated sewage not only harms aquatic ecosystems but also presents significant health hazards to communities depending on these water sources.

In addressing these complex and interrelated challenges, timely and accurate decision-making in environmental sciences is paramount. Successful management and mitigation efforts rely on real-time environmental monitoring, accurate trend prediction, and proactive responses to emerging threats. Conventional monitoring methods, which typically involve intermittent data collection and manual analysis, are becoming insufficient given the accelerating pace of environmental changes and the vast amounts of data produced. As a result, there is an urgent demand for innovative technological solutions that can improve the accuracy, efficiency, and scalability of environmental data acquisition and analysis.

1.2. Role of Technology in Environmental Monitoring

The development of environmental monitoring tools [36–38] has significantly progressed in recent decades, fueled by technological advancements and the growing need for comprehensive, real-time environmental data. Early environmental monitoring efforts were largely manual and labor-intensive, involving field surveys, laboratory analyses, and paper-based record-keeping [39,40]. Although these approaches offered important insights, their effectiveness was constrained by limited scope, infrequent data collection, and the risk of human error. The advent of digital technologies has revolutionized environmental monitoring [41,42] by enabling automated data collection, storage, and analysis. The Internet of Things (IoT) has become a key technology in this evolution, enabling the use of interconnected sensors and devices for the continuous monitoring of diverse environmental parameters [43–45]. IoT-based sensors can monitor various environmental parameters, such as air and water quality, temperature, humidity, and soil moisture, while transmitting real-time data to centralized platforms for analysis [46–48]. In conjunction with IoT, Artificial Intelligence (AI) technologies have brought advanced capabilities for processing and interpreting the large datasets produced by environmental sensors [49,50]. Machine learning algorithms can detect patterns, forecast trends, and extract actionable insights from complex environmental data, thereby improving the decision-making process [51–53]. AI-driven models can forecast pollution levels, predict climate anomalies, and optimize resource management strategies, enabling environmental scientists and policymakers to respond swiftly and effectively to emerging challenges. The combination of IoT and AI [54] creates a synergistic framework that harnesses the advantages of both technologies. IoT establishes the foundation for continuous and extensive data collection, while AI delivers the analytical capabilities needed to convert raw data into actionable insights. This integration enables quicker and more precise decision making, ultimately enhancing environmental management and sustainability efforts.

This article aims to examine the integration of artificial intelligence (AI) agents and the Internet of Things (IoT) in environmental sciences, with a particular emphasis on improving decision-making processes concerning water quality and climate data. By examining the interplay between these technologies, this article aims to elucidate how their combined application can address the pressing environmental challenges of our time. Specifically, the article seeks to achieve the following objectives:

1. Define and characterize AI agents within the context of environmental sciences, highlighting their various types, functions, and capabilities.
2. Give a summary of IoT technologies applicable to environmental monitoring, highlighting the various sensors utilized for collecting water quality and climate data.
3. Examine the interaction between IoT and AI, explaining how their integration enhances data accuracy, enables real-time monitoring, and supports proactive decision making.
4. Examine case studies and practical applications where AI and IoT have been successfully implemented to monitor and manage environmental parameters.
5. Explore the advantages, obstacles, and future prospects of implementing integrated AI–IoT systems in environmental sciences.

2. Methodology of Literature Review

A systematic literature review was carried out to examine the integration of AI and IoT in environmental sciences, with a focus on water quality and climate monitoring. The review highlights major research trends, effective applications, existing challenges, and potential future developments.

A systematic search was performed across IEEE Xplore, SpringerLink, ScienceDirect, Wiley Online Library, and PubMed, supplemented by industry reports (WHO, EPA, IEA) and conference proceedings. Keywords included "AI agents", "IoT", "environmental monitoring", and "predictive analytics", with Boolean operators to refine results.

Studies published between 2010 and 2024 were included if they addressed AI–IoT integration in environmental sciences, prioritizing peer-reviewed research. Non-scholarly sources, outdated publications, and theoretical-only studies without empirical validation were excluded. Global research diversity was considered to ensure a broad perspective.

Titles and abstracts were screened based on selection criteria, followed by full-text analysis. Extracted data included study objectives, methodologies, AI–IoT technologies used, key findings, and challenges. Thematic analysis categorized studies by AI techniques, IoT applications, benefits, and limitations, while comparative and meta-analysis highlighted trends and best practices.

The synthesis revealed improvements in real-time monitoring, predictive analytics, and automated decision–making through AI–IoT integration. However, challenges such as data quality, interoperability, ethical concerns, and long-term sustainability remain. The review acknowledges limitations, including potential publication bias, language constraints, and the exclusion of purely theoretical advancements. Future research should address scalability, security, interdisciplinary collaboration, and emerging AI techniques like reinforcement learning and federated learning.

3. Understanding AI Agents in Environmental Sciences

Artificial intelligence (AI) agents have become essential instruments in advancing environmental sciences [55–57]. Leveraging their diverse capabilities, these agents improve monitoring [58–60], facilitate analysis [61–64], and optimize decision-making processes [55,65,66], all of which are crucial for tackling complex environmental issues. This chapter provides an in-depth examination of AI agents, outlining their definitions, classifications, functionalities, and practical applications in environmental settings (Figure 1).

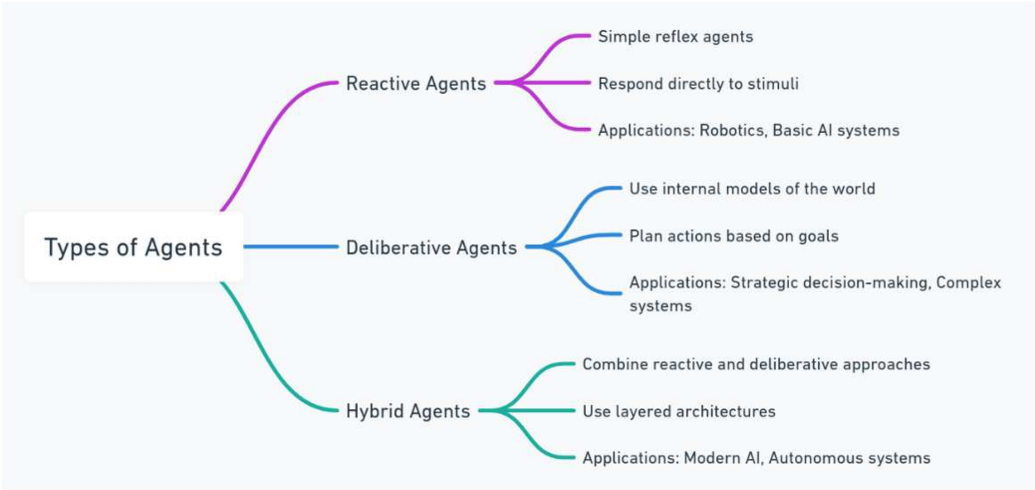

Figure 1. Classification of AI agents in environmental sciences.

3.1. Definition and Types of AI Agents

AI agents are self-governing systems capable of sensing their surroundings, processing data, and executing actions to accomplish predefined goals. In environmental sciences, they support the handling and interpretation of large datasets, allowing for more efficient and timely decision making. Based on their operational mechanisms and decision-making approaches, AI agents are generally classified into three main types: reactive agents, deliberative agents, and hybrid agents [67]. Reactive agents [68,69] operate by responding directly to environmental stimuli based on predefined rules. They lack the capacity to maintain internal states or plan for future actions, making their behavior entirely dependent on the current input from their sensors. In environmental applications, reactive agents are commonly employed for real-time monitoring and alerting systems [70]. For example, a reactive AI agent might activate an alarm when sensor data indicate a sudden increase in water pollution levels, facilitating immediate remedial actions [71]. These agents are valued for their simplicity and speed, although they are limited in their adaptability and lack of long-term planning capabilities. Deliberative agents [72], on the other hand, possess the ability to plan and reason about future actions based on internal models of their environment. Unlike reactive agents, deliberative agents maintain an internal state that allows them to consider the consequences of their actions over time [73]. In environmental sciences, deliberative agents are utilized for tasks requiring strategic planning and long-term decision making, such as climate modeling and ecosystem management [74]. For example, a deliberative AI agent can assess historical climate data to forecast future temperature patterns and recommend appropriate mitigation strategies [75]. These agents are characterized by their complexity and adaptability, though they require more computational resources and extensive data for effective operation [76]. Hybrid agents [77,78] combine the strengths of both reactive and deliberative agents, enabling them to respond swiftly to immediate changes while also engaging in long-term planning. This dual capability makes hybrid agents particularly suitable for dynamic and complex environmental systems [79] where both real-time responsiveness and strategic foresight are necessary. For example, a hybrid AI agent deployed in a smart irrigation system can adjust water distribution in real-time based on current soil moisture levels while also planning future irrigation [80] schedules based on weather forecasts and crop growth models [81,82]. Hybrid agents offer versatility and enhanced performance by integrating multiple operational modes, thereby providing a superior functionality in various environmental applications (Table 1).

Table 1. Comparison of AI agent types.

AI Agent Type	Characteristics	Functionalities	Advantages	Typical Applications
Reactive	Operate based on predefined rules; no internal state or future planning	Real-time monitoring and alerting [70]	Simplicity, speed	Pollution detection [83,84], immediate remedial actions
Deliberative	Maintain internal state; capable of planning and reasoning about future actions	Climate modeling, ecosystem management	Complex reasoning, adaptability	Climate forecasting, resource management [85]
Hybrid	Combine reactive and deliberative capabilities; handle both immediate and long-term tasks	Smart irrigation systems, autonomous vehicles	Versatility, enhanced performance	Dynamic resource allocation, adaptive systems [40,86]

3.2. Functions and Capabilities

In environmental sciences, AI agents fulfill various functions that improve the efficiency, precision, and effectiveness of monitoring and management processes [87]. Their capabilities encompass data collection and processing, predictive analytics, and automated decision making, each contributing to a comprehensive approach to environmental stewardship [88]. Data collection and processing represent the core functions of AI agents. By utilizing IoT devices and sensor networks, these agents capture real-time data on key environmental parameters, including air and water quality, temperature, humidity, and pollutant concentrations [89–92]. The ability to process large volumes of data rapidly allows AI agents to filter, clean, and organize information for further analysis. Sensor [93] integration ensures seamless data acquisition from diverse sources, while automated data cleaning identifies and corrects anomalies and inconsistencies in the raw data, maintaining data quality and reliability [91,94,95]. This high-speed data processing capability ensures that environmental scientists have access to up-to-date information essential for accurate assessments and timely interventions. Predictive analytics represents another significant capability of AI agents. By analyzing historical and current data, AI agents can forecast future environmental conditions and trends. This predictive power is crucial for anticipating events such as natural disasters, pollution spikes, and climate anomalies, enabling proactive measures to mitigate adverse impacts. Machine learning models, such as regression, classification, and neural networks, are utilized to detect patterns and generate predictions from the collected data. Scenario simulation allows AI agents to create various environmental scenarios, assessing potential outcomes and informing decision making. Continuous trend analysis ensures that emerging patterns and shifts in environmental parameters are detected promptly, supporting long-term planning and sustainability efforts. Automated decision making strengthens the role of AI agents in environmental sciences by delivering data-driven insights and recommendations. AI algorithms assess available options and identify the most effective actions based on predefined criteria and real-time data inputs. This functionality is especially crucial in situations demanding swift responses, such as emergency management and resource distribution. Decision support systems powered by AI present relevant data and analytical outcomes through visualization tools, aiding human decision makers in interpreting complex information. Optimization algorithms identify the best possible solutions for resource management, pollution control, and conservation efforts, while autonomous actions implement predefined measures without the need for human intervention, especially in time-sensitive situations.

Algorithm Selection Criteria

The suitability of AI algorithms for environmental monitoring was determined based on three key criteria: data type, computational efficiency, and interpretability.

Data type played a crucial role in algorithm selection. Supervised learning models, such as random forests and support vector machines (SVMs), were used for labeled datasets, such as water quality measurements with known contamination levels. In contrast, unsupervised clustering techniques like K-Means were applied for anomaly detection in unlabeled climate datasets, identifying deviations in air pollution or temperature patterns. Deep learning architectures, such as convolutional neural networks (CNNs), were selected for high-dimensional data, particularly in remote sensing applications where feature extraction from satellite imagery was required.

Computational efficiency was another critical factor, especially for IoT-based monitoring solutions deployed in resource-constrained environments. Random forests and decision trees were preferred for edge devices due to their low computational overhead and real-time processing capabilities, making them ideal for on-device water quality assessments. In contrast, LSTM networks were chosen for time-series water quality prediction, leveraging their ability to capture long-term dependencies in sensor readings while running on cloud-based platforms. CNNs, while computationally intensive, were prioritized for high-resolution environmental image processing, where deep feature extraction provided significant advantages.

Interpretability was essential for ensuring stakeholder trust and regulatory compliance in AI-driven decision making. SHAP (Shapley additive explanations) values were used to explain feature contributions in pollution source identification, providing transparency for environmental policy enforcement. In regulatory contexts, where decision-making accountability was necessary, logistic regression and random forests were preferred due to their explainability, whereas deep learning models were primarily used in cases where accuracy outweighed interpretability concerns.

For example, LSTM networks were prioritized for time-series water quality prediction, effectively modeling seasonal variations and pollution trends in lakes and rivers [96–103]. Meanwhile, K-means clustering was applied to identify spatial pollution hotspots by grouping IoT sensor data based on air quality measurements. These algorithmic choices ensured that AI-driven environmental monitoring systems were optimized for accuracy, efficiency, and real-world applicability.

3.3. Real-World Applications of AI Agents in Environmental Monitoring and Management

AI agents have been utilized across diverse environmental applications, showcasing their potential to enhance sustainability efforts. Their use extends to resource management, biodiversity conservation, urban planning [96], emissions forecasting [97], and advanced robotics, highlighting the adaptability and influence of AI in environmental sciences. In the field of resource management and climate change mitigation [98–100], AI technologies play a crucial role in optimizing resource use, forecasting environmental trends [101,102], and enhancing decision-making processes. For instance, in the Great Lakes region, an AI-powered water quality monitoring system [103] utilizes IoT sensors to continuously measure parameters such as pH, turbidity, dissolved oxygen, and contaminant levels. AI agents process this data in real-time, identifying pollution events and forecasting future water quality trends. This approach has greatly enhanced proactive water quality management, helping to mitigate pollution-related challenges more effectively. Biodiversity preservation has also benefited from AI integration [104,105]. AI-driven drones and camera traps are utilized for wildlife monitoring, detecting potential threats and aiding conservation efforts [106]. Machine learning models evaluate ecosystem health, supporting sustainable management strategies to safeguard biodiversity [107]. However, the implementation of AI in conservation raises ethical and cybersecurity concerns that must be addressed to ensure responsible use and protect sensitive environmental data. Urban planning and green building technologies have seen significant advancements through AI applications [108]. In urban environments, AI algorithms analyze data on population density, land use, and infrastructure development to guide sustainable urban expansion. Machine learning models optimize building designs for energy efficiency, reducing resource consumption and lowering carbon emissions [109]. Additionally, AI systems monitor and control indoor environments, ensuring optimal air quality, temperature, and lighting for occupants. These AI-powered technologies support the creation of smart cities that integrate sustainable development with urban growth, improving residents' quality of life while reducing the environmental impact [110,111]. AI has also been pivotal in predicting CO_2 emissions [112,113]. The biogeography-based optimization (BBO) algorithm has been utilized to model and forecast emission trends, providing policymakers with data-driven insights necessary for formulating effective environmental policies and strategies [114]. This strategy enables the implementation of targeted initiatives to lower emissions and counteract climate change effects, ensuring that environmental management practices remain both efficient and sustainable [115,116]. Innovative applications of AI extend to the realm of robotics [117,118], where AI agents equip micro and nanoscale colloidal robots with deep reinforcement learning capabilities. These robots are capable of navigating unknown environments efficiently, making them particularly impactful in precision surgery and targeted nanodrug delivery [119]. AI-driven navigation enables robots to avoid obstacles and minimize travel time based on local sensory inputs, enhancing the precision and effectiveness of medical interventions [120]. Research on autonomous AI agents [121] in open-world environments is another frontier in environmental applications. These agents utilize integrative frameworks that combine reinforcement learning with symbolic planning to handle complex tasks and adapt to new conditions. Such capabilities are crucial for applications like autonomous vehicles and service robots, which operate in unpredictable settings and require robust adaptability to function effectively [122,123]. These autonomous systems represent the cutting edge of AI integration in dynamic and real-world environments, offering solutions that are both intelligent and resilient [124,125]. Finally, AI agents are being incorporated into extended reality (XR) applications [126] to deliver highly detailed and immersive training experiences [127]. In contexts such as LEGO brick assembly, AI agents use large language models and vision–language integration to decide actions based on past experiences [128], enhancing user interaction in XR environments [129]. This integration facilitates more effective and immersive training experiences, improving learning outcomes and user engagement through personalized and responsive AI-driven guidance. AI agents, through their diverse types and sophisticated capabilities, are transforming environmental sciences by enabling more effective monitoring, analysis, and decision making. Reactive, deliberative, and hybrid agents each offer unique advantages tailored to specific environmental applications, from real-time pollution detection to strategic climate modeling. The presented case studies demonstrate the concrete advantages of combining AI agents with IoT technologies, showcasing advancements in water quality monitoring, biodiversity conservation, urban planning, emissions forecasting, and cutting-edge robotics. As AI and IoT continue to progress, their integration is expected to further strengthen the ability of environmental scientists and policymakers to tackle urgent environmental issues, promoting sustainability and resilience through intelligent and forward-thinking management approaches.

3.4. Critical Analysis of Selected Case Studies

The application of AI in biodiversity conservation, urban planning, and CO_2 emissions forecasting has demonstrated significant potential, but critical challenges remain. This section provides an in-depth evaluation of selected case studies, analyzing their strengths, limitations, and areas for improvement. The comparative table below summarizes the key findings, offering a structured perspective on the effectiveness and scalability of AI-driven environmental monitoring solutions Table 2.

Table 2. Comparative analysis of AI applications in environmental monitoring.

Study	Domain	AI Technique	Strengths	Weaknesses
Raihan (2023) [104]	Biodiversity conservation	Machine learning	Comprehensive overview of AI in conservation; practical applications for resource management	Lacks empirical validation; limited discussion on AI adoption challenges
Ullah, Saqib and Xiong (2024) [105]	Biodiversity conservation	AI for ecosystem monitoring	Bridges classical and modern conservation approaches; emphasizes proactive monitoring	Theoretical focus with minimal real-world examples; insufficient analysis of AI limitations
Ayoola et al. (2024) [106]	Biodiversity conservation	Big Data and AI	Highlights predictive modeling and habitat monitoring; integrates big data approaches	Overemphasis on the USA, limiting generalizability; lacks discussion on ethical and regulatory aspects
Jha et al. (2021) [110]	Urban planning	AI for smart cities	Broad review of AI's role in urban planning; discusses smart infrastructure and sustainability	Largely conceptual; lacks real-world case studies and algorithmic details
Sanchez et al. (2023) [111]	Urban planning	AI for sustainability	Focuses on AI's role in minimizing ecological footprints; forward-looking perspective	Limited focus on practical implementation; insufficient exploration of ethical/social concerns
Chen et al. (2021) [112]	CO_2 Emissions forecasting	AI for energy efficiency	Strong methodological framework; practical insights for emissions reduction	Limited scalability discussion; lacks analysis of computational constraints
Aras and Hanifi Van (2022) [113]	CO_2 emissions forecasting	AI for energy and emissions	Proposes an interpretable forecasting framework; holistic approach to energy-emissions link	Focuses on forecasting but lacks policy integration
Nazir et al. (2024) [114]	CO_2 Emissions forecasting	AI ensemble strategies	Uses advanced AI techniques for predictive analytics; informs policy decisions	Preprint status—findings not yet peer-reviewed; lacks discussion on ethical and computational aspects

AI has played a crucial role in enhancing biodiversity conservation efforts, particularly in wildlife monitoring, ecosystem management, and habitat preservation. Raihan (2023) [104] provides an extensive overview of machine learning applications in conservation, demonstrating their role in optimizing resource management strategies. While the study highlights practical applications, it lacks empirical case studies that validate AI's effectiveness in real-world conservation settings. Addressing challenges related to AI adoption, data availability, and ethical concerns would strengthen its contribution to biodiversity science.

Ullah, Saqib, and Xiong (2024) [105] bridge traditional and AI-driven conservation approaches, emphasizing ecosystem monitoring and threat identification. The study effectively positions AI as a tool to complement classical biodiversity methods, but remains highly theoretical, lacking real-world applications and pilot projects. Further research should focus on practical implementation, incorporating interdisciplinary collaborations to address AI's algorithmic biases and interpretability concerns.

Ayoola et al. (2024) [106] examine AI's role in big data-driven biodiversity monitoring, particularly in habitat preservation and species tracking. This study underscores the benefits of predictive modeling for conservation planning, yet is heavily focused on the USA, limiting the generalizability of its findings to other ecological and socio-economic contexts. A more diverse dataset and regulatory discussion would enhance the study's applicability to global conservation efforts.

The use of AI in urban planning and smart city development has the potential to optimize infrastructure, reduce ecological footprints, and improve urban sustainability. Jha et al. (2021) [110] offer a broad conceptual review of AI's applications in urban design, particularly in smart infrastructure and indoor environment optimization. However, this study remains highly theoretical, lacking empirical validation and real-world case studies. Future research should focus on specific AI algorithms, such as biogeography-based optimization (BBO), which has demonstrated effectiveness in smart city planning.

Sanchez et al. (2023) [111] highlight AI's role in sustainable urban development, presenting a forward-looking perspective on how AI can minimize urban ecological footprints. While the study effectively discusses potential AI transformations, it lacks practical implementation strategies and case studies. Additionally, it overlooks critical ethical concerns, such as data privacy, urban bias, and accessibility in AI-driven planning decisions. Addressing these gaps through empirical studies and interdisciplinary frameworks would provide a more comprehensive understanding of AI's role in urban sustainability.

AI-driven approaches to CO_2 emissions modeling have shown promising results in enhancing energy efficiency and environmental policy formulation. Chen et al. (2021) [112] present a methodologically sound framework for AI-assisted energy and carbon footprint modeling, providing practical insights into emissions reduction. However, the study does not address scalability concerns or the computational costs of deploying AI models in large metropolitan regions. Including discussions on low-power AI models and edge computing applications could improve the study's applicability.

Aras and Hanifi Van (2022) [113] propose an interpretable forecasting framework for energy consumption and emissions modeling, offering a holistic view of energy–environment interactions. While the study's emphasis on interpretable AI is commendable, it focuses primarily on forecasting, lacking integration with urban policy planning and emissions reduction strategies. Future research should explore how AI-driven insights can directly inform and shape environmental policies.

Nazir et al. (2024) [114] explored AI ensemble strategies for CO_2 emissions forecasting, employing advanced deep learning methodologies. The study's strong predictive analytics approach makes it highly valuable for policymakers, yet its preprint status means that its findings have not been fully validated. Additionally, it does not sufficiently explore the computational and ethical challenges of AI-driven emissions modeling, limiting its practical relevance. Addressing these technical and ethical considerations will be crucial for ensuring the responsible deployment of AI in emissions forecasting.

Despite AI's growing role in environmental monitoring and decision making, several challenges remain across all case studies. A common limitation is the lack of real-world empirical validation, with many studies relying primarily on theoretical discussions rather than pilot implementations. Additionally, ethical and regulatory considerations are often underexplored, particularly concerning AI bias, transparency, and governance frameworks.

Future research should emphasize interdisciplinary collaborations, integrating environmental science, AI development, and policy making to create more comprehensive and impactful AI-driven environmental solutions. Expanding pilot projects, open source AI frameworks, and adaptive learning models will be essential for ensuring scalability, fairness, and long-term sustainability in AI applications for environmental monitoring.

3.5. AI Techniques: Rationale and Suitability

The selection of AI techniques in environmental monitoring depends on data characteristics, interpretability requirements, computational constraints, and the specific challenges of each application. The choice between supervised, unsupervised, and deep learning methods is guided by the nature of the dataset (labeled vs. unlabeled), the need for real-time processing, and the feasibility of deploying models on edge or cloud-based systems.

3.5.1. Supervised Learning for Predictive Modeling

Supervised learning algorithms, such as random forests, support vector machines (SVMs), and gradient boosting are widely used in environmental monitoring due to their ability to learn complex relationships between labeled input data (e.g., sensor readings) and output categories (e.g., pollution levels). In water quality prediction, these models excel at mapping chemical composition data (e.g., pH, turbidity, dissolved oxygen) to contamination risk levels. The ability to train on historical pollution events allows for accurate forecasting, enabling proactive environmental management. Additionally, ensemble methods like Random Forests improve robustness by reducing overfitting, making them well suited for noisy environmental data.

3.5.2. Unsupervised Learning for Anomaly Detection

When labeled data are scarce, unsupervised learning techniques become essential. K-means clustering, DBSCAN, and autoencoders are particularly useful for detecting anomalies in climate data, where sudden deviations in temperature, humidity, or atmospheric pressure may indicate early signs of extreme weather events. These models group similar data points, allowing for the identification of patterns that deviate from the norm. For example, K-means clustering can detect unexpected temperature spikes that may signal an impending heatwave, while autoencoders trained on normal air quality patterns can flag unusual pollutant concentrations as potential hazards.

3.5.3. Deep Learning for Complex Feature Extraction

For applications requiring high-dimensional data processing, such as remote sensing and satellite imagery, deep learning techniques outperform traditional models. Convolutional neural networks (CNNs) are particularly effective in aerial image analysis, where they leverage hierarchical feature extraction to identify deforestation patterns, land-use changes, and water contamination from spectral images. CNN-based models trained on multispectral satellite imagery can differentiate between healthy and stressed vegetation, providing insights into drought impact and illegal deforestation activities. Similarly, recurrent neural networks (RNNs) and long short-term memory (LSTM) networks are well suited for time-series predictions, such as climate trend forecasting based on historical temperature and precipitation data.

3.5.4. Balancing Interpretability and Computational Constraints

Model selection is not solely dictated by accuracy but also by interpretability and computational feasibility. Decision makers in environmental science often require transparent, explainable models to justify interventions. Decision trees and linear regression models provide straightforward rule-based outputs, making them preferable for regulatory compliance and policy making. Conversely, deep learning models, while highly accurate, are often seen as "black boxes", limiting their adoption in cases where interpretability is crucial.

Furthermore, computational constraints play a pivotal role in deployment feasibility. Edge computing applications, such as IoT-based real-time monitoring stations, require lightweight models due to power and processing limitations. Decision trees and logistic regression are commonly deployed on edge devices for rapid, low-power inference, whereas cloud-based architectures can accommodate more complex deep learning models, benefiting from scalable GPU resources.

3.5.5. Hybrid Approaches for Enhanced Performance

Increasingly, hybrid models combining multiple AI techniques offer superior performance in environmental monitoring. For instance, an unsupervised clustering method can first detect anomalies in water quality data, which are then fed into a supervised classification model to predict contamination sources. Similarly, CNNs can extract spatial features from satellite images, while traditional machine learning models use these features for classification, ensuring a balance between interpretability and computational efficiency.

4. Leveraging IoT and AI for Improved Environmental Decision Making

The fusion of the Internet of Things (IoT) and artificial intelligence (AI) [130–132] has brought significant advancements to environmental sciences [133], enabling more efficient and data-driven decision-making processes. By leveraging the complementary capabilities of these technologies, integrated systems facilitate improved data collection, real-time analysis, and the generation of actionable insights. This convergence enhances the ability to tackle complex environmental challenges with greater accuracy and speed. This chapter examines the synergy between IoT and AI, details the workflow of integrated systems, and explores the advantages of real-time monitoring and responsive management strategies (Figure 2).

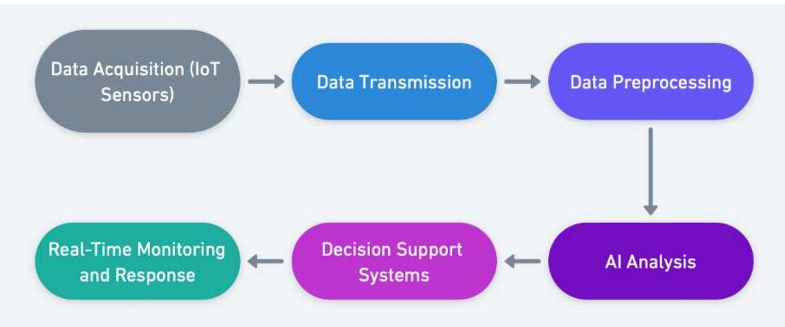

Figure 2. Integrated AI–IoT system workflow.

The combination of IoT and AI establishes a powerful framework for environmental monitoring and management [46,60,134]. IoT functions as the foundational layer, enabling the continuous and automated acquisition of extensive environmental data through a network of interconnected sensors and devices [135–137]. These sensors capture a diverse range of environmental parameters, including temperature [46,138], humidity [46], air and water quality [44,83], soil moisture [138–140], and pollutant concentrations, producing real-time data streams that offer a holistic perspective on environmental conditions (Table 3).

Table 3. Components of integrated AI–IoT Systems.

Component	Description	Role in Integrated Systems
IoT sensors [46,83,139]	Devices that collect environmental data such as temperature, humidity, pH, turbidity, etc.	Data acquisition from various environmental parameters
Data transmission [134,141,142]	Wireless communication standards (e.g., Wi-Fi, LoRaWAN, cellular networks)	Transmission of collected data to centralized repositories
Edge computing [143]	Local data processing units near data sources	Preliminary data analysis to reduce latency and bandwidth
AI algorithms [144–146]	Machine learning and deep learning models	Data analysis, pattern recognition, predictive modeling
Decision support systems (DSSs) [145,147]	Platforms that present data insights and recommendations to stakeholders	Facilitation of informed decision making
Visualization tools [148,149]	Dashboards and graphical interfaces	Presentation of complex data in an accessible format

AI amplifies these capabilities by converting raw data from IoT devices into actionable insights. Through machine learning algorithms and advanced data analytics, it identifies patterns, detects anomalies, and predicts future environmental trends. This analytical capability allows AI models to execute advanced tasks such as predictive modeling, which forecasts pollution incidents or climate irregularities, and automated decision making, which selects the most effective responses using real-time data inputs. Consequently, the synergy between IoT and AI not only enhances data richness but also imbues the system with intelligent processing capabilities, making it possible to respond swiftly and accurately to emerging environmental challenges.

4.1. Data Quality Challenges and Preprocessing

The accuracy of AI-driven environmental monitoring depends on high-quality input data. However, IoT sensors, satellite imagery, and monitoring stations often generate incomplete, noisy, and inconsistent data. Missing values arise from sensor failures and transmission errors, while sensor drift and human error introduce noise. Integrating diverse data sources—satellite imagery, IoT networks, and meteorological stations—requires harmonization to ensure consistency. Temporal and spatial gaps further disrupt data streams, complicating predictive modeling.

To address these issues, preprocessing techniques improve data reliability. Missing data imputation methods include mean, median, or mode replacement for minor gaps, time-series interpolation for continuous datasets, and machine learning-based imputation using k-nearest neighbors or autoencoders. Noise reduction techniques such as moving average smoothing and Kalman filters refine real-time sensor readings, while outlier detection methods like isolation forest and DBSCAN identify anomalies in pollution and water quality data.

Normalization and standardization ensure consistency across datasets. Min-max scaling normalizes sensor readings such as temperature and pollution levels, while z-score normalization standardizes distributions. Feature engineering techniques like principal component analysis (PCA) reduce dimensionality in satellite images, while Fourier transform and wavelet analysis extract patterns from climate data.

Multi-source data integration is essential for accurate AI predictions. Data fusion techniques include low-level fusion, which merges raw sensor data, feature-level fusion, which combines extracted attributes from multiple datasets, and decision-level fusion, which aggregates independent AI model outputs. Spatial and temporal alignment ensures consistency, with geospatial harmonization linking satellite and ground-based sensor data, while time-series synchronization corrects inconsistencies in climate datasets. Ontology-based data standardization unifies formats across environmental domains, and edge computing allows local preprocessing before cloud-based AI analysis.

Effective data preprocessing enhances AI-driven environmental monitoring by improving accuracy, reducing noise, and ensuring interoperability. Future research should focus on automated preprocessing pipelines, self-learning imputation models, and AI-enhanced real-time data fusion for improved environmental prediction and decision making.

4.2. Workflow of Integrated Systems

The integration of IoT and AI in environmental sciences follows a structured workflow, ensuring a smooth transition from data collection to decision making. The process begins with data acquisition, where IoT devices are strategically positioned to continuously gather environmental data. These sensors transmit information using communication protocols such as Wi-Fi, LoRaWAN, or cellular networks to centralized repositories or cloud platforms [136,150]. In some cases, edge computing is utilized to perform initial data processing near the source, minimizing latency and bandwidth consumption.

Once acquired, the data undergo preprocessing [151] and analysis to enhance its quality and usability for AI models. This stage includes data cleaning to eliminate noise and correct errors, ensuring accuracy and consistency. Data integration merges information from various sensors and sources to create a unified dataset, offering a comprehensive perspective on environmental conditions. Feature engineering extracts and selects the most relevant attributes that characterize the environmental phenomena under investigation [152].

Following preprocessing, AI model training applies machine learning and deep learning techniques to learn patterns from the refined dataset, enabling accurate predictions and decision making. Finally, real-time analytics processes incoming data streams instantaneously, generating immediate insights and facilitating proactive responses [153]. The final phase of the workflow involves decision support systems (DSSs) that leverage the outputs of AI models to aid stakeholders in making informed decisions [145]. Visualization tools present data and AI-driven insights through interactive dashboards, making complex information accessible and comprehensible [148]. Automated alerts and notifications are generated based on predefined thresholds or anomaly detection [60,154] patt, enabling swift responses to emerging issues. Additionally, DSSs provide actionable recommendations and strategic options derived from AI analyses, guiding policymakers, environmental managers, and other stakeholders in their decision-making processes. Feedback loops are established to incorporate the outcomes of decisions back into the system, continuously enhancing the accuracy and reliability of AI models through ongoing learning and adaptation.

4.3. Instantaneous Monitoring and Adaptive Response

One of the key benefits of combining IoT and AI in environmental sciences is the ability to enable real-time monitoring and rapid response [155–157]. This capability facilitates the immediate detection of environmental changes and the swift deployment of corrective measures, helping to minimize potential negative impacts. Real-time data processing offers multiple benefits that enhance the accuracy, responsiveness, and overall effectiveness of environmental oversight and control. It enables the immediate detection of environmental anomalies [158] or pollution events, allowing for timely interventions that can reduce the severity of environmental damage [159]. AI models can dynamically adapt their analyses and predictions based on the latest data, ensuring that insights remain accurate and relevant even as environmental conditions change. This adaptability supports enhanced responsiveness, enabling stakeholders to make agile decisions in the face of rapidly evolving environmental challenges [160–162]. Moreover, real-time processing optimizes operational efficiency by minimizing delays between data collection and action, thereby streamlining resource allocation and workflow management. Several rapid response scenarios illustrate the practical benefits of instantaneous monitoring and data-driven decision making. In flood management, IoT sensors placed in river basins and flood-prone areas collect data on water levels, rainfall, and soil saturation [163]. AI models process and interpret these data instantaneously to predict flood risks, triggering automated alerts and initiating evacuation plans or water diversion strategies to mitigate flood impacts [164,165]. Similarly, in urban air quality control, IoT sensors continuously monitor pollutant levels. When AI algorithms detect sudden spikes in pollutants like $PM_{2.5}$ or NO_2, immediate measures such as traffic restrictions or industrial emission controls can be implemented to safeguard public health [166,167]. Another example is wildfire detection [168,169], where IoT-enabled smoke detectors and temperature sensors deployed in forested areas provide real-time data on fire conditions [170]. AI agents analyze these data to identify early signs of wildfires, activating emergency response protocols and deploying firefighting resources swiftly to contain the blaze [169,171]. In water quality assurance, IoT sensors monitor parameters such as pH [172], dissolved oxygen [172,173], and pollutant concentrations in aquatic ecosystems [174–176]. AI models detect anomalies indicative of pollution events, prompting immediate remediation actions like halting industrial discharges, notifying relevant authorities, and initiating cleanup operations to protect water quality and aquatic life. Energy grid management also benefits from instantaneous tracking and AI integration [177]. IoT sensors track energy consumption and generation in real-time within smart grids [146,178,179]. AI systems process these data to enhance energy distribution, predict demand surges, and manage renewable energy sources efficiently, ensuring grid stability and reducing energy wastage [105]. The integration of IoT and AI fundamentally enhances decision-making processes in environmental sciences [180,181] by combining comprehensive data collection with intelligent analysis and actionable insights. The synergy between these technologies facilitates the development of resilient, instantaneous monitoring systems capable of adapting to dynamic environmental conditions and support proactive management strategies [60]. By streamlining the workflow from data acquisition to decision support, integrated AI–IoT systems empower environmental scientists, policymakers, and key stakeholders in tackling complex issues with greater efficacy and responsiveness. As technology evolves, the synergy between IoT and AI is set to propel further innovations, promoting more sustainable and resilient approaches to environmental management.

5. Environmental Data Focus

Environmental data function as the cornerstone for efficient oversight and informed decision making in environmental sciences [182,183]. Among the various types of environmental data, water quality and climate data are particularly crucial as a result of their profound impacts on ecosystems, public health [184,185], and global climate patterns [186,187]. This section examines the critical parameters tracked in these domains, the role of artificial intelligence (AI) in data analysis, and the Internet of Things (IoT) solutions utilized to enable comprehensive and continuous monitoring.

5.1. Water Quality Data

Water quality monitoring [188,189] is crucial for preserving aquatic ecosystem health and safeguarding water resources for human consumption and industrial applications. Assessing water quality requires the evaluation of multiple parameters, which together offer a comprehensive understanding of the water's overall condition [175,190].

5.1.1. Key Parameters Monitored

Monitoring water quality requires the continuous assessment of several critical parameters. The pH level reflects the acidity or alkalinity of the water [117,191], with variations from the neutral pH of 7 signaling potential contamination from sources like industrial effluents or acid rain, which may negatively impact aquatic ecosystems and water suitability [192]. Turbidity assesses the clarity of water by measuring the presence of suspended particles. High turbidity levels may result from soil erosion, algal blooms, or industrial effluents, which can harm aquatic organisms and complicate water treatment processes [193,194]. Dissolved oxygen (DO) is a crucial parameter that indicates the oxygen concentration in water [195,196], which is vital for the survival of fish and other aquatic organisms. Low DO levels can lead to hypoxic conditions, killing fish and disrupting aquatic ecosystems. Additionally, monitoring contaminants, including heavy metals [197,198] like lead and mercury, nutrients such as nitrates and phosphates, pathogens including bacteria and viruses [199,200], and various organic compounds, is crucial for ensuring water safety for consumption, recreation, and wildlife (Table 4).

Table 4. Key parameters monitored in water quality.

Parameter	Significance	Common Measurement Methods
pH [192,201,202]	Indicates acidity or alkalinity; deviations signal pollution sources	pH meters, colorimetric tests
Turbidity [192,193,203,204]	Measures water clarity; high levels indicate suspended particles	Turbidity meters, nephelometers
Dissolved Oxygen [195,196]	Essential for aquatic life; low levels can lead to hypoxic conditions	DO meters, titration methods
Contaminants [197,200]	Includes heavy metals, nutrients, pathogens, organic compounds	Spectroscopy, chromatography, biosensors

5.1.2. AI Applications in Water Quality

Artificial intelligence has revolutionized water quality monitoring [205] by enhancing predictive capabilities and automating detection processes. Predictive modeling utilizes AI-powered algorithms to examine historical and real-time data, enabling the anticipation of potential pollution events [206]. By recognizing patterns and relationships within the data, these models can predict contamination events like industrial spills or agricultural runoff, enabling proactive measures to reduce their impact [207,208]. Furthermore, AI facilitates automated detection and alerts by processing continuous streams of data from connected IoT devices [209,210]. Machine learning models have the capability to identify anomalies in parameters like pH or DO, automatically triggering notifications to environmental authorities and stakeholders. This enables swift response actions to contain and remediate pollution sources, thereby minimizing environmental and public health risks [211,212].

5.1.3. IoT Devices for Water Monitoring

The deployment of IoT devices is integral to the comprehensive and continuous monitoring of water quality. Various types of sensors are strategically deployed to ensure robust data collection and real-time monitoring. pH sensors [213] are installed at multiple depths and locations within water bodies to continuously monitor acidity levels. Turbidity sensors are placed upstream and downstream of potential pollution sources to detect changes in water clarity [214]. Dissolved oxygen sensors are deployed in critical zones such as breeding grounds and habitats to ensure adequate oxygen levels for aquatic life [215,216]. Additionally, specialized contaminant sensors are positioned near industrial discharge points and agricultural runoff areas to detect specific pollutants like heavy metals or organic compounds [217,218]. Case studies highlight the impact of IoT-integrated water quality tracking systems. For instance, in the Great Lakes region, an integrated system employs IoT sensors across various points to collect data on pH, turbidity, dissolved oxygen, and contaminants. AI agents analyze these data in real-time, detecting pollution events and predicting future trends, which informs remediation strategies [103]. This system significantly improved the region's ability to manage water quality proactively, reducing the incidence of pollution-related issues. Similarly, smart irrigation systems in agricultural settings utilize IoT-enabled soil and water sensors to monitor irrigation water quality, ensuring that crops receive optimal water conditions. AI algorithms analyze sensor data to dynamically adjust irrigation practices, preventing nutrient runoff and minimizing water waste. This method improves crop yields while conserving water resources and minimizing environmental impact [103].

5.1.4. Successful AI–IoT Integrations in Water Monitoring

AI–IoT systems have been successfully implemented across various environmental monitoring applications, demonstrating significant improvements in accuracy, efficiency, and real-time decision making. These integrations have been particularly effective in water quality assessment, pollution detection, and climate impact analysis. The following case studies highlight notable implementations of AI–IoT solutions in diverse environmental settings.

One notable application of AI–IoT integration is in real-time environmental monitoring, where sensor networks continuously collect data on water parameters such as temperature, pH, turbidity, and dissolved oxygen levels. AI-driven models process these data to detect anomalies and predict hazardous conditions. For instance, a study by Khan et al. (2024) [134] developed an IoT-based water quality monitoring system in smart cities, leveraging low-cost sensors and machine learning algorithms to forecast pollution events, enhancing urban water safety. Similarly, Ooko et al. (2024) [219] demonstrated the effectiveness of AI–IoT solutions in monitoring and predicting rural household air pollution in Africa, with potential applications for real-time water contamination tracking.

Beyond urban applications, AI–IoT has transformed smart agriculture by enabling the real-time monitoring of soil moisture, temperature, and nutrient levels. A study by Konar (2024) [220] introduced an AI–IoT framework for automated crop management in urban farming, integrating predictive analytics to optimize irrigation and fertilization schedules [221]. These systems have improved water efficiency, reducing resource consumption while maximizing agricultural yields.

In remote and resource-limited regions, dynamic AI–IoT architectures have enhanced adaptability by enabling updatable AI models on ultra-low-power IoT devices. Alselek et al. (2024) [222] proposed a framework where AI models are dynamically updated within 5G-enabled IoT networks, eliminating the need for firmware modifications and enhancing long-term deployment feasibility. This innovation is particularly beneficial for water monitoring networks in disaster-prone areas, where AI models must adjust dynamically to evolving environmental conditions.

AI–IoT has also been instrumental in biodiversity assessment and conservation. Rathoure et al. (2024) [223] demonstrated how IoT sensor networks and deep learning models were used to monitor species diversity and habitat health in marine and freshwater ecosystems. These systems provided real-time ecological insights, enabling more effective conservation strategies [224].

5.2. Climate Data

Climate data encompass a wide array of indicators that reflect the state and dynamics of the global climate system. The precise monitoring and analysis of climate data are crucial for comprehending climate change, forecasting future trends, and developing effective mitigation and adaptation strategies [225–227].

5.2.1. Essential Climate Indicators

Several key climate indicators provide insights into various aspects of the climate system [228,229]. Temperature measurements, both surface and atmospheric, are critical for assessing global warming trends, heatwave occurrences, and their impacts on ecosystems and human populations. Humidity levels measure the amount of moisture in the air, influencing weather patterns, precipitation, and the formation of phenomena such as fog and thunderstorms. Precipitation data, including rainfall and snowfall, are vital for water resource management, agriculture, and flood forecasting. Wind patterns, which analyze wind speed and direction, are essential for understanding weather systems, ocean currents, and the dispersal of pollutants and aerosols (Table 5).

Table 5. Key climate indicators.

Climate Indicator	Importance	Monitoring Methods
Temperature [230,231]	Assesses global warming trends and heatwave impacts	Thermometers, satellite sensors, weather stations
Humidity [232,233]	Influences weather patterns and precipitation	Hygrometers, weather balloons, ground-based sensors
Precipitation [234,235]	Vital for water resource management and flood forecasting	Rain gauges, radar systems, satellite observations
Wind patterns [236]	Essential for understanding weather systems and pollutant dispersion	Anemometers, Doppler radar, weather satellites

5.2.2. AI in Climate Data Analysis

The role of AI in the analysis of climate data, enhancing the accuracy of climate models and identifying significant trends and anomalies is crucial [100]. Climate modeling and forecasting benefit from AI algorithms, particularly deep learning models, which simulate complex climate interactions and predict future climate scenarios with greater precision. These models incorporate vast datasets from historical records and real-time observations, improving the accuracy of predictions related to temperature changes, precipitation and extreme weather phenomena [237]. Moreover, AI techniques facilitate the identification of trends and anomalies within climate data. Machine learning algorithms process extensive climate datasets to identify long-term patterns and sudden irregularities, such as rapid ice melt in polar areas or unforeseen shifts in rainfall patterns [238]. These insights are vital for informing focused climate action initiatives and developing strategies to address emerging climate-related issues.

5.2.3. IoT Solutions for Climate Monitoring

Role of IoT technologies in the comprehensive and continuous collection of climate data through a system of sensors and remote sensing devices is crucial [239]. A network of IoT-enabled weather stations is distributed across various regions to collect live data on temperature, humidity, precipitation, wind speed, and other climate indicators. These weather stations provide granular data that enhance the resolution and accuracy of climate models and forecasts [137]. Alongside weather stations based on ground [240], satellite imaging technologies [241,242] and drones equipped [243] with climate monitoring instruments gather data from remote and inaccessible regions. These devices measure atmospheric composition, sea surface temperatures, and ice coverage, helping to provide a more comprehensive understanding of global climate dynamics. The integration of IoT solutions with AI-driven analytics ensures that climate data are not only collected comprehensively but also efficiently analyzed, providing timely and actionable insights for climate scientists and policymakers [154]. Water quality and climate data are fundamental components of environmental monitoring, underpinning efforts to sustain ecosystems, protect public health, and address climate change. The integration of those technologies has significantly enhanced the capabilities to monitor these data streams comprehensively and in real time. AI-driven predictive modeling and automated detection systems improve the responsiveness and accuracy of environmental management practices, while IoT-enabled sensor networks ensure continuous and detailed data collection. Combined, AI and IoT enable more informed and prompt decision making, allowing for preventive measures to preserve water quality, reduce climate impacts, and support environmental sustainability.

6. Advantages of Combining IoT and AI in Environmental Sciences

The combination of the Internet of Things (IoT) and Artificial Intelligence (AI) in environmental sciences offers numerous advantages that greatly improve the effectiveness, efficiency, and sustainability of environmental monitoring and management practices [180]. This integration enhances the precision and accuracy of data collection and analysis, optimizes resource use, supports scalable and adaptable monitoring systems, and enables proactive environmental management [60,238]. These benefits are key to tackle complex environmental challenges and fostering sustainable practices (Table 6).

Table 6. Comparative analysis of benefits from AI–IoT integration.

Benefit	Description	Impact on Environmental Sciences
Enhanced accuracy and precision [211,244]	Improved data calibration, noise reduction, and high-resolution insights through AI-driven data processing	More reliable and detailed environmental assessments
Improved timeliness of data and decisions [245,246]	Real-time data processing and automated decision making facilitate swift responses to environmental changes	Faster and more effective interventions, reducing environmental impacts
Cost efficiency and resource optimization [247,248]	Automation reduces labor costs, AI optimizes energy and resource usage, and predictive maintenance minimizes operational expenses	More sustainable and economically viable environmental initiatives
Scalability and flexibility of monitoring systems [246]	IoT networks can be easily expanded and adapted to new parameters, supported by edge computing and modular design	Ability to handle increasing data volumes and diverse monitoring needs
Facilitating proactive environmental management [249]	Early warning systems, predictive maintenance, and strategic planning enabled by AI insights	Shift from reactive to proactive management, enhancing sustainability and resilience

6.1. Enhanced Accuracy and Precision

The combination of IoT and AI significantly enhances the accuracy and precision of environmental data gathering and analysis. IoT devices, outfitted with high-precision sensors, constantly collect detailed and comprehensive data on a range of environmental parameters [211]. These sensors track variables like temperature, humidity, air and water quality, soil moisture, and pollutant levels with exceptional precision [244]. AI algorithms analyze the massive volume of data produced by these sensors, uncovering complex patterns and correlations that might be missed by conventional analysis techniques. This sophisticated data processing ensures the accuracy and reliability of the measurements, greatly minimizing the margin of error in environmental evaluations. For instance, in water quality monitoring systems like those deployed in the Great Lakes region [103], IoT sensors collect live data on pH, turbidity, pollutants and dissolved oxygen levels [250]. AI agents analyze these data continuously, detecting even slight deviations that may indicate pollution events. This level of precision allows for early detection and prompt remediation actions and ensuring the safety of water resources.

6.2. Improved Timeliness of Data and Decisions

Timeliness is a critical factor in environmental sciences, where delayed responses to emerging issues can exacerbate problems and lead to significant environmental and public health impacts. The integration of IoT technology and AI ensures that data are not only collected in real-time but also processed and analyzed swiftly, facilitating prompt decision making [246]. IoT devices transmit data continuously, and AI systems are designed to process this information instantaneously, eliminating delays between data acquisition and actionable insights [147]. The automated decision-making capabilities of AI further enhance timeliness by enabling systems to respond autonomously to specific environmental conditions. For instance, in managing urban air quality, AI algorithms process data from

IoT sensors that monitor pollutant levels in real-time [156]. When pollutant levels surpass safe thresholds, the AI system can autonomously initiate measures such as adjusting traffic signals, activating pollution control mechanisms, or issuing public health advisories [251]. This swift responsiveness ensures that interventions are timely and effective, mitigating adverse effects on public health and the environment.

6.3. Cost Efficiency and Resource Optimization

Integrating IoT and AI leads to significant cost savings and the optimal utilization of resources by streamlining processes, minimizing the need for manual intervention, and enhancing operational efficiencies [247]. Automated data collection and analysis minimize the reliance on extensive manual monitoring efforts, thereby lowering labor costs and reallocating human resources to more strategic tasks [248]. Additionally, AI-driven predictive maintenance of IoT infrastructure anticipates equipment failures and schedules timely maintenance, preventing costly downtimes and extending the lifespan of monitoring systems. Energy efficiency is another area where cost savings are realized. AI algorithms may optimize the operation of IoT technology, managing energy consumption effectively [252]. In smart irrigation systems, for instance, AI determines the precise amount of water needed based on the live data of soil moisture, reducing water and energy usage [81]. This targeted approach not only conserves valuable resources but also lowers operational costs for farmers, enhancing agricultural productivity and sustainability. Furthermore, AI systems facilitate the efficient allocation of resources by analyzing data to identify potential terrains of environmental risk or resource scarcity. This informed allocation ensures that limited resources such as water, energy, and funding are utilized where they are most needed, maximizing their impact and promoting sustainable environmental management practices [253].

6.4. Scalability and Flexibility of Monitoring Systems

A key advantage of combining IoT and AI is the unmatched scalability and flexibility it provides to environmental monitoring systems. IoT networks can be easily expanded by adding more sensors to cover larger geographical areas or to monitor additional environmental parameters [254]. This scalability ensures that monitoring systems can grow in tandem with expanding environmental monitoring needs without compromising performance. The modular design of IoT devices and AI algorithms allows for the customization and expansion based on specific environmental requirements [255]. For example, a monitoring system initially designed to track water quality can be seamlessly adapted to include additional sensors for detecting specific contaminants or to integrate climate data parameters as needed. This flexibility ensures that monitoring systems remain relevant and effective as environmental conditions and monitoring objectives evolve over time. Moreover, the marriage of edge computing with IoT devices enhances the scalability and flexibility of these systems [256]. By conducting initial data processing at the edge, close to the data source, the system lowers latency and reduces bandwidth consumption, allowing for quicker initial analyses and more efficient data handling [257]. This decentralized approach supports the deployment of large-scale sensor networks in diverse and remote locations, ensuring comprehensive and real-time environmental monitoring.

6.5. Facilitating Proactive Environmental Management

Perhaps the most transformative benefit of integrating IoT and AI is the facilitation of proactive environmental management [258]. This proactive approach shifts the focus from reactive responses to environmental issues to anticipating and preventing them before they escalate. Live data acquisition and forecasts enable stakeholders to identify future environmental hazards early and implement preventive measures to mitigate their influence [259].

Early warning systems exemplify proactive management by detecting the signs of potential environmental hazards such as floods, wildfires, or pollution events before they fully develop. For example, IoT sensors that monitor water levels and rainfall intensity in flood-prone areas provide real-time data that AI models analyze to predict flood risks [260]. This prediction allows automated alerts to be activated and evacuation plans or water diversion strategies are initiated, effectively reducing the severity of flood impacts [261]. In addition to emergency response, proactive environmental management encompasses strategic planning and dynamic resource management [258]. AI-driven analytics offer insights into long-term environmental trends, supporting the formulation of sustainable policies and strategies aimed at climate resilience and resource conservation. For example, in renewable energy management [262], AI systems optimize the distribution and storage of energy based on live consumption of data and predictive forecasts, ensuring efficient utilization of renewable resources and improving the stability of the network [263]. Furthermore, proactive management extends to infrastructure maintenance, where AI predicts maintenance needs based on data from IoT sensors, preventing infrastructure failures and ensuring the continuous operation of crucial environmental monitoring systems [157]. This foresight not only enhances the reliability of environmental management practices, but also promotes long-term sustainability and resilience to evolving environmental challenges [254]. The integration of these technologies into environmental sciences offers a suite of benefits that profoundly enhance environmental monitoring and management capabilities. Enhanced accuracy and precision ensure reliable and detailed data collection, while improved timeliness facilitates swift and informed decision making. Cost efficiency and resource optimization make environmental initiatives more sustainable and economically viable, and the scalability and adaptability of AI–IoT systems enable flexible and comprehensive monitoring across diverse environments. Most importantly, the shift towards proactive environmental management enables the anticipation and mitigation of environmental challenges, fostering a sustainable and resilient future. As IoT and AI technologies evolve, their combined integration will undoubtedly be crucial in tackling the complex and ever-changing environmental challenges of our era, fostering innovations that support sustainability, resilience, and data-driven and informed decision making.

7. Challenges and Considerations

There are many challenges and considerations despite the transformative adoption of IoT and AI technologies that must be addressed to ensure effective and responsible deployment. This section explores the main challenges related to data quality and reliability, system integration and interoperability, security and privacy issues, technical and infrastructure limitations, as well as ethical and regulatory concerns (Table 7) (Figure 3).

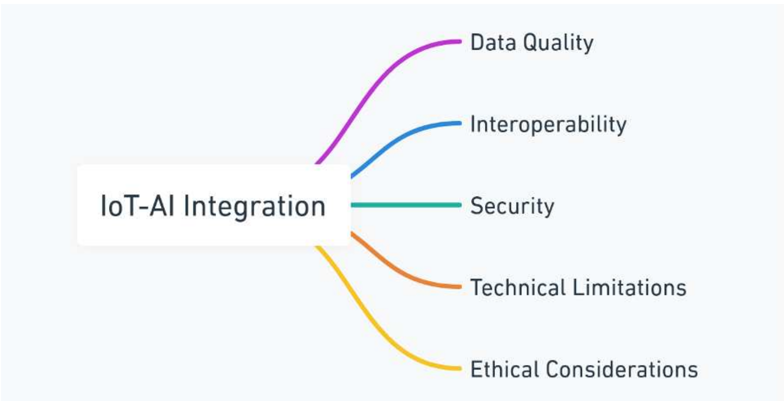

Figure 3. Overview of challenges in AI–IoT integration.

Table 7. Overview of challenges in AI–IoT integration.

Challenge	Description	Potential Solutions
Data quality and reliability [264–267]	The IoT sensors must provide accurate, consistent, and complete data; dealing with sensor drift and environmental interference	Regular calibration, robust data cleaning protocols, redundancy
Integration and interoperability [268–271]	Combining heterogeneous IoT devices and AI systems with diverse protocols and data formats; legacy system compatibility	Standardized protocols, middleware solutions, scalable frameworks
Security and privacy concerns [150,272–274]	Securing data from cyberattacks and unauthorized access; ensuring the protection of sensitive environmental and personal information.	Advanced encryption, authentication mechanisms, compliance with regulations
Technical and infrastructure limitations [221,275]	Reliable connectivity and power supply in remote areas; sufficient computational resources for AI models; maintenance of IoT infrastructure	Energy harvesting solutions, edge computing, robust maintenance plans
Ethical and regulatory considerations [224,276,277]	Tackling biases in AI models, ensuring transparency and interpretability, obtaining informed consent for data collection, and complying with data protection regulations	Fairness-aware algorithms, explainable AI techniques, clear governance frameworks

7.1. Data Quality and Reliability

The effectiveness of AI-powered environmental monitoring systems depends on the quality and dependability of the data gathered by IoT devices [266]. High-quality data ensure accurate analysis, reliable predictions, and trustworthy decision making, whereas poor data quality can lead to erroneous conclusions and ineffective interventions. Ensuring sensor accuracy and regular calibration is essential to maintain precise measurements. Over time, sensors may drift or degrade [264], necessitating ongoing maintenance to uphold data integrity. Additionally, data consistency and completeness are critical; incomplete or inconsistent data [267] can impair the performance of AI models, leading to inaccurate assessments. Environmental factors can also interfere with sensor performance [265], as IoT devices deployed in harsh or variable conditions may suffer from physical damage or exposure to extreme weather, thereby compromising data reliability. Robust data validation and cleaning protocols are necessary to identify and rectify anomalies, outliers, and errors in the dataset, maintaining the overall quality of the data being utilized.

7.2. Integration and Interoperability Issues

Achieving the smooth integration of IoT and AI technologies across various platforms and systems is essential for developing unified environmental monitoring solutions. However, this integration is often hampered by the presence of heterogeneous devices, differing data formats, and varying communication protocols [268]. IoT devices typically utilize different communication standards, which can complicate the aggregation of data into a unified AI system [269]. Additionally, current environmental monitoring infrastructures may depend on legacy systems that are not naturally compatible with modern IoT and AI technologies [270], requiring careful planning and possible system upgrades for seamless integration. The scalability of this integration also presents challenges; as the number of IoT devices increases, managing and consolidating data from a growing number of sensors becomes more complicated [271]. To enable effective AI model training and deployment, it is crucial to establish standardized data formats and ensure consistent data semantics across various IoT devices and platforms, facilitating comprehensive and coherent environmental analysis.

Interoperability Challenges

Interoperability between heterogeneous IoT devices and AI systems remains a key challenge in environmental monitoring, particularly in diverse environmental contexts where different sensor networks, communication protocols, and data formats must seamlessly integrate. Many environmental monitoring systems rely on IoT devices from multiple vendors, each using distinct data transmission standards, leading to compatibility issues that hinder AI-driven analysis.

To address these challenges, middleware platforms such as FIWARE [269] have been utilized to standardize data formats and APIs, enabling seamless communication across diverse IoT ecosystems. For example, in a multi-sensor flood monitoring network deployed in Southeast Asia, data from disparate sources—including pH sensors from Vendor A and turbidity sensors from Vendor B—were harmonized using JSON-LD schemas, ensuring that AI models could interpret and analyze the data consistently [165].

Infrastructure flexibility was further enhanced by deploying AI models within containerized environments, such as Docker, which facilitated seamless model execution across edge and cloud computing systems. This approach allowed real-time AI processing on IoT edge devices while ensuring scalability and cross-platform deployment when computational resources were available.

Despite these advancements, several interoperability challenges persist. Vendor-specific communication protocols, such as Zigbee and LoRaWAN, require adaptive gateways to enable cross-network integration, increasing system complexity. Furthermore, many environmental monitoring infrastructures, such as legacy wastewater treatment plants, operate on outdated SCADA (Supervisory Control and Data Acquisition) systems, which lack modern API support and require custom-built integration layers [275].

Future research should focus on developing unified IoT interoperability frameworks, integrating open source data exchange standards, and creating AI-driven protocol adaptation layers to enhance compatibility across legacy and next-generation IoT monitoring systems. By addressing these challenges, AI–IoT integration can become more scalable, adaptable, and effective in diverse environmental applications.

7.3. Security and Privacy Concerns

The widespread use of IoT devices and the vast amount of data they collect present significant security and privacy challenges [272]. IoT devices are often placed in remote or unprotected locations, making them susceptible to both physical tampering and cyberattacks. It is crucial to implement strong encryption, authentication, and access control mechanisms to safeguard data integrity and prevent unauthorized access [273]. Furthermore, environmental data might inadvertently capture sensitive information about individuals or organizations, raising privacy concerns. For example, IoT sensors in agricultural fields could collect data that expose proprietary farming techniques, which could be exploited if not properly protected [274]. Additionally, AI-driven systems face various cybersecurity threats, such as data breaches, ransomware attacks [150], and adversarial machine learning attacks that can manipulate AI models to generate incorrect results. Compliance with data protection regulations and the implementation of comprehensive security measures are vital to protect sensitive environmental data and preserve the trust of stakeholders.

7.4. Technical and Infrastructure Limitations

The deployment of integrated IoT and AI systems in environmental sciences is often constrained by technical and infrastructure limitations that can impede their effectiveness and scalability. Reliable Internet connectivity is crucial for the real-time transmission of data from IoT devices to AI systems [275]; however, in remote or underdeveloped areas, limited bandwidth and connectivity challenges can disrupt data flow and impair system performance [221]. Additionally, many IoT devices operate in environments where access to a stable power supply is challenging, relying instead on batteries or renewable energy sources, which necessitate efficient energy management to ensure continuous operation. AI models, especially deep learning-based ones, demand significant computational resources for both training and inference, which can be a limiting factor in environments with constrained resources. Deploying these models in such environments requires optimized algorithms and possibly edge computing solutions to handle the computational demands locally. Moreover, ensuring the ongoing maintenance and technical support of AI–IoT systems is critical for their sustained operation, involving the management of hardware failures, software updates, and addressing technical glitches promptly.

7.5. Ethical Considerations

The integration of IoT and AI in environmental sciences raises several ethical challenges that must be addressed to ensure responsible and equitable technology use. One major concern is algorithmic bias, where AI models inadvertently perpetuate biases from training data, potentially leading to unfair or discriminatory environmental management decisions [276]. Mitigating these biases requires implementing fairness-aware algorithms and ensuring the use of diverse and representative datasets.

Enhancing explainable AI (XAI) capabilities is crucial for ensuring accountability in decision-making processes, validating AI-driven recommendations, and building trust, as complex AI models, particularly deep learning systems, often function as "black boxes", making it difficult for stakeholders to understand how decisions are made.

Additionally, privacy concerns arise when AI–IoT systems collect environmental data that may indirectly involve human subjects. This includes data from agricultural landowners, industrial facilities, or community water sources. Informed consent and clear data usage policies must be established to protect individuals' rights and ensure ethical data collection practices [224].

Accountability is another critical factor. AI-driven decision-making in environmental monitoring, such as automated pollution detection and resource allocation, requires clear accountability mechanisms to address potential errors or unintended consequences. Establishing governance frameworks that define who is responsible for AI-driven actions will be crucial to ensure responsible deployment.

7.6. Regulatory Considerations

The evolving regulatory landscape governing AI and IoT in environmental sciences necessitates compliance with data privacy, security, environmental protection, and ethical AI usage laws [277]. Various international and regional regulations, such as the General Data Protection Regulation (GDPR) in Europe and industry-specific guidelines, impose stringent requirements on data collection, processing, and sharing.

Data protection laws emphasize the need for secure storage and handling of environmental data, particularly when IoT sensors monitor industrial emissions, water usage, or air quality, where data misuse could have legal and financial implications. Strong encryption, anonymization, and secure access controls must be implemented to safeguard sensitive information.

Interoperability between different AI–IoT systems also requires standardized regulatory frameworks to ensure compatibility and security. Without clear regulations, inconsistencies in data formats, communication protocols, and compliance standards can hinder seamless integration across industries. Regulatory bodies are increasingly advocating for the establishment of common AI governance policies that ensure fairness, security, and accountability in automated decision-making systems.

Moreover, environmental regulations are incorporating AI-driven compliance monitoring tools to enforce pollution controls, sustainable resource usage, and emissions tracking. AI-powered compliance mechanisms must align with existing environmental laws and industry standards to avoid legal risks.

By proactively addressing these regulatory challenges through standardized protocols and collaborative policymaking, stakeholders can ensure the secure, transparent, and legally compliant deployment of AI–IoT systems [254]. Effective regulatory frameworks will not only mitigate risks but also foster innovation and trust in AI-driven environmental monitoring solutions.

7.7. Socioeconomic Factors in AI–IoT Adoption for Environmental Sciences

The integration of AI and IoT in environmental monitoring is not solely a technological advancement; it is also influenced by socioeconomic factors that determine accessibility, scalability, and long-term sustainability. The successful deployment of these technologies depends on financial investment, economic feasibility, policy incentives, public perception, and workforce readiness.

The cost of deploying AI–IoT systems in environmental sciences remains a significant barrier, particularly for developing regions. High initial investment costs for sensor networks, cloud computing infrastructure, and AI model development can deter widespread adoption. While large corporations and government agencies may afford sophisticated AI-driven environmental monitoring systems, smaller municipalities and developing countries often lack the financial resources to implement such solutions at scale.

To address these challenges, cost-effective alternatives, such as edge computing and low-power IoT devices, are being explored to reduce dependency on expensive cloud-based processing. Additionally, public–private partnerships and government-funded initiatives can bridge financial gaps by subsidizing AI-driven environmental monitoring projects.

The acceptance of AI–IoT solutions in environmental sciences also depends on public trust and awareness. While AI-driven monitoring systems offer increased accuracy and efficiency, concerns about data privacy, job displacement, and decision-making transparency can create resistance to adoption.

For example, automated environmental monitoring systems may replace human-led inspections, raising concerns about job losses in traditional monitoring sectors. Additionally, communities may oppose AI-driven decision making if they perceive it as favoring corporate interests over public welfare. Addressing these concerns through transparent AI governance, participatory decision making, and public engagement campaigns can help build trust and ensure equitable access to AI-driven environmental solutions.

The widespread adoption of AI–IoT solutions in environmental sciences requires a skilled workforce capable of managing, maintaining, and interpreting AI-driven insights. However, many regions face a shortage of professionals with expertise in AI, machine learning, IoT integration, and environmental data analytics.

Investment in educational programs, vocational training, and interdisciplinary research initiatives can help bridge these skill gaps. Collaboration between universities, industries, and government agencies can further equip environmental scientists with AI literacy while encouraging AI professionals to specialize in environmental applications.

While AI–IoT solutions hold promise for sustainable environmental management, there is a risk that their benefits will be unevenly distributed. High-income countries and technologically advanced industries may leverage AI for superior environmental monitoring, while low-income regions remain vulnerable to climate change and pollution due to lack of resources.

Ensuring equitable access to AI–IoT technologies requires open source initiatives, technology-sharing agreements, and funding models that enable developing nations to adopt low-cost AI-driven environmental monitoring systems. By making these technologies more inclusive, AI and IoT can contribute not only to environmental sustainability but also to global economic and social resilience.

8. Future Directions and Emerging Trends

The precision and efficiency of monitoring and decision-making processes have already seen significant improvements in environmental sciences thanks to the contributions of technologies like the Internet of Things (IoT) and artificial intelligence (AI). However, the technological landscape continues to evolve rapidly, promising even greater advancements and innovative applications in the future. This section explores the anticipated future directions and emerging trends that are poised to further revolutionize environmental sciences, with a particular emphasis on water quality and climate data (Table 8).

Table 8. Emerging trends in AI and IoT technologies for environmental sciences.

Emerging Trend	Description	Potential Applications	Anticipated Impact
Advanced machine learning techniques [266,278–280]	Improvements in deep learning, transfer learning, federated learning, and reinforcement learning for more sophisticated environmental data analysis	Enhanced climate modeling, adaptive resource management	Greater predictive accuracy and adaptability
Evolution of IoT technologies [221,274–276,281]	Development of LPWAN, advanced sensors, energy harvesting, miniaturization, and edge computing for more robust and efficient environmental monitoring systems	Large-scale sensor networks, remote and real-time monitoring	Increased data granularity and operational efficiency
Integration with blockchain and edge Computing [224,238,254,277]	Utilizing blockchain for data integrity and traceability, and edge computing for decentralized processing	Secure data sharing, real-time analytics	Enhanced security, reduced latency, and improved scalability
Global environmental monitoring networks [278–280]	Establishment of standardized global networks for synchronized data collection and analysis	Comprehensive climate monitoring, disaster response coordination	Unified global efforts in addressing environmental challenges
Community engagement and citizen science [281–285]	Empowering communities through citizen-driven data collection, educational programs, interactive platforms, and collaborative research opportunities	Expanded data collection, enhanced public awareness	Democratized environmental monitoring and increased public participation

8.1. Advancements in AI and Machine Learning Techniques

Machine learning algorithms are constantly evolving, providing increasingly advanced tools and methodologies that can be applied to environmental sciences [63,286].

Advancements in deep learning architectures, including convolutional neural networks and recurrent neural networks, are enhancing the accuracy of pattern recognition and predictive modeling, enabling more precise outcomes in various fields. These advancements allow for the better interpretation of complex environmental data, including satellite imagery for climate monitoring and sensor data for water quality assessment [280,287]. Transfer learning and domain adaptation are emerging as crucial techniques, enabling AI models trained on particular data to be adapted for use in different but related domains. This is particularly beneficial in environmental sciences, where data scarcity in certain regions or parameters can be addressed by leveraging existing models trained on more abundant datasets [288]. Explainable AI (XAI) is another significant advancement, providing insights into how AI models make predictions [289]. This transparency of the AI system is crucial for ensuring trust and ensuring accountability in environmental decision making [290]. Gaining traction as a decentralized machine learning approach, federated learning [291] enables models to be trained across multiple devices or servers that hold local data samples, without the need to exchange the data itself [292]. This enhances data privacy and security, which is crucial for sensitive environmental data collected from various sources. Additionally, reinforcement learning is being explored for dynamic and adaptive environmental management tasks, such as optimizing water distribution [279] in smart irrigation systems or managing renewable energy [278] resources within smart grids.

8.2. Evolution of IoT Technologies for Environmental Applications

Long-range communication with minimal energy consumption, provided by low-power wide-area networks (LPWAN) [293], which includes LoRaWAN [274,276] and NB-IoT [221,275] makes these technologies ideal for deploying large-scale sensor networks in remote or hard-to-reach areas, offering robust, efficient, and versatile solutions for environmental monitoring. Advanced sensor technologies are also being developed, enhancing the sensitivity, accuracy, and multifunctionality of environmental sensors. Innovations such as biosensors for detecting biological contaminants in water and advanced meteorological sensors for detailed climate data collection are expanding the scope of environmental monitoring [281]. Energy harvesting and sustainable power solutions are addressing one of the critical challenges of IoT deployment—power supply. Advances in solar, wind, and kinetic energy harvesting enable IoT devices to operate sustainably without relying on traditional power sources. This is particularly beneficial for long-term deployments in environmentally sensitive or remote locations [294]. Additionally, the trend toward the miniaturization and integration of IoT devices [255] allows for the deployment of dense sensor networks with minimal environmental footprint. This enables detailed and extensive environmental monitoring, which is crucial for detecting complex spatial and temporal variations in water quality and climate data. Edge computing is also becoming integral to IoT technologies, allowing for preliminary data processing and analysis at the source. This reduces latency and bandwidth usage, enabling quicker initial analyses and more efficient data handling. The integration of edge computing with IoT enhances the scalability and flexibility of environmental monitoring systems, ensuring that they can adapt to growing data volumes and diverse environmental conditions.

8.3. Integration with Other Technologies

The combination of IoT and AI with emerging technologies is set to significantly boost their impact on environmental sciences. A notable example is blockchain technology, which can ensure the integrity and transparency of environmental data collected by IoT devices [254]. Through its decentralized ledger, blockchain facilitates the secure sharing of data among various stakeholders, promoting trust and accountability in environmental monitoring and reporting. Furthermore, blockchain-based smart contracts can automate and enforce environmental policies and agreements, using data from IoT devices and AI analyses to ensure adherence and improve resource management efficiency.

As discussed earlier, edge computing enhances the functionality of AI–IoT systems by enabling decentralized data processing. This integration allows for real-time analytics and decision making to occur closer to the source of the data, reducing reliance on centralized cloud systems and increasing resilience. Additionally, augmented reality (AR) and virtual reality (VR) technologies are being combined with IoT and AI [224,295] to provide immersive visualizations of complex environmental data. These technologies make it easier for stakeholders to engage with and interpret environmental conditions and trends, thus supporting more effective decision making.

Although still in its early stages, quantum computing presents the potential to transform environmental modeling and simulation [296]. Quantum algorithms are capable of solving complex environmental problems much more rapidly than traditional computers, offering the possibility of more precise climate models, the better optimization of renewable energy systems, and large-scale environmental simulations [238,277]. As quantum computing continues to evolve, its integration with IoT and AI could lead to groundbreaking advancements in the field of environmental sciences.

8.4. Potential for Global Environmental Monitoring Networks

The establishment of global environmental monitoring networks powered by IoT and AI promises comprehensive and synchronized data collection and analysis on a planetary scale. Developing standardized protocols and data formats is essential for integrating diverse sensor networks and ensuring seamless data exchange across different regions and countries [279]. International collaboration is crucial to establish common standards that facilitate global monitoring efforts, enabling the aggregation of data from various sources into centralized or federated data repositories [280]. Collaborative platforms that enable data sharing and collaboration among international environmental agencies, research institutions, and governments can enhance the effectiveness of global monitoring efforts [278]. These platforms enable the sharing of best practices, technologies, and insights derived from AI-driven analyses, fostering a collaborative, unified approach to tackling global environmental challenges. Through real-time global dashboards that visualize environmental data alongside AI-generated insights, stakeholders gain immediate access to vital information, which in turn supports worldwide efforts to address critical issues like climate change, water scarcity, and other urgent environmental concerns.

Additionally, global monitoring networks play an essential role in coordinating disaster response efforts. By analyzing data from various regions, AI algorithms can predict the spread and potential impact of natural disasters, helping to streamline and enhance emergency response actions. This comprehensive approach ensures the efficient allocation of resources and ensures that communities are better prepared to handle and mitigate the effects of environmental crises.

8.5. Enhancing Community Engagement and Citizen Science

Empowering communities and involving citizens in environmental monitoring can significantly change the adoption power and reach of IoT and AI technologies. Citizen-driven data collection expands the scope and granularity of environmental data, providing valuable insights from diverse locations [285]. Initiatives that encourage individuals to deploy IoT devices and contribute data to environmental monitoring projects can leverage smartphones, wearable sensors, and DIY IoT kits. This could enable widespread participation in data collection, fostering a sense of ownership and accountability among community members. Educational programs and workshops that provide training and resources on how to use IoT and AI tools for environmental monitoring are essential for fostering greater participation and engagement. These programs equip citizens with the skills needed to deploy sensors, interpret data, and contribute to AI-driven analyses, thereby enhancing the overall effectiveness of environmental monitoring systems [284]. Engaging platforms and mobile apps that enable citizens to view, explore, and interact with environmental data can significantly boost involvement [283]. These platforms provide real-time updates, personalized insights, and opportunities for community-driven initiatives, making environmental data more accessible and actionable for the general public. Feedback systems that enable citizens to share observations, propose improvements, and contribute to decision-making processes help ensure that environmental monitoring systems address community needs and perspectives [281]. Incentivizing participation through recognition programs, rewards, or contributions to community projects can motivate greater involvement in citizen science initiatives. This increased participation leads to more extensive data collection and fosters a culture of environmental stewardship. Collaborative research opportunities that involve citizens in data analysis and solution development bridge the gap between scientific communities and the public, promoting a deeper understanding of environmental issues and the co-creation of innovative solutions. The future of environmental sciences is set to be profoundly influenced by the ongoing advancements and emerging trends in AI and IoT technologies. As AI and machine learning techniques continue to progress, they will improve the analytical capabilities and forecasting abilities of environmental monitoring systems. At the same time, the development of IoT technologies will offer more robust, efficient, and adaptable data collection methods. The incorporation of additional technologies, such as blockchain and edge computing, will enhance both the functionality and security of these systems. Moreover, the potential creation of global environmental monitoring networks holds the promise of comprehensive and coordinated data collection on a worldwide scale.

Fostering greater community involvement and supporting citizen science initiatives will democratize environmental monitoring [282], broadening the impact and reach of IoT and AI technologies. As these trends advance, the integrated use of IoT and AI will be central to promoting environmental sustainability, resilience, and data-driven decision making. Embracing these emerging directions will empower environmental scientists, policymakers, and communities to work together in addressing the urgent environmental challenges of our time, leading to a more sustainable and resilient future.

8.6. Research Gaps and Future Directions

Despite significant advancements in AI–IoT integration for environmental monitoring, several critical gaps remain, limiting the scalability, reliability, and societal impact of these technologies. Addressing these challenges will be essential for ensuring the long-term effectiveness of AI-driven environmental solutions.

One major gap is long-term system sustainability. While numerous studies demonstrate successful short-term AI–IoT deployments, longitudinal data on sensor drift, model degradation, and hardware resilience remain scarce. Most AI models are trained on static datasets, yet real-world environmental monitoring systems require adaptive mechanisms to detect and correct sensor inaccuracies over extended periods [264]. Future research should explore self-healing AI architectures, incorporating automated recalibration techniques to maintain accuracy in evolving environmental conditions.

Another key challenge is real-time explainability. While methods like SHAP (Shapley Additive Explanations) provide transparency for static AI predictions, explainable AI (XAI) techniques for streaming IoT data remain underdeveloped [290]. Environmental monitoring applications require dynamic interpretability frameworks that can clarify why AI models issue real-time alerts or classify specific pollution events. Edge-based XAI approaches could improve on-device decision-making by providing interpretable insights at the point of data collection.

Socio-technical governance is another underexplored area, particularly in balancing data privacy regulations (e.g., GDPR) with public interest in pollution transparency [224]. While the AI–IoT systems generate large-scale environmental data, few governance frameworks address how regulatory compliance, community engagement, and ethical considerations should be integrated into AI deployment strategies. Future work should prioritize participatory design approaches, ensuring that environmental monitoring technologies are developed collaboratively with affected communities, policymakers, and industry stakeholders.

To address these gaps, future efforts should focus on three key priorities: (1) federated learning for privacy-preserving AI collaborations, enabling decentralized model training without exposing raw environmental data; (2) Digital Twins for scenario testing, allowing researchers to simulate AI–IoT system performance in diverse environmental conditions before large-scale deployment; and (3) inclusive AI frameworks that incorporate perspectives from marginalized communities, ensuring that environmental monitoring systems equitably benefit all populations. By addressing these challenges, AI–IoT solutions can become more resilient, transparent, and socially responsible, supporting sustainable environmental management on a global scale.

9. Comparative Analysis with Existing Reviews

Several recent studies have explored the integration of AI and IoT for environmental monitoring, focusing on water quality and climate data. While these reviews contribute valuable insights, the present study distinguishes itself by offering a broader perspective that includes methodological advancements, interdisciplinary applications, and a structured evaluation of case studies. The following comparative analysis highlights key differences and novel contributions.

Novel Contributions of This Study

Unlike Popescu (2024) [60], which primarily examines machine learning for pollution monitoring, this study provides a structured analysis of AI–IoT applications across multiple environmental domains. It expands on real-time AI–IoT integration, addressing preprocessing challenges, data harmonization, and multi-source sensor fusion, aspects that are only partially covered in existing reviews.

Khan (2024) [134] focuses on real-time AI-driven trend prediction using GRU-Autoencoder, demonstrating adaptive AI techniques for environmental monitoring. However, this study goes further by evaluating long-term ecosystem monitoring and discussing AI model scalability. Unlike Khan's work, which is limited to short-term data predictions, this study incorporates historical climate analysis and ecosystem-based AI modeling, offering a comprehensive approach to environmental management.

Arabelli (2024) [297] presents case studies on AI–IoT efficiency in environmental change detection, but does not explore ethical concerns, governance frameworks, or regulatory compliance. In contrast, this study examines data governance, privacy concerns, and explainable AI (XAI) for environmental monitoring, ensuring that AI-driven decision making aligns with regulatory standards.

Arowolo (2024) [298] emphasizes AI–IoT applications for long-term ecosystem analysis, but lacks an in-depth evaluation of predictive models and data scalability. This study bridges that gap by presenting a comparative analysis of AI models, exploring hybrid approaches that combine deep learning with traditional predictive analytics, making AI-based environmental monitoring more robust and adaptable.

Panduman (2024) [155] introduces the SEMAR platform, focusing on AI in IoT applications. While it presents a system-level approach, it does not discuss interoperability challenges, multi-source data harmonization, or environmental-specific AI applications. This study offers a broader perspective on AI techniques tailored to environmental challenges, ensuring seamless data integration from heterogeneous sources.

Manongga (2024) [299] proposes the AIKU model for real-time air quality monitoring, demonstrating high accuracy and scalability. However, it remains focused on air pollution and wireless sensor networks, without expanding into water quality, climate monitoring, or multi-environmental AI applications. This study extends beyond air monitoring by addressing AI applications in hydrological and meteorological contexts, providing a more comprehensive environmental perspective.

This comparative analysis highlights the novel contributions of this study, particularly in AI–IoT integration for water quality and climate monitoring, case study-based evaluations, preprocessing techniques, and ethical considerations. Unlike existing reviews, which focus on specific AI applications, this study presents a holistic approach, discussing AI model comparisons, multi-source data integration, and regulatory compliance. Future research could further explore explainable AI (XAI) for environmental monitoring, as well as low-resource AI deployment for regions with limited computational infrastructure.

10. Conclusions

The integration of artificial intelligence (AI) agents with the Internet of Things (IoT) marks a transformative advancement in environmental sciences, offering exceptional capabilities for monitoring, analyzing, and managing environmental data. This article has highlighted the multifaceted applications of AI and IoT in tackling critical environmental challenges, particularly focusing on water quality and climate data. These technologies synergistically enhance the precision and reliability of environmental monitoring while facilitating informed decision making, setting the stage for sustainable and resilient environmental management practices.

Comprehensive monitoring and data collection are enabled through IoT sensors deployed in diverse environmental contexts. These sensors continuously gather granular data, such as pH values, turbidity levels, dissolved oxygen concentrations in aquatic systems, as well as climate parameters like temperature, humidity, precipitation, and wind patterns. The substantial volume and diversity of data provided by these devices form a robust foundation for AI-driven analysis, ensuring real-time access to high-quality information for environmental scientists.

AI agents employ advanced machine learning and deep learning techniques to process and interpret the data collected by IoT devices. Through predictive modeling and automated detection systems, these technologies anticipate pollution events, climate anomalies, and other environmental shifts. This capability empowers stakeholders to take proactive measures, minimizing adverse impacts and enhancing the overall efficacy of environmental management strategies.

Operational efficiency and cost optimization are other benefits of AI and IoT integration. Automating data collection and analysis reduces dependency on manual efforts, minimizes operational costs, and ensures the efficient allocation of resources. Moreover, the AI-powered predictive maintenance of IoT infrastructure prevents costly equipment failures and prolongs the lifespan of monitoring systems.

The scalability and flexibility of AI–IoT systems make them adaptable to evolving environmental conditions and emerging challenges. These systems can expand sensor networks and incorporate new parameters as required, maintaining their effectiveness and relevance over time. This adaptability allows for proactive environmental management, shifting the focus from reactive responses to strategic, forward-thinking solutions. Real-time data processing supports early warning systems, dynamic resource management, and informed planning, promoting sustainability and resilience.

Despite their significant advantages, the integration of AI and IoT in environmental sciences poses challenges such as ensuring data quality, achieving seamless integration, safeguarding security and privacy, addressing technical limitations, and managing ethical and regulatory concerns. Overcoming these challenges requires the development of robust frameworks, standardized protocols, and collaborative initiatives.

Looking forward, advancements in AI and IoT technologies, combined with innovations like blockchain and edge computing, hold immense potential to enhance environmental monitoring and management. Establishing global environmental monitoring networks and engaging communities through citizen science initiatives will democratize data collection, fostering inclusive approaches to environmental stewardship. As these technologies evolve, their synergistic application will play a pivotal role in addressing pressing environmental issues, driving innovations that support sustainability, resilience, and informed decision making.

The convergence of AI and IoT is a significant milestone in environmental sciences. By leveraging these technologies, environmentalists and data scientists can develop strategies to monitor and protect vital resources. As we navigate complex environmental challenges, the integrated AI–IoT framework emerges as a cornerstone for advancing sustainable and resilient management practices. Embracing these innovations equips us with the tools to anticipate and mitigate future challenges, ensuring a healthier, more sustainable world for future generations.

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References

1. Brauch, H.G. Introduction: Globalization and Environmental Challenges: Reconceptualizing Security in the 21st Century. In *Globalization and Environmental Challenges*; Brauch, H.G., Spring, Ú.O., Mesjasz, C., Grin, J., Dunay, P., Behera, N.C., Chourou, B., Kameri-Mbote, P., Liotta, P.H., Eds.; Hexagon Series on Human and Environmental Security and Peace; Springer: Berlin/Heidelberg, Germany, 2008; Volume 3, pp. 27–43, ISBN 978-3-540-75976-8.
2. Crompton, T.; Kasser, T. *Meeting Environmental Challenges: The Role of Human Identity*; WWF-UK: Surrey, UK, 2009; ISBN 978-1-900322-64-5.
3. Conca, K.; Dabelko, G.D. (Eds.) *Green Planet Blues: Critical Perspectives on Global Environmental Politics*, 6th ed.; Taylor & Francis Group: New York, NY, USA; London, UK, 2020; ISBN 978-0-429-32220-4.

4. Arthington, A.H.; Bunn, S.E.; Poff, N.L.; Naiman, R.J. The Challenge of Providing Environmental Flow Rules to Sustain River Ecosystems. *Ecol. Appl.* **2006**, *16*, 1311–1318. [CrossRef]
5. Palomino, J.; Muellerklein, O.C.; Kelly, M. A Review of the Emergent Ecosystem of Collaborative Geospatial Tools for Addressing Environmental Challenges. *Comput. Environ. Urban Syst.* **2017**, *65*, 79–92. [CrossRef]
6. Hu, Y.; Cheng, H.; Tao, S. Environmental and Human Health Challenges of Industrial Livestock and Poultry Farming in China and Their Mitigation. *Environ. Int.* **2017**, *107*, 111–130. [CrossRef] [PubMed]
7. Mwangi, W.; De Figueiredo, P.; Criscitiello, M.F. One Health: Addressing Global Challenges at the Nexus of Human, Animal, and Environmental Health. *PLoS Pathog.* **2016**, *12*, e1005731. [CrossRef] [PubMed]
8. Mellor, J.W. The Intertwining of Environmental Problems Poverty. *Environ. Sci. Policy Sustain. Dev.* **1988**, *30*, 6–30. [CrossRef]
9. Mabogunje, A.L. Poverty and Environmental Degradation: Challenges within the Global Economy. *Environ. Sci. Policy Sustain. Dev.* **2002**, *44*, 8–19. [CrossRef]
10. Masron, T.A.; Subramaniam, Y. Does Poverty Cause Environmental Degradation? Evidence from Developing Countries. *J. Poverty* **2019**, *23*, 44–64. [CrossRef]
11. Patz, J.A.; Frumkin, H.; Holloway, T.; Vimont, D.J.; Haines, A. Climate Change: Challenges and Opportunities for Global Health. *JAMA* **2014**, *312*, 1565. [CrossRef] [PubMed]
12. Solecki, W. Urban Environmental Challenges and Climate Change Action in New York City. *Environ. Urban.* **2012**, *24*, 557–573. [CrossRef]
13. Roberts, D.; O'Donoghue, S. Urban Environmental Challenges and Climate Change Action in Durban, South Africa. *Environ. Urban.* **2013**, *25*, 299–319. [CrossRef]
14. Zhou, Y.; Khu, S.-T.; Xi, B.; Su, J.; Hao, F.; Wu, J.; Huo, S. Status and Challenges of Water Pollution Problems in China: Learning from the European Experience. *Environ. Earth Sci.* **2014**, *72*, 1243–1254. [CrossRef]
15. Han, D.; Currell, M.J.; Cao, G. Deep Challenges for China's War on Water Pollution. *Environ. Pollut.* **2016**, *218*, 1222–1233. [CrossRef] [PubMed]
16. Tang, W.; Pei, Y.; Zheng, H.; Zhao, Y.; Shu, L.; Zhang, H. Twenty Years of China's Water Pollution Control: Experiences and Challenges. *Chemosphere* **2022**, *295*, 133875. [CrossRef] [PubMed]
17. Carr, D.L.; Suter, L.; Barbieri, A. Population Dynamics and Tropical Deforestation: State of the Debate and Conceptual Challenges. *Popul. Environ.* **2005**, *27*, 89–113. [CrossRef] [PubMed]
18. Haigh, M.J.; Jansky, L.; Hellin, J. Headwater Deforestation: A Challenge for Environmental Management. *Glob. Environ. Chang.* **2004**, *14*, 51–61. [CrossRef]
19. Kumar, R.; Kumar, A.; Saikia, P. Deforestation and Forests Degradation Impacts on the Environment. In *Environmental Degradation: Challenges and Strategies for Mitigation*; Singh, V.P., Yadav, S., Yadav, K.K., Yadava, R.N., Eds.; Water Science and Technology Library; Springer International Publishing: Cham, Switzerland, 2022; Volume 104, pp. 19–46, ISBN 978-3-030-95541-0.
20. Rands, M.R.W.; Adams, W.M.; Bennun, L.; Butchart, S.H.M.; Clements, A.; Coomes, D.; Entwistle, A.; Hodge, I.; Kapos, V.; Scharlemann, J.P.W.; et al. Biodiversity Conservation: Challenges Beyond 2010. *Science* **2010**, *329*, 1298–1303. [CrossRef]
21. Arora, N.K.; Fatima, T.; Mishra, I.; Verma, M.; Mishra, J.; Mishra, V. Environmental Sustainability: Challenges and Viable Solutions. *Environ. Sustain.* **2018**, *1*, 309–340. [CrossRef]
22. Kim, J.W. The Environmental Impact of Industrialization in East Asia and Strategies toward Sustainable Development. *Sustain. Sci.* **2006**, *1*, 107–114. [CrossRef]
23. Perreault, T.A.; Bridge, G.; McCarthy, J. (Eds.) *The Routledge Handbook of Political Ecology*; Routledge International Handbooks; Routledge: London, UK; Taylor & Francis Group: New York, NY, USA, 2015; ISBN 978-1-138-79433-7.
24. Patnaik, R. Impact of Industrialization on Environment and Sustainable Solutions–Reflections from a South Indian Region. *IOP Conf. Ser. Earth Environ. Sci.* **2018**, *120*, 012016. [CrossRef]
25. Keiner, M.; Koll-Schretzenmayr, M.; Schmid, W.A. *Managing Urban Futures: Sustainability and Urban Growth in Developing Countries*; Routledge: London, UK, 2016; ISBN 978-1-315-24982-7.
26. Dodman, D. Environment and Urbanization. In *International Encyclopedia of Geography*; Richardson, D., Castree, N., Goodchild, M.F., Kobayashi, A., Liu, W., Marston, R.A., Eds.; Wiley: Hoboken, NJ, USA, 2017; pp. 1–9, ISBN 978-0-470-65963-2.
27. Akash, M.; Akter, J.; Tamanna, T.; Kabir, M.R. The Urbanization and Environmental Challenges in Dhaka City. *SSRN Electron. J.* **2018**, 145–157. [CrossRef]
28. Iyiola, A.O.; Akinsorotan, O.A.; Ojeleye, A.E.; Fajimolu, A.O. An Overview of Environmental Resources in Africa: Emerging Issues and Sustainable Exploitation. In *Sustainable Utilization and Conservation of Africa's Biological Resources and Environment*; Izah, S.C., Ogwu, M.C., Eds.; Sustainable Development and Biodiversity; Springer: Singapore, 2023; Volume 32, pp. 543–570, ISBN 978-981-19-6973-7.
29. Numbere, A.O.; Maduike, E.M. The Impact of Unsustainable Exploitation of Forest and Aquatic Resources of the Niger Delta, Nigeria. In *Biodiversity in Africa: Potentials, Threats and Conservation*; Chibueze Izah, S., Ed.; Sustainable Development and Biodiversity; Springer: Singapore, 2022; Volume 29, pp. 239–265, ISBN 978-981-19-3325-7.

30. Nukusheva, A.; Ilyassova, G.; Rustembekova, D.; Zhamiyeva, R.; Arenova, L. Global Warming Problem Faced by the International Community: International Legal Aspect. *Int. Environ. Agreements Politics Law Econ.* **2021**, *21*, 219–233. [CrossRef]
31. Xiong, J.; Yang, Y. Climate Change and Hydrological Extremes. *Curr. Clim. Chang. Rep.* **2024**, *11*, 1. [CrossRef]
32. Sulistiawati, L.Y. Climate Change Related Litigation in Indonesia. *Commun. Earth Environ.* **2024**, *5*, 522. [CrossRef]
33. Malik, I.H.; Ford, J.D. Monitoring Climate Change Vulnerability in the Himalayas. *Ambio* **2025**, *54*, 1–19. [CrossRef]
34. Du Plessis, A. Primary Water Quality Challenges, Contaminants and the World's Dirtiest Places. In *Water as an Inescapable Risk*; Springer Water; Springer International Publishing: Cham, Switzerland, 2019; pp. 79–114, ISBN 978-3-030-03185-5.
35. Singh, N.; Poonia, T.; Siwal, S.S.; Srivastav, A.L.; Sharma, H.K.; Mittal, S.K. Challenges of Water Contamination in Urban Areas. In *Current Directions in Water Scarcity Research*; Elsevier: Amsterdam, The Netherlands, 2022; Volume 6, pp. 173–202, ISBN 978-0-323-91838-1.
36. McDonald, T.L. Review of Environmental Monitoring Methods: Survey Designs. *Environ. Monit. Assess.* **2003**, *85*, 277–292. [CrossRef] [PubMed]
37. Lovett, G.M.; Burns, D.A.; Driscoll, C.T.; Jenkins, J.C.; Mitchell, M.J.; Rustad, L.; Shanley, J.B.; Likens, G.E.; Haeuber, R. Who Needs Environmental Monitoring? *Front. Ecol. Environ.* **2007**, *5*, 253–260. [CrossRef]
38. Kumar, A.; Kim, H.; Hancke, G.P. Environmental Monitoring Systems: A Review. *IEEE Sens. J.* **2013**, *13*, 1329–1339. [CrossRef]
39. Namieśnik, J. Trends in Environmental Analytics and Monitoring. *Crit. Rev. Anal. Chem.* **2000**, *30*, 221–269. [CrossRef]
40. Bourgeois, W.; Romain, A.-C.; Nicolas, J.; Stuetz, R.M. The Use of Sensor Arrays for Environmental Monitoring: Interests and Limitations. *J. Environ. Monit.* **2003**, *5*, 852. [CrossRef] [PubMed]
41. Brammer, J.R.; Brunet, N.D.; Burton, A.C.; Cuerrier, A.; Danielsen, F.; Dewan, K.; Herrmann, T.M.; Jackson, M.V.; Kennett, R.; Larocque, G.; et al. The Role of Digital Data Entry in Participatory Environmental Monitoring. *Conserv. Biol.* **2016**, *30*, 1277–1287. [CrossRef] [PubMed]
42. Trevathan, J.; Johnstone, R. Smart Environmental Monitoring and Assessment Technologies (SEMAT)—A New Paradigm for Low-Cost, Remote Aquatic Environmental Monitoring. *Sensors* **2018**, *18*, 2248. [CrossRef] [PubMed]
43. Abraham, S.; Beard, J.; Manijacob, R. Remote Environmental Monitoring Using Internet of Things (IoT). In Proceedings of the 2017 IEEE Global Humanitarian Technology Conference (GHTC), San Jose, CA, USA, 19–22 October 2017; IEEE: Piscataway, NJ, USA, 2017; pp. 1–6.
44. Ullo, S.L.; Sinha, G.R. Advances in Smart Environment Monitoring Systems Using IoT and Sensors. *Sensors* **2020**, *20*, 3113. [CrossRef] [PubMed]
45. Chamara, N.; Islam, M.D.; Bai, G.; Shi, Y.; Ge, Y. Ag-IoT for Crop and Environment Monitoring: Past, Present, and Future. *Agric. Syst.* **2022**, *203*, 103497. [CrossRef]
46. Fang, S.; Xu, L.D.; Zhu, Y.; Ahati, J.; Pei, H.; Yan, J.; Liu, Z. An Integrated System for Regional Environmental Monitoring and Management Based on Internet of Things. *IEEE Trans. Ind. Inform.* **2014**, *10*, 1596–1605. [CrossRef]
47. Kishorebabu, V.; Sravanthi, R. Real Time Monitoring of Environmental Parameters Using IOT. *Wirel. Pers. Commun.* **2020**, *112*, 785–808. [CrossRef]
48. Narayana, T.L.; Venkatesh, C.; Kiran, A.; J, C.B.; Kumar, A.; Khan, S.B.; Almusharraf, A.; Quasim, M.T. Advances in Real Time Smart Monitoring of Environmental Parameters Using IoT and Sensors. *Heliyon* **2024**, *10*, e28195. [CrossRef] [PubMed]
49. Essamlali, I.; Nhaila, H.; El Khaili, M. Advances in Machine Learning and IoT for Water Quality Monitoring: A Comprehensive Review. *Heliyon* **2024**, *10*, e27920. [CrossRef] [PubMed]
50. Forhad, H.M.; Uddin, M.R.; Chakrovorty, R.S.; Ruhul, A.M.; Faruk, H.M.; Kamruzzaman, S.; Sharmin, N.; Jamal, A.S.I.M.; Haque, M.M.-U.; Morshed, A.M. IoT Based Real-Time Water Quality Monitoring System in Water Treatment Plants (WTPs). *Heliyon* **2024**, *10*, e40746. [CrossRef] [PubMed]
51. Hino, M.; Benami, E.; Brooks, N. Machine Learning for Environmental Monitoring. *Nat. Sustain.* **2018**, *1*, 583–588. [CrossRef]
52. Jesus, G.; Casimiro, A.; Oliveira, A. Using Machine Learning for Dependable Outlier Detection in Environmental Monitoring Systems. *ACM Trans. Cyber-Phys. Syst.* **2021**, *5*, 1–30. [CrossRef]
53. Kubečka, J.; Knattrup, Y.; Engsvang, M.; Jensen, A.B.; Ayoubi, D.; Wu, H.; Christiansen, O.; Elm, J. Current and Future Machine Learning Approaches for Modeling Atmospheric Cluster Formation. *Nat. Comput. Sci.* **2023**, *3*, 495–503. [CrossRef] [PubMed]
54. Esenogho, E.; Djouani, K.; Kurien, A.M. Integrating Artificial Intelligence Internet of Things and 5G for Next-Generation Smartgrid: A Survey of Trends Challenges and Prospect. *IEEE Access* **2022**, *10*, 4794–4831. [CrossRef]
55. Cortés, U.; Sànchez-Marrè, M.; Ceccaroni, L.; R-Roda, I.; Poch, M. Artificial Intelligence and Environmental Decision Support Systems. *Appl. Intell.* **2000**, *13*, 77–91. [CrossRef]
56. Haupt, S.E.; Pasini, A.; Marzban, C. (Eds.) *Artificial Intelligence Methods in the Environmental Sciences*; Springer: Dordrecht, The Netherlands, 2009; ISBN 978-1-4020-9117-9.
57. Shuford, J. Interdisciplinary Perspectives: Fusing Artificial Intelligence with Environmental Science for Sustainable Solutions. *J. Artif. Intell. Gen. Sci. (JAIGS)* **2024**, *1*, 106–123. [CrossRef]

58. Himeur, Y.; Rimal, B.; Tiwary, A.; Amira, A. Using Artificial Intelligence and Data Fusion for Environmental Monitoring: A Review and Future Perspectives. *Inf. Fusion* **2022**, *86–87*, 44–75. [CrossRef]
59. Szramowiat-Sala, K. Artificial Intelligence in Environmental Monitoring: Application of Artificial Neural Networks and Machine Learning for Pollution Prevention and Toxicity Measurements. 2023. Available online: https://www.preprints.org/manuscript/202307.1298 (accessed on 23 December 2024).
60. Popescu, S.M.; Mansoor, S.; Wani, O.A.; Kumar, S.S.; Sharma, V.; Sharma, A.; Arya, V.M.; Kirkham, M.B.; Hou, D.; Bolan, N.; et al. Artificial Intelligence and IoT Driven Technologies for Environmental Pollution Monitoring and Management. *Front. Environ. Sci.* **2024**, *12*, 1336088. [CrossRef]
61. Yetilmezsoy, K.; Ozkaya, B.; Cakmakci, M. Artificial Intelligence-Based Prediction Models for Environmental Engineering. *Neural Netw. World* **2011**, *21*, 193–218. [CrossRef]
62. Bagheri, M.; Bazvand, A.; Ehteshami, M. Application of Artificial Intelligence for the Management of Landfill Leachate Penetration into Groundwater, and Assessment of Its Environmental Impacts. *J. Clean. Prod.* **2017**, *149*, 784–796. [CrossRef]
63. Maganathan, T.; Senthilkumar, S.; Balakrishnan, V. Machine Learning and Data Analytics for Environmental Science: A Review, Prospects and Challenges. *IOP Conf. Ser. Mater. Sci. Eng.* **2020**, *955*, 012107. [CrossRef]
64. Kosovic, I.N.; Mastelic, T.; Ivankovic, D. Using Artificial Intelligence on Environmental Data from Internet of Things for Estimating Solar Radiation: Comprehensive Analysis. *J. Clean. Prod.* **2020**, *266*, 121489. [CrossRef]
65. Suguna, S.K.; Dhivya, M.; Paiva, S. (Eds.) *Artificial Intelligence (AI): Recent Trends and Applications*; CRC Press: Boca Raton, FL, USA; Taylor & Francis Group: London, UK; New York, NY, USA, 2021; ISBN 978-1-003-00562-9.
66. Wankhede, V.A.; Agrawal, R.; Kumar, A.; Luthra, S.; Pamucar, D.; Stević, Ž. Artificial Intelligence an Enabler for Sustainable Engineering Decision-Making in Uncertain Environment: A Review and Future Propositions. *J. Glob. Oper. Strateg. Sourc.* **2024**, *17*, 384–401. [CrossRef]
67. Wooldridge, M.; Jennings, N.R. Intelligent Agents: Theory and Practice. *Knowl. Eng. Rev.* **1995**, *10*, 115–152. [CrossRef]
68. Kabanza, F.; Barbeau, M.; St-Denis, R. Planning Control Rules for Reactive Agents. *Artif. Intell.* **1997**, *95*, 67–113. [CrossRef]
69. Rebera, A.P. Reactive Attitudes and AI-Agents–Making Sense of Responsibility and Control Gaps. *Philos. Technol.* **2024**, *37*, 126. [CrossRef]
70. Hayes-Roth, B. Integrating Real-Time AI Techniques in Adaptive Intelligent Agents. In *Artificial Intelligence in Real-Time Control 1994*; Elsevier: Oxford, UK, 1995; pp. 1–11, ISBN 978-0-08-042236-7.
71. Mounce, S.R.; Boxall, J.B.; Machell, J. Development and Verification of an Online Artificial Intelligence System for Detection of Bursts and Other Abnormal Flows. *J. Water Resour. Plan. Manag.* **2010**, *136*, 309–318. [CrossRef]
72. Ontañón, S.; Plaza, E. Learning and Joint Deliberation through Argumentation in Multiagent Systems. In Proceedings of the 6th International Joint Conference on Autonomous Agents and Multiagent Systems, Honolulu, HI, USA, 14–18 May 2007; ACM: New York, NY, USA, 2007; pp. 1–8.
73. Corchado, J.M.; Laza, R. Constructing Deliberative Agents with Case-Based Reasoning Technology. *Int. J. Intell. Syst.* **2003**, *18*, 1227–1241. [CrossRef]
74. Boddy, M.; Dean, T.L. Deliberation Scheduling for Problem Solving in Time-Constrained Environments. *Artif. Intell.* **1994**, *67*, 245–285. [CrossRef]
75. Singh, M.; Arora, V.; Kulshreshta, K. AI and the Environment: Innovative Approaches to Climate Change. In *Practice, Progress, and Proficiency in Sustainability*; Singh, B., Kaunert, C., Vig, K., Dutta, S., Eds.; IGI Global: Hershey, PA, USA, 2024; pp. 1–22, ISBN 979-8-3693-6336-2.
76. Zhao, T.; Wang, S.; Ouyang, C.; Chen, M.; Liu, C.; Zhang, J.; Yu, L.; Wang, F.; Xie, Y.; Li, J.; et al. Artificial Intelligence for Geoscience: Progress, Challenges, and Perspectives. *Innovation* **2024**, *5*, 100691. [CrossRef]
77. Guessoum, Z. A Hybrid Agent Model: A Reactive and Cognitive Behavior. In Proceedings of the Third International Symposium on Autonomous Decentralized Systems (ISADS 97), Berlin, Germany, 9–11 April 1997; IEEE Computer Society Press: Los Alamitos, CA, USA, 1997; pp. 25–32.
78. Palanca, J.; Rincon, J.A.; Carrascosa, C.; Julian, V.J.; Terrasa, A. Flexible Agent Architecture: Mixing Reactive and Deliberative Behaviors in SPADE. *Electronics* **2023**, *12*, 659. [CrossRef]
79. De Paola, A.; Ferraro, P.; Lo Re, G.; Morana, M.; Ortolani, M. A Fog-Based Hybrid Intelligent System for Energy Saving in Smart Buildings. *J. Ambient. Intell. Humaniz. Comput.* **2020**, *11*, 2793–2807. [CrossRef]
80. Janssen, M.; De Vries, B. The Battle of Perspectives: A Multi-Agent Model with Adaptive Responses to Climate Change. *Ecol. Econ.* **1998**, *26*, 43–65. [CrossRef]
81. Figueiredo, J.; Botto, M.A.; Rijo, M. SCADA System with Predictive Controller Applied to Irrigation Canals. *Control Eng. Pract.* **2013**, *21*, 870–886. [CrossRef]
82. Ayala-Cabrera, D.; Herrera, M.; Izquierdo, J.; Pérez-García, R. GPR Data Analysis Using Multi-Agent and Clustering Approaches: A Tool for Technical Management of Water Supply Systems. *Digit. Signal Process.* **2014**, *27*, 140–149. [CrossRef]

83. Asha, P.; Natrayan, L.; Geetha, B.T.; Beulah, J.R.; Sumathy, R.; Varalakshmi, G.; Neelakandan, S. IoT Enabled Environmental Toxicology for Air Pollution Monitoring Using AI Techniques. *Environ. Res.* **2022**, *205*, 112574. [CrossRef] [PubMed]
84. Nti, E.K.; Cobbina, S.J.; Attafuah, E.E.; Senanu, L.D.; Amenyeku, G.; Gyan, M.A.; Forson, D.; Safo, A.-R. Water Pollution Control and Revitalization Using Advanced Technologies: Uncovering Artificial Intelligence Options towards Environmental Health Protection, Sustainability and Water Security. *Heliyon* **2023**, *9*, e18170. [CrossRef] [PubMed]
85. Castelfranchi, C.; Dignum, F.; Jonker, C.M.; Treur, J. Deliberative Normative Agents: Principles and Architecture. In *Intelligent Agents VI. Agent Theories, Architectures, and Languages*; Jennings, N.R., Lespérance, Y., Eds.; Lecture Notes in Computer Science; Springer: Berlin/Heidelberg, Germany, 2000; Volume 1757, pp. 364–378. [CrossRef]
86. Hare, M.; Deadman, P. Further Towards a Taxonomy of Agent-Based Simulation Models in Environmental Management. *Math. Comput. Simul.* **2004**, *64*, 25–40. [CrossRef]
87. Sánchez-Fibla, M.; Moulin-Frier, C.; Solé, R. Cooperative Control of Environmental Extremes by Artificial Intelligent Agents. *J. R. Soc. Interface* **2024**, *21*, 20240344. [CrossRef] [PubMed]
88. Bezborodova, O.E.; Bodin, O.N.; Paschenko, D.V. Improving Data Collection and Processing Efficiency by Using Hierarchies of Intelligent Agents in Multi-Agent Systems. *IOP Conf. Ser. Mater. Sci. Eng.* **2021**, *1061*, 012009. [CrossRef]
89. Grzonka, D.; Jakóbik, A.; Kołodziej, J.; Pllana, S. Using a Multi-Agent System and Artificial Intelligence for Monitoring and Improving the Cloud Performance and Security. *Future Gener. Comput. Syst.* **2018**, *86*, 1106–1117. [CrossRef]
90. Zhang, X.; Shu, K.; Rajkumar, S.; Sivakumar, V. Research on Deep Integration of Application of Artificial Intelligence in Environmental Monitoring System and Real Economy. *Environ. Impact Assess. Rev.* **2021**, *86*, 106499. [CrossRef]
91. Luzolo, P.H.; Elrawashdeh, Z.; Tchappi, I.; Galland, S.; Outay, F. Combining Multi-Agent Systems and Artificial Intelligence of Things: Technical Challenges and Gains. *Internet Things* **2024**, *28*, 101364. [CrossRef]
92. Vald, G.; Sermet, M.; Mount, J.; Shrestha, S.; Samuel, D.J.; Cwiertny, D.; Demir, I. Integrating Conversational AI Agents for Enhanced Water Quality Analytics: Development of a Novel Data Expert System. 2024, *in press*.
93. Hart, J.K.; Martinez, K. Environmental Sensor Networks: A Revolution in the Earth System Science? *Earth-Sci. Rev.* **2006**, *78*, 177–191. [CrossRef]
94. El Khediri, S.; Benfradj, A.; Thaljaoui, A.; Moulahi, T.; Ullah Khan, R.; Alabdulatif, A.; Lorenz, P. Integration of Artificial Intelligence (AI) with Sensor Networks: Trends, Challenges, and Future Directions. *J. King Saud Univ.-Comput. Inf. Sci.* **2024**, *36*, 101892. [CrossRef]
95. Janga, B.; Asamani, G.; Sun, Z.; Cristea, N. A Review of Practical AI for Remote Sensing in Earth Sciences. *Remote Sens.* **2023**, *15*, 4112. [CrossRef]
96. Solomou, S.; Sengupta, U. Simulating Complex Urban Behaviours with AI: Incorporating Improved Intelligent Agents in Urban Simulation Models. *Urban Plan.* **2024**, *10*, 8561. [CrossRef]
97. Bouziane, S.E.; Khadir, M.T.; Dugdale, J. A Collaborative Predictive Multi-Agent System for Forecasting Carbon Emissions Related to Energy Consumption. *Multiagent Grid Syst.* **2021**, *17*, 39–58. [CrossRef]
98. Jones, J.; Harris, E.; Febriansah, Y.; Adiwijaya, A.; Nuril Hikam, I. AI for Sustainable Development: Applications in Natural Resource Management, Agriculture, and Waste Management. *Int. Trans. Artif. Intell. (ITALIC)* **2024**, *2*, 143–149. [CrossRef]
99. Kumar, S.; Verma, A.K.; Mirza, A. Artificial Intelligence and Climate Change Mitigation. In *Digital Transformation, Artificial Intelligence and Society*; Frontiers of Artificial Intelligence, Ethics and Multidisciplinary Applications; Springer: Singapore, 2024; pp. 147–160, ISBN 978-981-97-5655-1.
100. Amiri, Z.; Heidari, A.; Navimipour, N.J. Comprehensive Survey of Artificial Intelligence Techniques and Strategies for Climate Change Mitigation. *Energy* **2024**, *308*, 132827. [CrossRef]
101. Alawi, O.A.; Kamar, H.M.; Alsuwaiyan, A.; Yaseen, Z.M. Temporal Trends and Predictive Modeling of Air Pollutants in Delhi: A Comparative Study of Artificial Intelligence Models. *Sci. Rep.* **2024**, *14*, 30957. [CrossRef] [PubMed]
102. Reza, S.A.; Chowdhury, M.S.R.; Hossain, S.; Hasanuzzaman, M.; Shawon, R.E.R.; Chowdhury, B.R.; Rana, M.S. Global Plastic Waste Management: Analyzing Trends, Economic and Social Implications, and Predictive Modeling Using Artificial Intelligence. *J. Environ. Agric. Stud.* **2024**, *5*, 42–58. [CrossRef]
103. Lee, C.C.; Barnes, B.B.; Sheridan, S.C.; Smith, E.T.; Hu, C.; Pirhalla, D.E.; Ransibrahmanakul, V.; Adams, R. Using Machine Learning to Model and Predict Water Clarity in the Great Lakes. *J. Great Lakes Res.* **2020**, *46*, 1501–1510. [CrossRef]
104. Raihan, A. Artificial Intelligence and Machine Learning Applications in Forest Management and Biodiversity Conservation. *Nat. Resour. Conserv. Res.* **2023**, *6*, 3825. [CrossRef]
105. Ullah, F.; Saqib, S.; Xiong, Y.-C. Integrating Artificial Intelligence in Biodiversity Conservation: Bridging Classical and Modern Approaches. *Biodivers. Conserv.* **2024**. [CrossRef]
106. Ayoola, V.B.; Idoko, I.P.; Eromonsei, S.O.; Afolabi, O.; Apampa, A.R.; Oyebanji, O.S. The Role of Big Data and AI in Enhancing Biodiversity Conservation and Resource Management in the USA. *World J. Adv. Res. Rev.* **2024**, *23*, 1851–1873. [CrossRef]
107. Silvestro, D.; Goria, S.; Sterner, T.; Antonelli, A. Improving Biodiversity Protection through Artificial Intelligence. *Nat. Sustain.* **2022**, *5*, 415–424. [CrossRef]

108. Kamrowska-Załuska, D. Impact of AI-Based Tools and Urban Big Data Analytics on the Design and Planning of Cities. *Land* **2021**, *10*, 1209. [CrossRef]
109. Yigitcanlar, T.; Kankanamge, N.; Regona, M.; Ruiz Maldonado, A.; Rowan, B.; Ryu, A.; Desouza, K.C.; Corchado, J.M.; Mehmood, R.; Li, R.Y.M. Artificial Intelligence Technologies and Related Urban Planning and Development Concepts: How Are They Perceived and Utilized in Australia? *J. Open Innov. Technol. Mark. Complex.* **2020**, *6*, 187. [CrossRef]
110. Jha, A.K.; Ghimire, A.; Thapa, S.; Jha, A.M.; Raj, R. A Review of AI for Urban Planning: Towards Building Sustainable Smart Cities. In Proceedings of the 2021 6th International Conference on Inventive Computation Technologies (ICICT), Coimbatore, India, 20–22 January 2021; IEEE: Piscataway, NJ, USA, 2021; pp. 937–944.
111. Sanchez, T.W.; Shumway, H.; Gordner, T.; Lim, T. The Prospects of Artificial Intelligence in Urban Planning. *Int. J. Urban Sci.* **2023**, *27*, 179–194. [CrossRef]
112. Chen, C.-Y.; Chai, K.K.; Lau, E. AI-Assisted Approach for Building Energy and Carbon Footprint Modeling. *Energy AI* **2021**, *5*, 100091. [CrossRef]
113. Aras, S.; Hanifi Van, M. An Interpretable Forecasting Framework for Energy Consumption and CO_2 Emissions. *Appl. Energy* **2022**, *328*, 120163. [CrossRef]
114. Nazir, T.; Nagra, H.F.; Bhatti, M.H.; Shahid, R.N.; Shaukat, N.; Tariq, N.U.H. Predictive Analytics for Environmental Impact: Deep Learning and AI Ensemble Strategies in Forecasting CO_2 Emissions. 2024. Available online: https://www.researchsquare.com/article/rs-4081410/v1 (accessed on 23 December 2024).
115. Meng, Y.; Noman, H. Predicting CO_2 Emission Footprint Using AI through Machine Learning. *Atmosphere* **2022**, *13*, 1871. [CrossRef]
116. Gaur, L.; Afaq, A.; Arora, G.K.; Khan, N. Artificial Intelligence for Carbon Emissions Using System of Systems Theory. *Ecol. Inform.* **2023**, *76*, 102165. [CrossRef]
117. Brady, M. Artificial Intelligence and Robotics. *Artif. Intell.* **1985**, *26*, 79–121. [CrossRef]
118. Rajan, K.; Saffiotti, A. Towards a Science of Integrated AI and Robotics. *Artif. Intell.* **2017**, *247*, 1–9. [CrossRef]
119. Moglia, A.; Georgiou, K.; Georgiou, E.; Satava, R.M.; Cuschieri, A. A Systematic Review on Artificial Intelligence in Robot-Assisted Surgery. *Int. J. Surg.* **2021**, *95*, 106151. [CrossRef]
120. Giordano, G.; Murali Babu, S.P.; Mazzolai, B. Soft Robotics towards Sustainable Development Goals and Climate Actions. *Front. Robot. AI* **2023**, *10*, 1116005. [CrossRef]
121. Putta, P.; Mills, E.; Garg, N.; Motwani, S.; Finn, C.; Garg, D.; Rafailov, R. Agent Q: Advanced Reasoning and Learning for Autonomous AI Agents. *arXiv* **2024**, arXiv:2408.07199.
122. Maes, P. Modeling Adaptive Autonomous Agents. *Artif. Life* **1993**, *1*, 135–162. [CrossRef]
123. Hauptman, A.I.; Schelble, B.G.; McNeese, N.J.; Madathil, K.C. Adapt and Overcome: Perceptions of Adaptive Autonomous Agents for Human-AI Teaming. *Comput. Hum. Behav.* **2023**, *138*, 107451. [CrossRef]
124. Totschnig, W. Fully Autonomous AI. *Sci. Eng. Ethics* **2020**, *26*, 2473–2485. [CrossRef] [PubMed]
125. Candrian, C.; Scherer, A. Rise of the Machines: Delegating Decisions to Autonomous AI. *Comput. Hum. Behav.* **2022**, *134*, 107308. [CrossRef]
126. Hirzle, T.; Müller, F.; Draxler, F.; Schmitz, M.; Knierim, P.; Hornbæk, K. When XR and AI Meet–A Scoping Review on Extended Reality and Artificial Intelligence. In Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems, Hamburg, Germany, 19–24 April 2023; ACM: New York, NY, USA, 2023; pp. 1–45.
127. Reiners, D.; Davahli, M.R.; Karwowski, W.; Cruz-Neira, C. The Combination of Artificial Intelligence and Extended Reality: A Systematic Review. *Front. Virtual Real.* **2021**, *2*, 721933. [CrossRef]
128. Pei, J.; Viola, I.; Huang, H.; Wang, J.; Ahsan, M.; Ye, F.; Yiming, J.; Sai, Y.; Wang, D.; Chen, Z.; et al. Autonomous Workflow for Multimodal Fine-Grained Training Assistants Towards Mixed Reality. *arXiv* **2024**, arXiv:2405.13034.
129. Stanney, K.M.; Archer, J.; Skinner, A.; Horner, C.; Hughes, C.; Brawand, N.P.; Martin, E.; Sanchez, S.; Moralez, L.; Fidopiastis, C.M.; et al. Performance Gains from Adaptive eXtended Reality Training Fueled by Artificial Intelligence. *J. Def. Model. Simul. Appl. Methodol. Technol.* **2022**, *19*, 195–218. [CrossRef]
130. Serrano, M.; Dang, H.N.; Nguyen, H.M.Q. Recent Advances on Artificial Intelligence and Internet of Things Convergence for Human-Centric Applications: Internet of Things Science. In Proceedings of the 8th International Conference on the Internet of Things (IoT), Santa Barbara, CA, USA, 15–18 October 2018; ACM: New York, NY, USA, 2018; pp. 1–5.
131. Shi, F.; Ning, H.; Huangfu, W.; Zhang, F.; Wei, D.; Hong, T.; Daneshmand, M. Recent Progress on the Convergence of the Internet of Things and Artificial Intelligence. *IEEE Netw.* **2020**, *34*, 8–15. [CrossRef]
132. Mastorakis, G.; Mavromoustakis, C.X.; Batalla, J.M.; Pallis, E. (Eds.) *Convergence of Artificial Intelligence and the Internet of Things*; Internet of Things Series; Springer International Publishing: Cham, Switzerland, 2020; ISBN 978-3-030-44906-3.
133. Bibri, S.E.; Alexandre, A.; Sharifi, A.; Krogstie, J. Environmentally Sustainable Smart Cities and Their Converging AI, IoT, and Big Data Technologies and Solutions: An Integrated Approach to an Extensive Literature Review. *Energy Inform.* **2023**, *6*, 9. [CrossRef] [PubMed]

134. Khan, S.A.; Kalifullah, A.H.; Ibragimova, K.; Singh, A.K.; Muniyandy, E.; Rachapudi, V. Integrating AI and IoT in Advanced Optical Systems for Sustainable Energy and Environment Monitoring. *Int. J. Adv. Comput. Sci. Appl.* **2024**, *15*. [CrossRef]
135. Yu, Q.; Xiong, F.; Wang, Y. Integration of Wireless Sensor Network and IoT for Smart Environment Monitoring System. *J. Interconnect. Netw.* **2022**, *22*, 2143010. [CrossRef]
136. Bin Mofidul, R.; Alam, M.M.; Rahman, M.H.; Jang, Y.M. Real-Time Energy Data Acquisition, Anomaly Detection, and Monitoring System: Implementation of a Secured, Robust, and Integrated Global IIoT Infrastructure with Edge and Cloud AI. *Sensors* **2022**, *22*, 8980. [CrossRef] [PubMed]
137. Sharma, A.; Singh, K.J.; Kapoor, D.S.; Thakur, K.; Mahajan, S. The Role of IoT in Environmental Sustainability: Advancements and Applications for Smart Cities. In *Mobile Crowdsensing and Remote Sensing in Smart Cities*; Kerrache, C.A., Sahraoui, Y., Calafate, C.T., Vegni, A.M., Eds.; Internet of Things; Springer: Cham, Switzerland, 2025; pp. 21–39, ISBN 978-3-031-72731-3.
138. Selvam, A.P.; Al-Humairi, S.N.S. *The Impact of IoT and Sensor Integration on Real-Time Weather Monitoring Systems: A Systematic Review*; Springer Science and Business Media LLC: Berlin, Germany, 2023.
139. Rahu, M.A.; Karim, S.; Ali, S.M.; Jatoi, G.M.; Sohu, N.D. Integration of Wireless Sensor Networks, Internet of Things, Artificial Intelligence, and Deep Learning in Smart Agriculture: A Comprehensive Survey. *J. Innov. Intell. Comput. Emerg. Technol. (JIICET)* **2024**, *1*, 8–18.
140. Alam, M.J.B.; Manzano, L.S.; Debnath, R.; Ahmed, A.A. Monitoring Slope Movement and Soil Hydrologic Behavior Using IoT and AI Technologies: A Systematic Review. *Hydrology* **2024**, *11*, 111. [CrossRef]
141. Ranjan, R.; Rana, O.; Nepal, S.; Yousif, M.; James, P.; Wen, Z.; Barr, S.; Watson, P.; Jayaraman, P.P.; Georgakopoulos, D.; et al. The Next Grand Challenges: Integrating the Internet of Things and Data Science. *IEEE Cloud Comput.* **2018**, *5*, 12–26. [CrossRef]
142. Meer, T.; Gupta, R.; Ailyn, D. Smart Sensor Integration: IoT Sensors for Real-Time Monitoring of Environmental Conditions. 2024. Available online: https://www.researchgate.net/publication/384402035_Smart_Sensor_Integration_IoT_sensors_for_real-time_monitoring_of_environmental_conditions (accessed on 27 December 2024).
143. Bibri, S.E.; Krogstie, J.; Kaboli, A.; Alahi, A. Smarter Eco-Cities and Their Leading-Edge Artificial Intelligence of Things Solutions for Environmental Sustainability: A Comprehensive Systematic Review. *Environ. Sci. Ecotechnol.* **2024**, *19*, 100330. [CrossRef] [PubMed]
144. Manavalan, M. Intersection of Artificial Intelligence, Machine Learning, and Internet of Things–An Economic Overview. *Glob. Discl. Econ. Bus.* **2020**, *9*, 119–128. [CrossRef]
145. Kalusivalingam, A.K.; Sharma, A.; Patel, N.; Singh, V. Enhancing Smart City Development with AI: Leveraging Machine Learning Algorithms and IoT-Driven Data Analytics. *Int. J. AI ML* **2021**, *2*.
146. Mazhar, T.; Irfan, H.M.; Haq, I.; Ullah, I.; Ashraf, M.; Shloul, T.A.; Ghadi, Y.Y.; Imran; Elkamchouchi, D.H. Analysis of Challenges and Solutions of IoT in Smart Grids Using AI and Machine Learning Techniques: A Review. *Electronics* **2023**, *12*, 242. [CrossRef]
147. Ali, S.I.; Abdulqader, D.M.; Ahmed, O.M.; Ismael, H.R.; Hasan, S.; Ahmed, L.H. Consideration of Web Technology and Cloud Computing Inspiration for AI and IoT Role in Sustainable Decision-Making for Enterprise Systems. *J. Inf. Technol. Inform.* **2024**, *3*, 4.
148. Protopsaltis, A.; Sarigiannidis, P.; Margounakis, D.; Lytos, A. Data Visualization in Internet of Things: Tools, Methodologies, and Challenges. In Proceedings of the 15th International Conference on Availability, Reliability and Security, Virtual Event, Ireland, 25 August 2020; ACM: New York, NY, USA, 2020; pp. 1–11.
149. Salamkar, M.A. Data Visualization: AI-Enhanced Visualization Tools to Better Interpret Complex Data Patterns. *J. Bioinform. Artif. Intell.* **2024**, *4*, 204–226. [CrossRef]
150. Singh, J. Sensor-Based Personal Data Collection in the Digital Age: Exploring Privacy Implications, AI-Driven Analytics, and Security Challenges in IoT and Wearable Devices. *Distrib. Learn. Broad Appl. Sci. Res.* **2019**, *5*, 785–809.
151. Kanungo, S. Revolutionizing Data Processing: Advanced Cloud Computing and AI Synergy for IoT Innovation. *Int. Res. J. Mod. Eng. Technol. Sci.* **2020**, *2*, 1032–1040.
152. Tawakuli, A.; Havers, B.; Gulisano, V.; Kaiser, D.; Engel, T. Survey: Time-Series Data Preprocessing: A Survey and an Empirical Analysis. *J. Eng. Res.* 2024, *in press*.
153. Dhawas, P.; Ramteke, M.A.; Thakur, A.; Polshetwar, P.V.; Salunkhe, R.V.; Bhagat, D. Big Data Analysis Techniques: Data Preprocessing Techniques, Data Mining Techniques, Machine Learning Algorithm, Visualization. In *Big Data Analytics Techniques for Market Intelligence*; IGI Global: Hershey, PA, USA, 2024; pp. 183–208.
154. Pattyam, S.P. AI-Driven Data Science for Environmental Monitoring: Techniques for Data Collection, Analysis, and Predictive Modeling. *Aust. J. Mach. Learn. Res. Appl.* **2021**, *1*, 132–169.
155. Panduman, Y.Y.F.; Funabiki, N.; Fajrianti, E.D.; Fang, S.; Sukaridhoto, S. A Survey of AI Techniques in IoT Applications with Use Case Investigations in the Smart Environmental Monitoring and Analytics in Real-Time IoT Platform. *Information* **2024**, *15*, 153. [CrossRef]
156. Ramadan, M.N.A.; Ali, M.A.H.; Khoo, S.Y.; Alkhedher, M.; Alherbawi, M. Real-Time IoT-Powered AI System for Monitoring and Forecasting of Air Pollution in Industrial Environment. *Ecotoxicol. Environ. Saf.* **2024**, *283*, 116856. [CrossRef]

157. Villegas-Ch, W.; García-Ortiz, J.; Sánchez-Viteri, S. Towards Intelligent Monitoring in IoT: AI Applications for Real-Time Analysis and Prediction. *IEEE Access* 2024, *in press*.
158. Habeeb, R.A.A.; Nasaruddin, F.; Gani, A.; Hashem, I.A.T.; Ahmed, E.; Imran, M. Real-Time Big Data Processing for Anomaly Detection: A Survey. *Int. J. Inf. Manag.* **2019**, *45*, 289–307. [CrossRef]
159. Trilles, S.; Belmonte, Ò.; Schade, S.; Huerta, J. A Domain-Independent Methodology to Analyze IoT Data Streams in Real-Time. A Proof of Concept Implementation for Anomaly Detection from Environmental Data. *Int. J. Digit. Earth* **2017**, *10*, 103–120. [CrossRef]
160. Srivastava, A.; Maity, R. Assessing the Potential of AI–ML in Urban Climate Change Adaptation and Sustainable Development. *Sustainability* **2023**, *15*, 16461. [CrossRef]
161. Bibri, S.E.; Huang, J.; Jagatheesaperumal, S.K.; Krogstie, J. The Synergistic Interplay of Artificial Intelligence and Digital Twin in Environmentally Planning Sustainable Smart Cities: A Comprehensive Systematic Review. *Environ. Sci. Ecotechnol.* **2024**, *20*, 100433. [CrossRef] [PubMed]
162. Bala Dhandayuthapani, V. AI, IoT, and Smart Technologies for Environmental Resilience and Sustainability–Comprehensive Review. *Int. J. Inf. Eng. Electron. Bus.* **2024**, *16*, 75–84.
163. Muhammad, A. Managing River Basins with Thinking Machines. In Proceedings of the 2016 IEEE Conference on Norbert Wiener in the 21st Century (21CW), Melbourne, Australia, 13–15 July 2016; IEEE: Piscataway, NJ, USA, 2016; pp. 1–6.
164. Moreno, C.; Aquino, R.; Ibarreche, J.; Pérez, I.; Castellanos, E.; Álvarez, E.; Rentería, R.; Anguiano, L.; Edwards, A.; Lepper, P. RiverCore: IoT Device for River Water Level Monitoring over Cellular Communications. *Sensors* **2019**, *19*, 127. [CrossRef] [PubMed]
165. Zakaria, M.I.; Jabbar, W.A.; Sulaiman, N. Development of a Smart Sensing Unit for LoRaWAN-Based IoT Flood Monitoring and Warning System in Catchment Areas. *Internet Things Cyber-Phys. Syst.* **2023**, *3*, 249–261. [CrossRef]
166. Wei, J.; Liu, S.; Li, Z.; Liu, C.; Qin, K.; Liu, X.; Pinker, R.T.; Dickerson, R.R.; Lin, J.; Boersma, K.F.; et al. Ground-Level NO_2 Surveillance from Space Across China for High Resolution Using Interpretable Spatiotemporally Weighted Artificial Intelligence. *Environ. Sci. Technol.* **2022**, *56*, 9988–9998. [CrossRef]
167. Arat, M. Detection of Anomalous Nitrogen Dioxide (NO_2) Concentration of a District in Ankara: A Reconstruction-Based Approach. *J. Polytech.-Politek Derg.* 2024, *in press*.
168. Divya, A.; Kavithanjali, T.; Dharshini, P. IoT Enabled Forest Fire Detection and Early Warning System. In Proceedings of the 2019 IEEE International Conference on System, Computation, Automation and Networking (ICSCAN), Puducherry, India, 29–30 March 2019; IEEE: Piscataway, NJ, USA, 2019; pp. 1–5. [CrossRef]
169. Chan, C.C.; Alvi, S.A.; Zhou, X.; Durrani, S.; Wilson, N.; Yebra, M. A Survey on IoT Ground Sensing Systems for Early Wildfire Detection: Technologies, Challenges and Opportunities. *IEEE Access* 2024, *in press*.
170. Bhardwaj, N.; Joshi, P. A MATTER-Enabled IoT Framework for Enhanced Fire Detection and Real-Time Decision-Making. *SN Comput. Sci.* **2024**, *5*, 1088. [CrossRef]
171. Kanakaraja, P.; Sundar, P.S.; Vaishnavi, N.; Reddy, S.G.K.; Manikanta, G.S. IoT Enabled Advanced Forest Fire Detecting and Monitoring on Ubidots Platform. *Mater. Today Proc.* **2021**, *46*, 3907–3914. [CrossRef]
172. Manoj, M.; Dhilip Kumar, V.; Arif, M.; Bulai, E.-R.; Bulai, P.; Geman, O. State of the Art Techniques for Water Quality Monitoring Systems for Fish Ponds Using IoT and Underwater Sensors: A Review. *Sensors* **2022**, *22*, 2088. [CrossRef] [PubMed]
173. Zainurin, S.N.; Wan Ismail, W.Z.; Mahamud, S.N.I.; Ismail, I.; Jamaludin, J.; Ariffin, K.N.Z.; Wan Ahmad Kamil, W.M. Advancements in Monitoring Water Quality Based on Various Sensing Methods: A Systematic Review. *Int. J. Environ. Res. Public Health* **2022**, *19*, 14080. [CrossRef]
174. Chowdury, M.S.U.; Emran, T.B.; Ghosh, S.; Pathak, A.; Alam, M.M.; Absar, N.; Andersson, K.; Hossain, M.S. IoT Based Real-Time River Water Quality Monitoring System. *Procedia Comput. Sci.* **2019**, *155*, 161–168. [CrossRef]
175. Prapti, D.R.; Mohamed Shariff, A.R.; Che Man, H.; Ramli, N.M.; Perumal, T.; Shariff, M. Internet of Things (IoT)-Based Aquaculture: An Overview of IoT Application on Water Quality Monitoring. *Rev. Aquac.* **2022**, *14*, 979–992. [CrossRef]
176. Islam, M.M.; Kashem, M.A.; Alyami, S.A.; Moni, M.A. Monitoring Water Quality Metrics of Ponds with IoT Sensors and Machine Learning to Predict Fish Species Survival. *Microprocess. Microsyst.* **2023**, *102*, 104930. [CrossRef]
177. Avancini, D.B.; Rodrigues, J.J.P.C.; Rabêlo, R.A.L.; Das, A.K.; Kozlov, S.; Solic, P. A New IoT-based Smart Energy Meter for Smart Grids. *Int. J. Energy Res.* **2021**, *45*, 189–202. [CrossRef]
178. Mohamed, A.; Mohammed, O. Real-Time Energy Management Scheme for Hybrid Renewable Energy Systems in Smart Grid Applications. *Electr. Power Syst. Res.* **2013**, *96*, 133–143. [CrossRef]
179. Morello, R.; De Capua, C.; Fulco, G.; Mukhopadhyay, S.C. A Smart Power Meter to Monitor Energy Flow in Smart Grids: The Role of Advanced Sensing and IoT in the Electric Grid of the Future. *IEEE Sens. J.* **2017**, *17*, 7828–7837. [CrossRef]
180. Konya, A.; Nematzadeh, P. Recent Applications of AI to Environmental Disciplines: A Review. *Sci. Total. Environ.* **2024**, *906*, 167705. [CrossRef] [PubMed]

181. Santos, M.R.; Carvalho, L.C. AI-Driven Participatory Environmental Management: Innovations, Applications, and Future Prospects. *J. Environ. Manag.* **2025**, *373*, 123864. [CrossRef] [PubMed]
182. Chen, Y. IoT, Cloud, Big Data and AI in Interdisciplinary Domains. *Simul. Model. Pract. Theory* **2020**, *102*, 102070. [CrossRef]
183. Hamza, M.A.; Shaiba, H.; Marzouk, R.; Alhindi, A.; Asiri, M.M.; Yaseen, I.; Motwakel, A.; Rizwanullah, M. Big Data Analytics with Artificial Intelligence Enabled Environmental Air Pollution Monitoring Framework. *Comput. Mater. Contin.* **2022**, *73*, 3235–3250.
184. Kumar, A.; Madaan, G.; Sharma, P.; Kumar, A. Application of Disruptive Technologies on Environmental Health: An Overview of Artificial Intelligence, Blockchain and Internet of Things. *Asia Pac. J. Health Manag.* **2021**, *16*, 251–259. [CrossRef]
185. Basu, M.; Nath, M.D. A Study of the Role of Artificial Intelligence in Monitoring Environmental and Health Issues in the Post-COVID-19 Pandemic Era for Sustainable Living. In *Artificial Intelligence for Multimedia Information Processing*; CRC Press: Boca Raton, FL, USA, 2024; pp. 132–166.
186. Kumari, N.; Pandey, S. Application of Artificial Intelligence in Environmental Sustainability and Climate Change. In *Visualization Techniques for Climate Change with Machine Learning and Artificial Intelligence*; Elsevier: Amsterdam, The Netherlands, 2023; pp. 293–316.
187. Khallaf, A.N. Using AI to Help Reduce the Effect of Global Warming. *Power Syst. Technol.* **2024**, *48*, 1927–1947. [CrossRef]
188. Wang, Y.; Ho, I.W.-H.; Chen, Y.; Wang, Y.; Lin, Y. Real-Time Water Quality Monitoring and Estimation in AIoT for Freshwater Biodiversity Conservation. *IEEE Internet Things J.* **2021**, *9*, 14366–14374. [CrossRef]
189. Zulkifli, C.Z.; Garfan, S.; Talal, M.; Alamoodi, A.H.; Alamleh, A.; Ahmaro, I.Y.; Sulaiman, S.; Ibrahim, A.B.; Zaidan, B.B.; Ismail, A.R. IoT-Based Water Monitoring Systems: A Systematic Review. *Water* **2022**, *14*, 3621. [CrossRef]
190. Mustafa, H.M.; Mustapha, A.; Hayder, G.; Salisu, A. Applications of IoT and Artificial Intelligence in Water Quality Monitoring and Prediction: A Review. In Proceedings of the 2021 6th International Conference on Inventive Computation Technologies (ICICT), Coimbatore, India, 20–22 January 2021; IEEE: Piscataway, NJ, USA, 2021; pp. 968–975. [CrossRef]
191. Bradley, R.W.; Sprague, J.B. The Influence of pH, Water Hardness, and Alkalinity on the Acute Lethality of Zinc to Rainbow Trout (*Salmo gairdneri*). *Can. J. Fish. Aquat. Sci.* **1985**, *42*, 731–736. [CrossRef]
192. Sigdel, B. *Water Quality Measuring Station: pH, Turbidity and Temperature Measurement*; Technical Report; Metropolia University of Applied Sciences: Helsinki, Finland, 2017.
193. Lloyd, D.S.; Koenings, J.P.; Laperriere, J.D. Effects of Turbidity in Fresh Waters of Alaska. *N. Am. J. Fish. Manag.* **1987**, *7*, 18–33. [CrossRef]
194. Gorde, S.P.; Jadhav, M.V. Assessment of Water Quality Parameters: A Review. *J. Eng. Res. Appl.* **2013**, *3*, 2029–2035.
195. Kannel, P.R.; Lee, S.; Lee, Y.-S.; Kanel, S.R.; Khan, S.P. Application of Water Quality Indices and Dissolved Oxygen as Indicators for River Water Classification and Urban Impact Assessment. *Environ. Monit. Assess.* **2007**, *132*, 93–110. [CrossRef] [PubMed]
196. Best, M.A.; Wither, A.W.; Coates, S. Dissolved Oxygen as a Physico-Chemical Supporting Element in the Water Framework Directive. *Mar. Pollut. Bull.* **2007**, *55*, 53–64. [CrossRef]
197. Nazeer, S.; Hashmi, M.Z.; Malik, R.N. Heavy Metals Distribution, Risk Assessment and Water Quality Characterization by Water Quality Index of the River Soan, Pakistan. *Ecol. Indic.* **2014**, *43*, 262–270. [CrossRef]
198. Mokarram, M.; Saber, A.; Sheykhi, V. Effects of Heavy Metal Contamination on River Water Quality Due to Release of Industrial Effluents. *J. Clean. Prod.* **2020**, *277*, 123380. [CrossRef]
199. Rabeh, S.A. Bacteria and Viruses in the Nile. In *The Nile*; Dumont, H.J., Ed.; Monographiae Biologicae; Springer: Dordrecht, The Netherlands, 2009; Volume 89, pp. 407–429, ISBN 978-1-4020-9725-6.
200. Lin, J.; Ganesh, A. Water Quality Indicators: Bacteria, Coliphages, Enteric Viruses. *Int. J. Environ. Health Res.* **2013**, *23*, 484–506. [CrossRef]
201. Working EIFAC. Water Quality Criteria for European Freshwater Fish—Extreme pH Values and Inland Fisheries. *Water Res.* **1969**, *3*, 593–611. [CrossRef]
202. Banna, M.H.; Najjaran, H.; Sadiq, R.; Imran, S.A.; Rodriguez, M.J.; Hoorfar, M. Miniaturized Water Quality Monitoring pH and Conductivity Sensors. *Sens. Actuators Chem.* **2014**, *193*, 434–441. [CrossRef]
203. Bilotta, G.S.; Brazier, R.E. Understanding the Influence of Suspended Solids on Water Quality and Aquatic Biota. *Water Res.* **2008**, *42*, 2849–2861. [CrossRef]
204. Yalaletdinova, A.V.; Beloliptsev, I.I.; Galimova, Y.O.; Vozhdaeva, M.Y.; Kantor, E.A. Probability Analysis of Water Quality by Turbidity. *Iop Conf. Ser. Earth Environ. Sci.* **2019**, *315*, 062019. [CrossRef]
205. Gunda, N.S.; Gautam, S.; Mitra, S. Artificial Intelligence for Water Quality Monitoring. In *ECS Meeting Abstracts*; The Electrochemical Society: Pennington, NJ, USA, 2018; p. 1997.
206. Biraghi, C.A.; Loftian, M.; Carrion, D.; Brovelli, M.A. AI in Support to Water Quality Monitoring. In Proceedings of the XXIV ISPRS Congress, Virtual, 5–9 July 2021.
207. Strobl, R.O.; Robillard, P.D. Artificial Intelligence Technologies in Surface Water Quality Monitoring. *Water Int.* **2006**, *31*, 198–209. [CrossRef]

208. Tung, T.M.; Yaseen, Z.M. A Survey on River Water Quality Modelling Using Artificial Intelligence Models: 2000–2020. *J. Hydrol.* **2020**, *585*, 124670. [CrossRef]
209. Nvs, B.; Saranya, P.L. Water Pollutants Monitoring Based on Internet of Things. In *Inorganic Pollutants in Water*; Elsevier: Amsterdam, The Netherlands, 2020; pp. 371–397. [CrossRef]
210. Singh, Y.; Walingo, T. Smart Water Quality Monitoring with IoT Wireless Sensor Networks. *Sensors* **2024**, *24*, 2871. [CrossRef] [PubMed]
211. Hossain, M.S.; Rahman, M.K.; Dalim, H.M. Leveraging AI for Real-Time Monitoring and Prediction of Environmental Health Hazards: Protecting Public Health in the USA. *Rev. Intell. Artif. Med. Appl.* **2024**, *15*, 1117–1145.
212. Mohanty, A.; Mohanty, S.K.; Mohapatra, A.G. Real-Time Monitoring and Fault Detection in AI-Enhanced Wastewater Treatment Systems. In *The AI Cleanse: Transforming Wastewater Treatment Through Artificial Intelligence*; Garg, M.C., Ed.; Springer Water; Springer: Cham, Switzerland, 2023; pp. 165–199, ISBN 978-3-031-67236-1.
213. Singh, S.; Kumar, A.; Prasad, A.; Bharadwaj, N. IoT Based Water Quality Monitoring System. In Proceedings of the IRFIC 2016, New Delhi, India, 10 January 2016; Institute of Research and Journals (IRAJ): Bhubaneswar, India, 2016.
214. Sugiharto, W.H.; Susanto, H.; Prasetijo, A.B. Real-Time Water Quality Assessment via IoT: Monitoring pH, TDS, Temperature, and Turbidity. *J. Inf. Intell. Eng. Appl.* **2023**, *28*, 823–831. [CrossRef]
215. Yunfeng, L.; Tianpei, Z. A Design of Dissolved Oxygen Monitoring System Based on NB-IoT. In Proceedings of the 2019 International Conference on Smart Grid and Electrical Automation (ICSGEA), Zhangjiajie, China, 7–9 June 2019; IEEE: Piscataway, NJ, USA, 2019; pp. 98–101. [CrossRef]
216. Wang, L.Y.K.; Bong, J.W.; Eng, Y.X.; Wong, W.S. IoT Based Wastewater Dissolved Oxygen and Total Dissolved Solids Monitoring with Data Analytics. In Proceedings of the 2024 11th International Conference on Future Internet of Things and Cloud (FiCloud), Istanbul, Turkey, 26–28 August 2024; IEEE: Piscataway, NJ, USA, 2024; pp. 98–103.
217. Bria, A.R.; Cerro, G.; Ferdinandi, M.; Marrocco, C.; Molinara, M. An IoT-Ready Solution for Automated Recognition of Water Contaminants. *Pattern Recognit. Lett.* **2020**, *135*, 188–195. [CrossRef]
218. Pamula, A.S.; Ravilla, A.; Madiraju, S.V.H. Applications of the Internet of Things (IoT) in Real-Time Monitoring of Contaminants in the Air, Water, and Soil. *Eng. Proc.* **2022**, *27*, 26. [CrossRef]
219. Ooko, S.O.; Rweyemamu, E. Monitoring and Predicting African Rural Household Air Pollution Using Internet of Things and Artificial Intelligence. *Pan-Afr. J. Health Environ. Sci.* **2024**, *3*, 59. [CrossRef]
220. Konar, M. Integrating IoT and AI for Automated Crop with Smart Urban Farming. In Proceedings of the 2024 International Conference on Emerging Innovations and Advanced Computing (INNOCOMP), Sonipat, India, 25–26 May 2024. [CrossRef]
221. Alahi, M.E.E.; Sukkuea, A.; Tina, F.W.; Nag, A.; Kurdthongmee, W.; Suwannarat, K.; Mukhopadhyay, S.C. Integration of IoT-Enabled Technologies and Artificial Intelligence (AI) for Smart City Scenario: Recent Advancements and Future Trends. *Sensors* **2023**, *23*, 5206. [CrossRef] [PubMed]
222. Alselek, M.; Alcaraz-Calero, J.; Wang, Q. Dynamic AI-IoT: Enabling Updatable AI Models in Ultralow-Power 5G IoT Devices. *IEEE Internet Things J.* **2024**, 14192. [CrossRef]
223. Rathoure, A.K.; Rathaur, A.K. AI and IoT in Biodiversity Assessment. *J. Aquac. Mar. Biol.* **2024**, *13*, 108. [CrossRef]
224. Gupta, S.; Hasan, W.; Singh, S.; Kumar, D.; Ansari, M.J.; Nisar, S. (Eds.) Ethical Considerations of AI and IoT in Farming, Chapter 16. In *Book Agriculture 4.0 Smart Farming with IoT and Artificial Intelligence*; CRC Press: London, UK, 2024. [CrossRef]
225. Yiou, P.; Baert, E.; Loutre, M.F. Spectral Analysis of Climate Data. *Surv. Geophys.* **1996**, *17*, 619–663. [CrossRef]
226. Mitchell, T.D.; Hulme, M.; New, M. Climate Data for Political Areas. *Area* **2002**, *34*, 109–112. [CrossRef]
227. Overpeck, J.T.; Meehl, G.A.; Bony, S.; Easterling, D.R. Climate Data Challenges in the 21st Century. *Science* **2011**, *331*, 700–702. [CrossRef] [PubMed]
228. Box, J.E.; Colgan, W.T.; Christensen, T.R.; Schmidt, N.M.; Lund, M.; Parmentier, F.-J.W.; Brown, R.; Bhatt, U.S.; Euskirchen, E.S.; Romanovsky, V.E. Key Indicators of Arctic Climate Change: 1971–2017. *Environ. Res. Lett.* **2019**, *14*, 045010. [CrossRef]
229. Kenney, M.A.; Janetos, A.C.; Gerst, M.D. A Framework for National Climate Indicators. *Clim. Chang.* **2020**, *163*, 1705–1718. [CrossRef]
230. Kjellström, E.; Boberg, F.; Castro, M.; Christensen, J.H.; Nikulin, G.; Sánchez, E. Daily and Monthly Temperature and Precipitation Statistics as Performance Indicators for Regional Climate Models. *Clim. Res.* **2010**, *44*, 135–150. [CrossRef]
231. Bowler, D.; Böhning-Gaese, K. Improving the Community-Temperature Index as a Climate Change Indicator. *PLoS ONE* **2017**, *12*, e0184275. [CrossRef] [PubMed]
232. Wypych, A. Twentieth Century Variability of Surface Humidity as the Climate Change Indicator in Kraków (Southern Poland). *Theor. Appl. Climatol.* **2010**, *101*, 475–482. [CrossRef]
233. Matthews, T. Humid Heat and Climate Change. *Prog. Phys. Geogr. Earth Environ.* **2018**, *42*, 391–405. [CrossRef]

234. Groisman, P.Y.; Karl, T.R.; Easterling, D.R.; Knight, R.W.; Jamason, P.F.; Hennessy, K.J.; Suppiah, R.; Page, C.M.; Wibig, J.; Fortuniak, K.; et al. Changes in the Probability of Heavy Precipitation: Important Indicators of Climatic Change. In *Weather and Climate Extremes*; Karl, T.R., Nicholls, N., Ghazi, A., Eds.; Springer: Dordrecht, The Netherlands, 1999; pp. 243–283, ISBN 978-90-481-5223-0.
235. Pal, I.; Al-Tabbaa, A. Trends in Seasonal Precipitation Extremes–An Indicator of 'Climate Change' in Kerala, India. *J. Hydrol.* **2009**, *367*, 62–69. [CrossRef]
236. Alpert, P.; Mandel, M. Wind Variability—An Indicator for a Mesoclimatic Change in Israel. *J. Clim. Appl. Meteorol.* **1986**, *25*, 1568–1576. [CrossRef]
237. Dewitte, S.; Cornelis, J.P.; Müller, R.; Munteanu, A. Artificial Intelligence Revolutionises Weather Forecast, Climate Monitoring and Decadal Prediction. *Remote Sens.* **2021**, *13*, 3209. [CrossRef]
238. Rahman, A.; Saha, R.; Goswami, D.; Mintoo, A.A. Climate Data Management Systems: Systematic Review of Analytical Tools for Informing Policy Decisions. *Front. Appl. Eng. Technol.* **2024**, *1*, 1–21. [CrossRef]
239. Salam, A. Internet of Things for Environmental Sustainability and Climate Change. In *Internet of Things for Sustainable Community Development*; Internet of Things; Springer International Publishing: Cham, Switzerland, 2024; pp. 33–69, ISBN 978-3-031-62161-1.
240. Gutman, S.I.; Benjamin, S.G. The Role of Ground-Based GPS Meteorological Observations in Numerical Weather Prediction. *GPS Solut.* **2001**, *4*, 16–24. [CrossRef]
241. De Sanctis, M.; Cianca, E.; Araniti, G.; Bisio, I.; Prasad, R. Satellite Communications Supporting Internet of Remote Things. *IEEE Internet Things J.* **2015**, *3*, 113–123. [CrossRef]
242. Chen, Y.; Zhang, M.; Li, X.; Che, T.; Jin, R.; Guo, J.; Yang, W.; An, B.; Nie, X. Satellite-Enabled Internet of Remote Things Network Transmits Field Data from the Most Remote Areas of the Tibetan Plateau. *Sensors* **2022**, *22*, 3713. [CrossRef] [PubMed]
243. Almalki, F.A.; Soufiene, B.O.; Alsamhi, S.H.; Sakli, H. A Low-Cost Platform for Environmental Smart Farming Monitoring System Based on IoT and UAVs. *Sustainability* **2021**, *13*, 5908. [CrossRef]
244. Revathi, S.; Ansari, A.; Susmi, S.J.; Madhavi, M.; Gunavathie, M.A.; Sudhakar, M. Integrating Machine Learning–IoT Technologies Integration for Building Sustainable Digital Ecosystems. In *Advances in Computational Intelligence and Robotics*; Kajla, T., Kansra, P., Singh, N., Eds.; IGI Global: Hershey, PA, USA, 2024; pp. 259–291, ISBN 979-8-3693-2432-5.
245. Ali, M.A.; Dhanaraj, R.K.; Nayyar, A. A High Performance-Oriented AI-Enabled IoT-Based Pest Detection System Using Sound Analytics in Large Agricultural Field. *Microprocess. Microsyst.* **2023**, *103*, 104946. [CrossRef]
246. Farhaoui, Y.; El Allaoui, A. Sustainability in the Internet of Things: Insights, Scope, and AI-Driven Optimized Water Management with Big Data Integration. In *Artificial Intelligence, Big Data, IOT and Block Chain in Healthcare: From Concepts to Applications*; Farhaoui, Y., Ed.; Information Systems Engineering and Management; Springer: Cham, Switzerland, 2024; Volume 6, pp. 468–475, ISBN 978-3-031-65017-8.
247. Maraveas, C.; Piromalis, D.; Arvanitis, K.G.; Bartzanas, T.; Loukatos, D. Applications of IoT for Optimized Greenhouse Environment and Resources Management. *Comput. Electron. Agric.* **2022**, *198*, 106993. [CrossRef]
248. Bale, A.S.; William, P.; Kondekar, V.H.; Sanamdikar, S.; Joshi, P.; Nigam, P.; Savadatti, M.B. Harnessing AI and IoT for Optimized Renewable Energy Integration and Resource Conservation. *Libr. Prog. Int.* **2024**, *44*, 1412–1426.
249. Bianchi, O.; Putro, H.P. Artificial Intelligence in Environmental Monitoring: Predicting and Managing Climate Change Impacts. *Int. Trans. Artif. Intell. (ITALIC)* **2024**, *3*, 85–96. [CrossRef]
250. Park, J.; Kim, K.T.; Lee, W.H. Recent Advances in Information and Communications Technology (ICT) and Sensor Technology for Monitoring Water Quality. *Water* **2020**, *12*, 510. [CrossRef]
251. Kaginalkar, A.; Kumar, S.; Gargava, P.; Niyogi, D. Review of Urban Computing in Air Quality Management as Smart City Service: An Integrated IoT, AI, and Cloud Technology Perspective. *Urban Clim.* **2021**, *39*, 100972. [CrossRef]
252. Chui, K.T.; Lytras, M.D.; Visvizi, A. Energy Sustainability in Smart Cities: Artificial Intelligence, Smart Monitoring, and Optimization of Energy Consumption. *Energies* **2018**, *11*, 2869. [CrossRef]
253. Kumar, D.; Shekhar, S.; Tewary, T. Data Analytics and Artificial Intelligence in Earth Resource Management. In *Data Analytics and Artificial Intelligence for Earth Resource Management*; Elsevier: Amsterdam, The Netherlands, 2025; pp. 1–17.
254. Rane, N.; Choudhary, S.; Rane, J. Leading-Edge Artificial Intelligence (AI), Machine Learning (ML), Blockchain, and Internet of Things (IoT) Technologies for Enhanced Wastewater Treatment Systems. *SSRN Electron. J.* **2023**. [CrossRef]
255. Amirian, H.; Dalvand, K.; Ghiasvand, A. Seamless Integration of Internet of Things, Miniaturization, and Environmental Chemical Surveillance. *Environ. Monit. Assess.* **2024**, *196*, 582. [CrossRef] [PubMed]
256. Salman, O.; Elhajj, I.; Kayssi, A.; Chehab, A. Edge Computing Enabling the Internet of Things. In Proceedings of the 2015 IEEE 2nd World Forum on Internet of Things (WF-IoT), Milan, Italy, 14–16 December 2015; IEEE: Piscataway, NJ, USA, 2015; pp. 603–608.
257. Hassan, N.; Gillani, S.; Ahmed, E.; Yaqoob, I.; Imran, M. The Role of Edge Computing in Internet of Things. *IEEE Commun. Mag.* **2018**, *56*, 110–115. [CrossRef]

258. Kaur, S.; Kumar, R.; Singh, K.; Huang, Y.L. Leveraging Artificial Intelligence for Enhanced Sustainable Energy Management. *J. Sustain. Energy* **2024**, *3*, 1–20. [CrossRef]
259. Whig, P.; Remala, R.; Mudunuru, K.R.; Quraishi, S.J. Integrating AI and Quantum Technologies for Sustainable Supply Chain Management. In *Quantum Computing and Supply Chain Management: A New Era of Optimization*; IGI Global: Hershey, PA, USA, 2024; pp. 267–283.
260. Bukhari, S.A.S.; Shafi, I.; Ahmad, J.; Butt, H.T.; Khurshaid, T.; Ashraf, I. Enhancing Flood Monitoring and Prevention Using Machine Learning and IoT Integration. *Nat. Hazards* **2024**. [CrossRef]
261. Indrakumari, R.; Sriramulu, S.; Partheeban, N.; Rajavel, R. FloodWatch: Suggesting an IoT-Driven Flood Monitoring and Early Warning System for the Flood-Prone Cuddalore District in the Indian State of Tamilnadu. In *Digital Twin Technology and Applications*; Auerbach Publications: Boca Raton, FL, USA, 2024; pp. 374–387.
262. Ukoba, K.; Olatunji, K.O.; Adeoye, E.; Jen, T.-C.; Madyira, D.M. Optimizing Renewable Energy Systems through Artificial Intelligence: A Review and Future Prospects. *Energy Environ.* **2024**, *35*, 3833–3879. [CrossRef]
263. Wen, X.; Shen, Q.; Zheng, W.; Zhang, H. AI-Driven Solar Energy Generation and Smart Grid Integration: A Holistic Approach to Enhancing Renewable Energy Efficiency. *Int. J. Innov. Res. Eng. Manag.* **2024**, *11*, 55–66. [CrossRef]
264. Teh, H.Y.; Kempa-Liehr, A.W.; Wang, K.I.-K. Sensor Data Quality: A Systematic Review. *J. Big Data* **2020**, *7*, 11. [CrossRef]
265. Concas, F.; Mineraud, J.; Lagerspetz, E.; Varjonen, S.; Liu, X.; Puolamäki, K.; Nurmi, P.; Tarkoma, S. Low-Cost Outdoor Air Quality Monitoring and Sensor Calibration: A Survey and Critical Analysis. *ACM Trans. Sens. Netw.* **2021**, *17*, 1–44. [CrossRef]
266. Deekshith, A. Data Engineering for AI: Optimizing Data Quality and Accessibility for Machine Learning Models. *Int. J. Manag. Educ. Sustain. Dev.* **2021**, *4*, 1–33.
267. Gade, K.R. Data Quality Metrics for the Modern Enterprise: A Data Analytics Perspective. *MZ J. Artif. Intell.* **2024**, *1*.
268. Qazi, S.; Khawaja, B.A.; Farooq, Q.U. IoT-Equipped and AI-Enabled Next Generation Smart Agriculture: A Critical Review, Current Challenges and Future Trends. *IEEE Access* **2022**, *10*, 21219–21235. [CrossRef]
269. Wang, X.; Li, X.; Leung, V.C.M. Artificial Intelligence-Based Techniques for Emerging Heterogeneous Network: State of the Arts, Opportunities, and Challenges. *IEEE Access* **2015**, *3*, 1379–1391. [CrossRef]
270. Pankaj, D.A.B. The Internet of Things and Cyber-Physical Systems: AI-Enhanced Interoperability and Efficiency. *Int. IT J. Res.* **2024**, *2*, 53–63.
271. Dave, D.M.K.; Mittapally, B.K. Data Integration and Interoperability in IoT: Challenges, Strategies and Future Direction. *Int. J. Comput. Eng. Technol. (IJCET)* **2024**, *15*, 45–60.
272. Tawalbeh, L.; Muheidat, F.; Tawalbeh, M.; Quwaider, M. IoT Privacy and Security: Challenges and Solutions. *Appl. Sci.* **2020**, *10*, 4102. [CrossRef]
273. Marengo, A. The Future of AI in IoT: Emerging Trends in Intelligent Data Analysis and Privacy Protection. 2023. Available online: https://www.researchgate.net/publication/377087354_The_Future_of_AI_in_IoT_Emerging_Trends_in_Intelligent_Data_Analysis_and_Privacy_Protection?_tp=eyJjb250ZXh0Ijp7ImZpcnN0UGFnZSI6Il9kaXJlY3QiLCJwYWdlIjoicHVibGljYXRpb24ifX0 (accessed on 27 December 2024).
274. Karale, A. The Challenges of IoT Addressing Security, Ethics, Privacy, and Laws. *Internet Things* **2021**, *15*, 100420. [CrossRef]
275. Čolaković, A.; Hadžialić, M. Internet of Things (IoT): A Review of Enabling Technologies, Challenges, and Open Research Issues. *Comput. Netw.* **2018**, *144*, 17–39. [CrossRef]
276. Falola, P.B.; Adeniyi, A.E.; Madamidola, O.A.; Awotunde, J.B.; Olukiran, O.A.; Akinola, S.O. Artificial Intelligence in Agriculture: The Potential for Efficiency and Sustainability, with Ethical Considerations. In *Exploring Ethical Dimensions of Environmental Sustainability and Use of AI*; IGI Global Scientific Publishing: Hershey, PA, USA, 2024; pp. 307–329, ISBN 979-8-3693-0892-9.
277. Akter, S. Ethical AI Development for Sustainable Enterprises: A Review of Integrating Responsible AI with IoT and Enterprise Systems. *J. Artif. Intell. Gen. Sci. (JAIGS)* **2024**, *6*, 94–125. [CrossRef]
278. Perera, A.T.D.; Kamalaruban, P. Applications of Reinforcement Learning in Energy Systems. *Renew. Sustain. Energy Rev.* **2021**, *137*, 110618. [CrossRef]
279. Dang, T.; Liu, J. Adaptive Water Environment Optimization Strategy Based on Reinforcement Learning. *Comput.-Aided Des. Appl.* **2024**, *21*, 1–18. [CrossRef]
280. Fan, Z.; Yan, Z.; Wen, S. Deep Learning and Artificial Intelligence in Sustainability: A Review of SDGs, Renewable Energy, and Environmental Health. *Sustainability* **2023**, *15*, 13493. [CrossRef]
281. Khanmohammadi, A.; Jalili Ghazizadeh, A.; Hashemi, P.; Afkhami, A.; Arduini, F.; Bagheri, H. An Overview to Electrochemical Biosensors and Sensors for the Detection of Environmental Contaminants. *J. Iran. Chem. Soc.* **2020**, *17*, 2429–2447. [CrossRef]
282. Manzano, L.G.; Boukabache, H.; Danzeca, S.; Heracleous, N.; Murtas, F.; Perrin, D.; Pirc, V.; Alfaro, A.R.; Zimmaro, A.; Silari, M. An IoT LoRaWAN Network for Environmental Radiation Monitoring. *IEEE Trans. Instrum. Meas.* **2021**, *70*, 1–12. [CrossRef]
283. Wang, L.; Yang, H. Design of Smart City Environment Monitoring and Optimisation System Based on NB-IoT Technology. *Int. J. Inf. Commun. Technol.* **2024**, *25*, 47–61. [CrossRef]

284. Niu, L. Design of Intelligent Agricultural Environmental Big Data Collection System Based on ZigBee and NB-IoT. In Proceedings of the 2023 IEEE 2nd International Conference on Electrical Engineering, Big Data and Algorithms (EEBDA), Beijing, China, 25–27 August 2023; IEEE: Piscataway, NJ, USA, 2023; pp. 1299–1304.
285. Jabbar, W.A.; Subramaniam, T.; Ong, A.E.; Shu'Ib, M.I.; Wu, W.; De Oliveira, M.A. LoRaWAN-Based IoT System Implementation for Long-Range Outdoor Air Quality Monitoring. *Internet Things* **2022**, *19*, 100540. [CrossRef]
286. Phupattanasilp, P.; Tong, S.-R. Augmented Reality in the Integrative Internet of Things (AR-IoT): Application for Precision Farming. *Sustainability* **2019**, *11*, 2658. [CrossRef]
287. Filipova, M.; Gospodinov, G.; Gotsev, L.; Kovatcheva, E.; Jekov, B. Quantum Computing Applications for Addressing Global Warming and Pollution: A Comprehensive Analysis. In Proceedings of the 15th International Scientific and Practical Conference "Environment. Technology. Resources", Rezekne, Latvia, 19–20 June 2024; Volume 1, pp. 154–160.
288. Vanderbilt, K.L.; Lin, C.-C.; Lu, S.-S.; Kassim, A.R.; He, H.; Guo, X.; Gil, I.S.; Blankman, D.; Porter, J.H. Fostering Ecological Data Sharing: Collaborations in the International Long Term Ecological Research Network. *Ecosphere* **2015**, *6*, 1–18. [CrossRef]
289. Fascista, A. Toward Integrated Large-Scale Environmental Monitoring Using WSN/UAV/Crowdsensing: A Review of Applications, Signal Processing, and Future Perspectives. *Sensors* **2022**, *22*, 1824. [CrossRef] [PubMed]
290. Okafor, N. Advances and Challenges in IoT Sensors Data Handling and Processing in Environmental Monitoring Systems. 2023. Available online: https://www.techrxiv.org/users/679289/articles/682738-advances-and-challenges-in-iot-sensors-data-handling-and-processing-in-environmental-monitoring-systems (accessed on 27 December 2024).
291. Gouveia, C.; Fonseca, A.; Câmara, A.; Ferreira, F. Promoting the Use of Environmental Data Collected by Concerned Citizens through Information and Communication Technologies. *J. Environ. Manag.* **2004**, *71*, 135–154. [CrossRef] [PubMed]
292. Conrad, C.C.; Hilchey, K.G. A Review of Citizen Science and Community-Based Environmental Monitoring: Issues and Opportunities. *Environ. Monit. Assess.* **2011**, *176*, 273–291. [CrossRef]
293. Berigüete, F.E.; Santos, J.S.; Rodriguez Cantalapiedra, I. Digital Revolution: Emerging Technologies for Enhancing Citizen Engagement in Urban and Environmental Management. *Land* **2024**, *13*, 1921. [CrossRef]
294. Cao, F.; Jian, Y. The Role of Integrating AI and VR in Fostering Environmental Awareness and Enhancing Activism among College Students. *Sci. Total Environ.* **2024**, *908*, 168200. [CrossRef]
295. Asuquo, A.; Agbor, C.; Bassey, A.; Omoogun, M. Artificial Intelligence (AI) Innovations for Sustainable Educational Institutions: Enhancing Efficiency and Environmental Responsibility. *Int. J. Innov. Technol. Integr. Educ.* **2024**, *7*, 84–101.
296. Ho, K.T.M.; Chen, K.-C.; Lee, L.; Burt, F.; Yu, S.; Lee, P.-H. Quantum Computing for Climate Resilience and Sustainability Challenges. 2024. Available online: https://arxiv.org/abs/2407.16296 (accessed on 28 December 2024).
297. Arabelli, R.; Boddepalli, E.; Buradkar, M.; Goriparti, N.V.S.; Chakravarthi, M.K. IoT-Enabled Environmental Monitoring System Using AI. In Proceedings of the 2024 International Conference on Advances in Computing, Communication and Applied Informatics (ACCAI), Chennai, India, 9–10 May 2024; pp. 1–6. [CrossRef]
298. Arowolo, M.E.; Aaron, W.C.; Eteng, U.S.; Divine, I.L.O.H.; Aguma, C.P.; Olagunju, A.O. Integrating AI-Enhanced Remote Sensing Technologies with IoT Networks for Precision Environmental Monitoring and Predictive Ecosystem Management. *World J. Adv. Res. Rev.* **2024**, *23*, 2156–2166. [CrossRef]
299. Manongga, D.; Rahardja, U.; Sembiring, I.; Aini, Q.; Wahab, A. Improving the Air Quality Monitoring Framework Using Artificial Intelligence for Environmentally Conscious Development. *HighTech Innov. J.* **2024**, *5*, 794–813. [CrossRef]