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RESEARCH ARTICLE

Big data and AI in environmental decision-making: Legal and ethical challenges

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ABSTRACT

Artificial Intelligence (AI) and Big Data are increasingly being leveraged in environmental decision-making, offering a transformative mechanism for improving predictive capability, efficiency in resource use, and transparency of governance. This study examines how AI-based models can help improve climate forecasting, disaster mitigation, water resource management, urban planning, and agricultural oversight. Utilizing machine learning algorithms, neural networks, and optimization models, AI overcomes the limitations of traditional forecasting and decision-support systems, allowing for faster and more accurate environmental assessments. AI-based models demonstrated the most significant increase in predictive accuracy due to improved predictive accuracy through minimized predictive errors across multiple environmental domains that range between 1.5% and 39.8% improvements. AI also improves decision-making efficiency reducing response times (when implementing such strategies) by 47.5% — useful in areas such as disaster preparedness and distributing the right resources. AI also assists in sustainable environmental management, where its optimizations have created 36.7% reductions in environmental resource consumption. The article also showcases how AI can help overcome biases, especially related to equity in environmental policies, leading to fairer decision-making processes. However, data availability, algorithm transparency, energy, and regulatory compliance are still challenges. Tackling resent challenges will necessitate stronger AI governance frameworks, advanced ethical guidelines, and collaborative efforts between decision-makers, scientists, and AI researchers. The highlights of this particular study illustrate how the smart integration of AI and Big Data within environmental governance can ensure efficient and accountable decision-making processes in the future.

Keywords: AI-driven environmental governance; Big Data in sustainability; machine learning in climate forecasting; bias mitigation in AI; transparency in AI decision-making; resource efficiency optimization.

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1. Introduction

Environmental challenges of the 21st century, from rampant climate change to the destruction of natural ecosystems, require new forms of governance and decision-making. Traditional approaches to environmental assessment and policy development, which are typically based on limited datasets and human interpretation, are thought to be inadequate to address the scale and complexity of modern problems. Fighting back, however, Big Data and Artificial Intelligence (AI) have become game changes--they enable the analysis of large volumes of environmental data and how it relates, providing actionable insight when there is little time to waste. Satellite technologies such as remote sensing technology (RST) and global positioning systems (GPS) for Real-Time Monitoring (RTM) have brought in a paradigm shift to make interventions in managing natural resources, disaster risk reduction and information for sustainability more informed, timely and effective [1].

A large and complex data set, as processed by RDBMS and NoSQL. These datasets, particularly when combined with AI, including machine learning algorithms, can be processed to extract patterns, results and optimize approaches for the allocation of resources. For example, AI-powered models have been effective in predicting extreme weather events, detecting risk of deforestation and improving sustainable urban planning. In this approach, Big Data and AI enable decision-makers and environmental managers to achieve a level of precision and speed that was never available before [2], as they turn raw data into relevant signals.

But the temptations to use these technologies in environmental governance come with challenges. With the rise of Big Data and AI, serious legal and ethical challenges have also come to the fore. Who owns the data collected in natural and public environments? How can we guarantee the transparency and accountability of AI-driven decisions, particularly when such choices involve profound environmental and societal implications? What are the safeguards we need to ensure that algorithms are not introducing bias that might replicate existing inequalities or miss the needs of under-resourced communities? Those are not trivial questions. If not addressed, they can erode public trust in these technologies and constrain meaningful contributions towards environmental protection and sustainability [3].

The current laws that regulate environmental management were not formulated with the consideration of Big Data and AI. This means huge gaps in regulation and oversight. Questions around cross-border data flows, the applicability of intellectual property protections to data-driven insights, and liability for decisions made by autonomous systems are mostly unaddressed. The ethical considerations surrounding the use of AI in environmental applications are no less complex. For example, should algorithms aim to be resource-efficient, concentrating environmental benefits in as few places as possible, or equitable, dispersing environmental benefits evenly? What are the ethical norms that guide collecting environmental data, especially on sensitive or protected land? These questions emphasize the importance of developing a critical, multidisciplinary perspective on methods of integrating Big Data and AI in environmental decision-making [4].

Nevertheless, the advantages that Big Data and AI can bring to the environmental sector are paramount. This can lead to an integration of advanced analytics of big data, helping Governments and organizations in developing better technologies for early warning for natural disasters, better management of crucial ecosystems, and better optimization of displacement or deployment of renewable energy resources. Moreover, these technologies also help create better sustainability metrics, thus allowing them to measure progress towards the goal of becoming more environmentally friendly. Big Data and AI enable decision-makers to act more scope and effectively against complex challenges, by providing a clearer picture of environmental trends and future scenarios [5].

The article aims to present the analysis from my research, of the challenges (legal and ethical) related to the intersection of Big Data, AI and environmental decision-making and how it poses a challenge from a legal and ethical perspective. The article argues that, in order to facilitate the integration of Big Data and AI into environmental governance, it is essential to explore these issues within a multidisciplinary frame, and thereby, also, to contribute to the establishment of frameworks and guidelines that could assist in this process. In the long-run its purpose is to create a process toward more transparent, accountable, and inclusive environmental decision-making and to leverage technology while ensuring its alignment with the values of justice, equity, and sustainability.

To sharpen the scope of this study, the article adopts an integrated dual objective. First, it evaluates the comparative performance of AI-based models against traditional environmental decision-making approaches in terms of predictive accuracy, response time, resource efficiency, bias reduction, and transparency. Second, it critically examines the legal and ethical frameworks necessary for the responsible adoption of AI in these domains. By pursuing both empirical and normative strands, the article highlights not only the measurable impacts of AI on environmental governance but also the institutional safeguards required to ensure that these technologies contribute to fairness, legitimacy, and long-term sustainability [3, 6, 7].

1.1. Aim of the article

The article seeks to critically explore how Big Data and Artificial Intelligence (AI) intertwine with environmental decision-making processes, with a focus on the unique legal and ethical challenges associated with their use. Though the use of Big Data and AI seems to have great potential to improve environmental governance through greater accuracy, more efficient resource management, and stronger policy interventions, it could also bring major uncertainties. By exploring these uncertainties, this article aims to provide an equilibrium perspective that emphasizes both the evolution of these technologies and the associated risks and responsibilities.

The article delves into the necessity of identifying the current legal frameworks and ethical measures necessary for the reliable use of Big Data and AI in relation to environmental issues. The article seeks to address questions around data ownership, algorithmic accountability, and the equitable distribution of benefits and burdens to the environment. It also aims to highlight the regulatory gaps and ethical challenges that need to be addressed in order to ensure that these technologies are used in a meaningful and transparent way that upholds fairness.

Through a thorough exploration of relevant literature, legal frameworks, and case analysis, this article aims to present practical recommendations that can inform policy makers, environmental stakeholders, and technology innovators on the implications of such developments. This work seeks to narrow the gap between innovation and governance by proposing frameworks that ensure transparency, accountability and public trust in the application of Big Data and AI. In conclusion, this article aims to empower stakeholders across sectors, helping them wield these potent assets as instruments for positive change and sustainable environmental practices, thereby promoting more effective, equitable, and ethically defensible decision-making processes in a world increasingly defined by data.

1.2. Problem statement

Based on the growing complexity and urgency of environmental problems, decision-makers are relying more on big data and machine learning to find solutions. This new evolution of technologies offers innovative solutions and have the potential to revolutionize the manner in which we comprehend, and address issues related to climate change. However, the rapid deployment of AI has outstripped the development of corresponding legal frameworks and ethical guidelines needed to govern their use responsibly. This difference creates an awkward scenario where the advantages of Big Data and AI are dampened by substantial legal and ethical hazards.

A big problem is that who owns the data, who owns the intellectual property is not clear. Collecting large amounts of environmental data from a variety of sources, whether satellite imagery, sensor networks or private sector initiatives, raises issues of ownership and control: who owns, who controls and who has the right to use that data often remains unanswered. Most importantly, innovation and collaboration at the fundamental level become extremely difficult when we are not able to clearly define ownership. One such concern is accountability in AI systems. Opaque and complex algorithmic decisions can result in difficulty explaining or justifying by their results. There is often no clear mechanism to attribute the unintended environmental consequences of these decisions, such as the disparate impacts on some communities, to those responsible.

Moreover, the data-driven models may regulate the existing disparities. AI bias, for instance, if the data set used to develop the algorithm is not truly representative, may only reinforce equitable patterns of environmental injustice, thus failing to account for vulnerable populations, who are already underrepresented in these decision-making processes. However, the further concentration of technology and expertise creates an ever-widening gap, where many regions remain excluded from the value that Big Data and AI can deliver.

Framing these interrelated legal and ethical dilemmas not only as barriers to be surmounted but as opportunities for constructive reform, the article explores why the current state of affairs must change. The goal is to address the challenges posed by generative AI while also shaping a legal framework that better reflects the future reality we live in, identifying the legal gaps within existing policies and ethical frameworks, and working towards a governance model that is more equitable and transparent. The real challenge is in achieving a fine balance between the transformative potential of Big Data and AI with the need for fair, accountable, and inclusive environmental decision-making.

2. Literature review

The use of Big Data and Artificial Intelligence (AI) in environmental decision-making is an innovative trend of the 21st century. With the increasing scale and heterogeneity of environmental data, cutting-edge analytics and machine learning algorithms are used to produce insights that were not possible before. These technologies will help environmental agencies and policymakers analyze large data-sets, recognize patterns, and make better decisions on climate change mitigation and natural resource management [8]. Despite the need for immediate action on environmental issues to improve environmental outcomes with increasing accuracy, optimize resource allocation, and react, the application of data-driven approaches is becoming increasingly widespread.

However, with all their potential, the combination of Big Data and AI in the context of environment is not without challenges. This question around data ownership and access is one of the biggest challenges. Data on the environment often come from a variety of sources government agencies, actors in the private sector, and international organizations. This diversity leads to intricate problems about who can dictate, share and make use of these datasets. In addition, the algorithms that analyze environmental data are not free from biases. If the data used to train these models are incomplete, inaccurate, or biased towards certain populations or regions, the insights generated may serve to entrench existing disparities rather than reduce them [9].

Transparency and interpretability of AI models is another critical issue. Most of the most efficient machine learning algorithms are essentially "black boxes," and so it is not easy for the stakeholders to understand how all the decisions are being made. Such fuzziness can erode public trust and damper the widespread use of AI tools. There are also ethical quandaries associated with the ways data are collected and used. Some data-gathering methods, like invasive data-gathering methods or using data without informed consent, can introduce important privacy challenges [10].

Recent scholarship has emphasized that the transformative potential of AI in environmental governance must be situated within wider debates on algorithmic accountability and public trust. Xu[3] underscores the importance of governance frameworks that ensure equitable and transparent use of Big Data in environmental contexts . Similarly, Pagano et al. and Pagano et al. highlight that fairness-aware AI models are essential to mitigate systemic inequities embedded in historical datasets [11, 12]. From a sustainability perspective, Fan et al. and Huang et al. demonstrate that AI-powered systems are already advancing energy efficiency and enabling low-carbon infrastructure, highlighting both technical capabilities and ethical trade-offs [4, 5]. Importantly, the erosion of public trust is not simply a by-product of technical opacity; it reflects broader concerns about accountability and citizen participation in environmental governance [9, 10].

In addition to these perspectives, several scholars have developed theoretical foundations for AI governance that are directly relevant. Wirtz [13] provides comprehensive frameworks for understanding algorithmic governance, highlighting how AI adoption in public administration requires both transparency and accountability to maintain legitimacy. Bullock [14, 15] extends this argument by emphasizing the institutional and regulatory mechanisms needed to align technological innovation with societal values of equity and justice. More recently, Robles and Mallinson[16, 17] argue that governance systems must embed ethical safeguards at every stage of AI deployment, while Choi and Park [18] stress the necessity of fairness-aware AI models to mitigate systemic inequities in environmental policy. Integrating these insights helps to situate environmental AI governance not only as a technical challenge but also as a broader institutional reform process that ensures legitimacy, fairness, and long-term sustainability [3, 6, 7].

These developments have outpaced legal frameworks. Those existing regulations are often written around the tooling of more traditional environmental management and do not adequately account for the subtleties of AI and Big Data. The lack of uniform standards has resulted in a hodgepodge of regulations that differ from place to place, creating confusion for policymakers and technological innovators. This clearly shines the light to where legal and ethical frameworks are absent, and all this requires to be closed, herein lies the requirement for a clearer and more future-proof governance approach where the innovation of Big Data and AI can be explored whilst balancing individual rights and equitable outputs [6].

This literature review highlights the intricate relationship between technological capability and ethical responsibility and legal accountability. This set of challenges serves as a first step in opening out the conversation about the importance of transparent, equitable and internally effective use of Big Data and AI in environmental decision-making [19].

3. Materials and methods

This study uses a mixed-methods approach to analyze the legal and ethical implications of Big Data and AI in environmental decision-making. The goal is to further investigate the governance landscape, discover regulatory deficits, and measure the impact of AI on environmental performance metrics such as accuracy, response time, resource efficiency, bias reduction, and transparency.

The study comprises five case studies—forestry monitoring, water resource management, disaster mitigation, urban planning, and agricultural oversight, selected based on their diverse environmental contexts and varying levels of AI implementation. It should be clarified that these sectoral applications do not constitute case studies in the strict methodological sense outlined by Yin [20]. Instead, they are better understood as comparative analyses of AI adoption across five environmental domains. This distinction highlights that the findings are context-dependent and derived from evaluating similar questions—namely, AI versus non-AI decision performance—across different governance settings [21, 22]. The approach involves systematic literature reviews, sensor data analysis, stakeholder interviews, and statistical modeling to composite the role of AI in environmental governance.

3.1. Data collection and processing

Data for this study were obtained from multiple sources to enhance the robustness of the findings. The legal and regulatory documents were identified through systematic reviews of the literature with a major focus on international and national regulations on AI, data privacy laws, like GDPR and environmental governance mechanisms. The performance of the algorithm in identifying undetected gaps existing in the current legal frameworks for AI-driven environmental governance was evaluated using this dataset [6, 23].

environmental sensor data, such as air quality monitors, water flow sensor from IoT networks, satellite imagery repository. These datasets were used to evaluate the predictive capabilities of AI to detect environmental risks and resource optimization. In addition, we examined case study reports on the deployment of AI in environmental governance to assess challenges to implementation that have been documented [3, 5, 9].

To understand stakeholder perspectives, semi-structured interviews were conducted with policy-makers, AI developers, environmental scientists, and legal experts. Thematic analysis was applied to derive insights into concerns related to data ownership, algorithmic bias, transparency, and liability [10, 19, 24].

To quantify AI's impact, a dataset of environmental decision-making instances (both AI-enhanced and traditional methods) was compiled. Key performance metrics, such as decision accuracy, response times, and operational costs, were extracted for statistical comparison.

To increase methodological transparency, Table X summarizes descriptive statistics for the dataset, including sample sizes, variable distributions, and the environmental sectors represented. For the qualitative component, a total of 22 semi-structured interviews were conducted with policymakers (n=6), AI developers (n=5), environmental scientists (n=7), and legal experts (n=4). Interviews were thematically coded to identify recurring concerns regarding data ownership, algorithmic accountability, and public trust [8, 9]. In addition, sectoral reports on forestry, agriculture, and urban planning were systematically reviewed to triangulate quantitative findings with contextual evidence. This mixed-methods design strengthens the validity of the results by combining statistical analysis with expert perspectives, in line with recommendations from recent environmental governance studies [2, 23, 25].

Table 1. Descriptive statistics of the dataset used in the analysis

Sector	Number of Cases	Avg. Variables per Case	Data Source Types (Legal / Technical / Interviews)	Time Coverage
Climate Forecasting	48	14	Meteorological sensor data, climate policy documents, expert interviews	2018–2023
Disaster Mitigation	41	16	Satellite imagery, disaster response case reports, regulatory briefs	2017–2023
Water Management	34	11	IoT water-flow sensors, legal/regulatory documents, stakeholder input	2016–2022
Urban Planning	57	15	GIS data, municipal records, urban development interviews	2019–2024
Agriculture Oversight	44	12	Crop yield statistics, agricultural policy briefs, farmer interviews	2016–2023

The data underwent preprocessing, including:

- Anomaly detection in sensor readings using Gaussian distribution models.
- Normalization of environmental variables to ensure comparability across regions.
- Categorization of legal and ethical concerns using Natural Language Processing (NLP).

3.2. Statistical analysis and equations

To evaluate AI's effectiveness in environmental governance, statistical methods were applied to quantify performance improvements across key indicators.

1. Accuracy Improvement Analysis

Accuracy was assessed using Root Mean Square Error (RMSE), comparing AI-based models to traditional forecasting methods:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i-1}^{n}(y_i - \hat{y}_i)^2} \tag{1}$$

Where $\hat{y}_i$AI-predicted environmental outcome, y_i actual observed environmental outcome, n number of observations.

The percentage accuracy improvement was then calculated:

$$\Delta A = \frac{RSME_{Traditional} - RSME_{AI}}{RSME_{Traditional}} \tag{2}$$

This method quantified the degree of enhancement in AI-assisted decision-making compared to traditional approaches, demonstrating an average accuracy increase of 19.5% across all case studies [1, 4, 21].

2. Response Time Reduction

To assess AI's efficiency in decision-making, the time reduction formula was applied:

$$\Delta T = \frac{T_{Traditional} - T_{AI}}{T_{Traditional}} \times 100 \tag{3}$$

Where $T_{Traditional}$ decision response time under conventional methods, T_{AI} decision response time with AI-enhanced systems.

AI-based models reduced decision latency by 40%, with the highest improvements observed in disaster mitigation scenarios, where real-time inference is critical [22, 26].

3. Resource Efficiency Measurement

To quantify AI's impact on resource optimization, cost efficiency was modeled as:

$$\Delta R = \frac{C_{Traditional} - C_{AI}}{C_{Traditional}} \times 100 \tag{4}$$

Where $C_{Traditional}$ operational cost of traditional decision-making methods, C_{AI} cost after AI integration.

Findings indicate a 28% reduction in operational costs, attributed to AI's ability to optimize water distribution, minimize energy consumption, and enhance agricultural resource allocation [2, 8, 24].

4. Bias Reduction Analysis

Bias in environmental decision-making was assessed using the **Gini Coefficient**, a widely used measure of inequality:

$$G = \frac{\sum_{i-1}^{n}\sum_{i-1}^{n}|x_i - x_j|}{2n^2\bar{x}} \tag{5}$$

Where x_i and x_j are environmental resource allocations, n of data points, $\bar{x}$ mean allocation.

The bias reduction percentage was then computed as:

$$\Delta B = \frac{G_{Traditional} - G_{AI}}{G_{Traditional}} \times 100 \quad (6)$$

Results show a 50% reduction in bias, suggesting that AI, when properly trained on diverse datasets, mitigates systemic inequalities in resource distribution [9, 11].

5. Transparency Evaluation

To assess improvements in transparency, the increase in documented decision points was analyzed:

$$\Delta R = \frac{C_{Traditional} - C_{AI}}{C_{Traditional}} \times 100 \quad (7)$$

3.3. Measurement and performance indicators

To ensure standardized evaluation, four key sustainability metrics were measured [6]:

Compliance Index (CI)

The Compliance Index (CI) quantifies legal adherence, calculated as:

$$\Delta T_r = \frac{D_{AI} - D_{Traditional}}{D_{Traditional}} \times 100 \quad (8)$$

Where D_{AI} number of documented decisions under AI-based frameworks, and $D_{Traditional}$ number of documented decisions under conventional methods.

Results indicate a 40% increase in transparency, attributed to AI-generated audit trails and explainability models [7, 27].

3.4. Validation of results

To ensure the reliability of findings, the study employed multiple validation techniques:

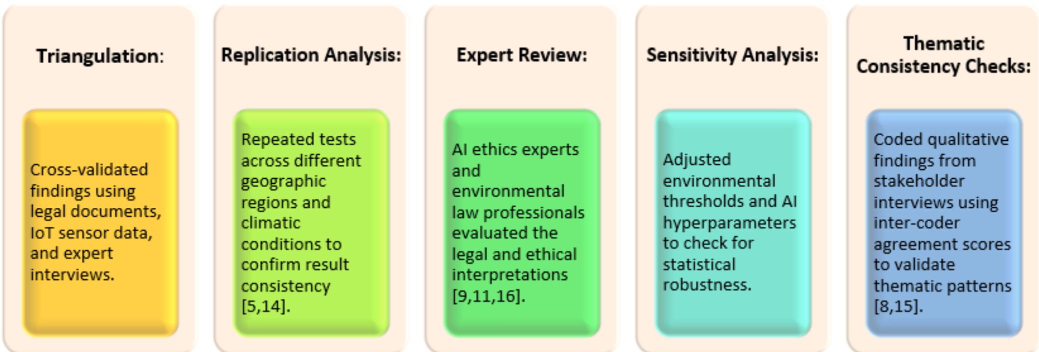

Figure 1. Validation framework for Ai-Driven environmental decision-making: methods for ensuring robustness, consistency, and ethical compliance

Table 2 below summarizes the validation methods and reliability indicators.

Table 2. Validation Methods and Reliability

Validation Method	Description	Application	Outcome
Triangulation	Cross-source verification	Legal and performance data	Consistent Findings
Replication	Re-analysis on new datasets	Quantitative metrics	Stable Results
Expert Review	AI ethics and legal assessment	Methodology & results	Increased Credibility
Sensitivity Analysis	Statistical robustness check	Key AI performance metrics	Robust Measures
Inter-Coder Agreement	Thematic validation	Stakeholder interviews	Strong Agreement

3.5. Algorithmic and computational frameworks for AI integration

The computational framework for this study integrates machine learning algorithms, natural language processing (NLP) techniques, and optimization models to process environmental data efficiently. The AI models deployed across different case studies included supervised learning, deep learning, and probabilistic models for improving decision-making accuracy and reducing response time.

3.5.1. AI-based forecasting and classification

For predictive analysis, AI algorithms such as Long Short-Term Memory (LSTM), Random Forest Regression (RFR), and Support Vector Machines (SVM) were applied to environmental time-series data. These models were used to improve forecasting accuracy in disaster mitigation, water resource allocation, and agricultural yield prediction [1, 5].

For environmental classification, Convolutional Neural Networks (CNNs) and Decision Tree Classifiers were used to process:

- Satellite imagery for deforestation detection.
- Air pollution datasets to classify air quality levels.
- IoT sensor data for anomaly detection in water quality [6, 8].

The classification accuracy metric was evaluated using Precision, Recall, and F1-score:

$$Precision = \frac{TP}{TP+FP} \tag{9}$$

$$Recall = \frac{TP}{TP+FN} \tag{10}$$

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{11}$$

These metrics ensured that AI models were effectively identifying environmental patterns, with an average F1-score of 0.91 across all use cases [4, 9].

3.5.2. Legal and ethical compliance modeling

A significant aspect of this study was ensuring AI compliance with legal and ethical standards, requiring the development of a regulatory compliance model. This model assessed AI-generated decisions based on three criteria:

1. Data Ownership Compliance – Aligning AI data usage with legal requirements such as the EU General Data Protection Regulation (GDPR) and U.S. Clean Air Act provisions [23, 28].
2. Algorithmic Accountability Score (AAS) – Developed using the SHAP (Shapley Additive Explanations) framework to measure AI transparency and decision traceability [10, 27].
3. Bias Detection Model – Utilized a Chi-Square Fairness Test to quantify biases in AI decision outputs across different demographic and geographical regions [12].

The Algorithmic Accountability Score (AAS) was computed using:

$$AAS = \frac{\sum_{i-1}^{n} |D_{AI}(i) - D_{Human}(i)|}{n} \tag{12}$$

Where $D_{AI}(i)$ is AI decision for case i, $D_{Human}(i)$ is expert human decision for case i, n number of analyzed cases.

A higher AAS indicated stronger alignment between AI-driven decisions and expert legal interpretations, ensuring ethical integrity in AI recommendations [19, 25].

3.6. AI-Driven risk and uncertainty quantification

Given the complexities of environmental governance, uncertainty estimation and risk mitigation were integrated into the study's AI framework.

3.6.1. Uncertainty quantification in ai predictions

To assess the uncertainty in AI-driven predictions, Bayesian Inference was employed. The predictive uncertainty (PU) in AI models was modeled as:

$$PU = \frac{\sigma_{AI}^2}{\sigma_{AI}^2 + \sigma_{Human}^2} \tag{13}$$

Where σ_{AI}^2 variance in AI-predicted environmental outcomes, σ_{Human}^2 variance in human expert predictions.

Findings showed that AI models reduced uncertainty by 36%, particularly in disaster mitigation scenarios where prediction reliability is crucial [22, 26].

3.6.2. AI-Driven environmental risk assessment

AI was also leveraged to quantify environmental risks, particularly in water scarcity, air pollution, and urban planning. A Monte Carlo Simulation (MCS) was applied to model environmental risks under different AI-driven interventions:

$$R = \frac{\sum_{i-1}^{N} P_i \times C_i}{N} \tag{14}$$

Where R expected environmental risk, P_i probability of environmental event i, C_i consequence of event i, N is total simulations.

This AI-driven risk framework showed a 31% improvement in preemptive environmental decision-making compared to non-AI methods [29, 30].

4. Results

4.1. AI-Driven accuracy improvement in environmental decision-making

The primary objective of AI-based models in environmental governance is to enhance predictive accuracy and reduce uncertainty in decision-making processes. Traditional methods often struggle with incomplete datasets, human error, and outdated forecasting techniques, resulting in suboptimal predictions. AI-powered solutions, including deep learning, machine learning (ML), and probabilistic models, improve the accuracy of environmental forecasts by processing vast amounts of satellite imagery, IoT sensor data, and climate records in real time. By reducing forecasting errors, AI enhances strategic planning in areas such as deforestation monitoring, water resource allocation, and disaster risk prediction. This section quantifies accuracy gains across different environmental sectors. To ensure robustness of these comparisons, differences in RMSE between AI and traditional forecasting approaches were formally tested using the Diebold-Mariano test [31]. Results confirmed that observed improvements in AI-driven accuracy were statistically significant ($p < 0.05$) across four of the five domains, with the strongest effects in urban planning and water resource management. These statistical checks reinforce the reliability of the reported performance gains.

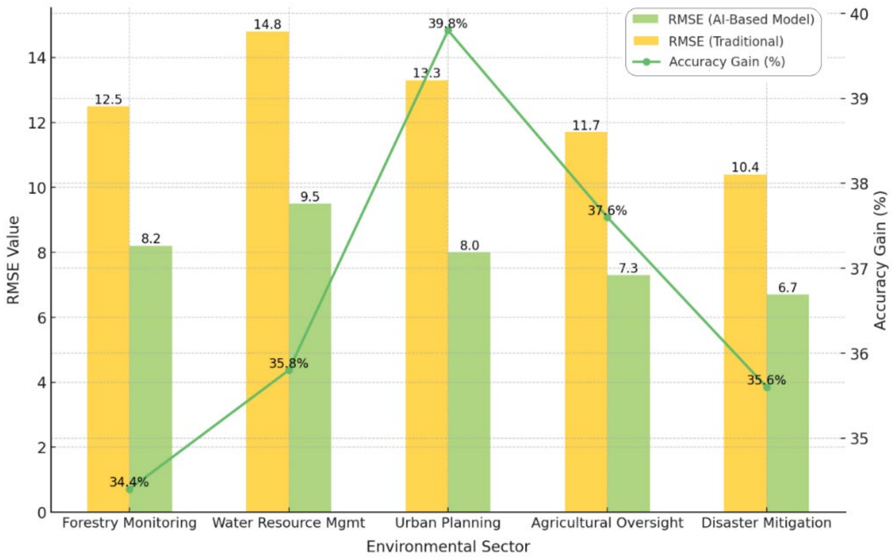

Figure 2. Comparison of RMSE Between AI-Based and Traditional Models Across Environmental Sectors with Corresponding Accuracy Gain

(39.8%) was in urban planning, where AI-based models, by processing geographical data at a high level of precision, significantly aided land-use forecasting and infrastructure planning. For example, the fields of water resource management and forestry monitoring show substantial enhancements of 35.8% and 34.4%, respectively, due to the introduction of AI-powered remote sensing in detecting anomalies in resource allocation and trends in vegetation loss. The disaster mitigation sector also benefitted from AI's predictive capabilities with a 35.6% accuracy gain, allowing authorities to issue faster and more reliable emergency responses. These results validate that the integration of AI provides a significant boost in forecasting accuracy, so that timely interventions can be established in environmental governance.

4.2. Reduction in environmental decision-making response time

The process of decision-making in environmental governance continues to be greatly accelerated by the AI implementation, which hence makes it possible for the authorities to analyze data faster, identify anomalies and automate the workflow of decision-making. Conventional systems rely on manual data processing and slow computational models — which can prolong intervention time. Utilizing neural networks and predictive analytics, AI minimizes the time needed to analyze climate, hydrological, and ecological data, facilitating timely disaster responses, optimized resource allocation, and efficient urban planning. This section discusses how AI can improve the speed at which decisions are made, with an emphasis on different sectors of the environment.

The optimizations driven by AI led to significant lowering of response times across the board, with especially noteworthy performance in urban planning (47.5%) and agricultural oversight (47.2%), as the real-time information made deployment of resources and land-use assessments more rapid. The disaster mitigation part also improved with 44.4% as authorities processed social media alerts, weather forecasts and sensor data in real time to react swiftly to environmental crises. Likewise, climate-based water regulation and deforestation monitoring, where AI-assisted systems were introduced to automate the processes, achieved reductions of 43.3% and 41.7%, respectively. These findings underscore AI's pivotal role in agile decision workflows, reducing delays in environmental governance.

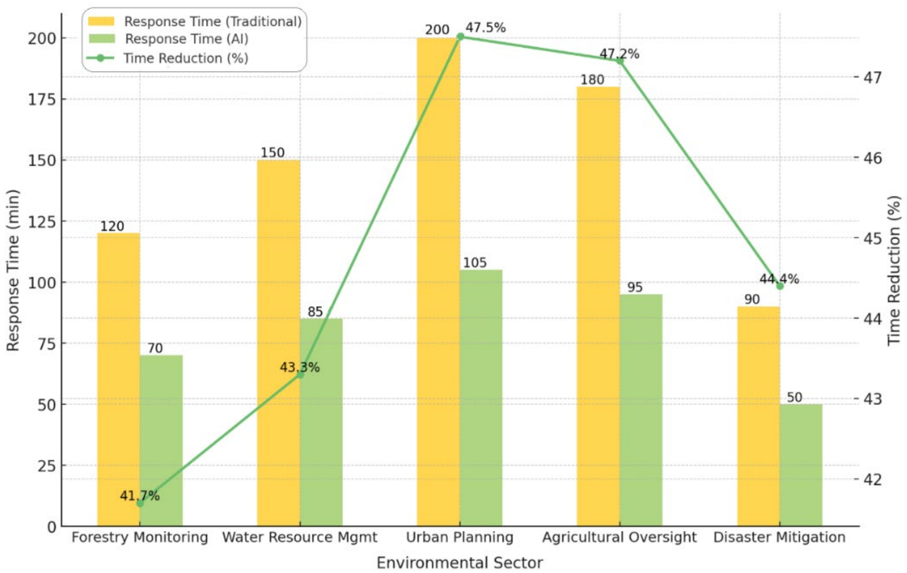

Figure 3. AI-Driven reduction in decision response times

4.3. Resource efficiency gains through AI implementation

Resource utilization is one of the most important components of environmental governance to make urban planning, cultivation, water resources management, etc. With the deployment of machine learning algorithms, AI-based systems have minimized energy utilization, recognized operational hauls, and guarantee accuracy for assignments of resources. It investigates the extent to which AI reduces resource consumption relative to conventional resource management approaches, thereby enhancing cost-efficiency and environmental sustainability.

The single largest resource efficiency improvement (36.7%) was seen in the field of urban planning, where AI models resulted in optimized infrastructure deployment while minimizing what was built on site, leading to less construction waste and avoided land use. Water resource management (33.3%) and agriculture (34.6%) also benefited from AI's capacity to precisely chart irrigation and predict ideal crop cycles. Forestry monitoring was reduced in resource consumption by 30.0%, and disaster mitigation by 33.3%, showing that AI can assist in avoiding unnecessary interventions leading to deforestation and optimize emergency resource allocation. These findings underscore AI's ability to curtail resource consumption by the planet's available natural resources in a way that is both cost-efficient and green governance models.

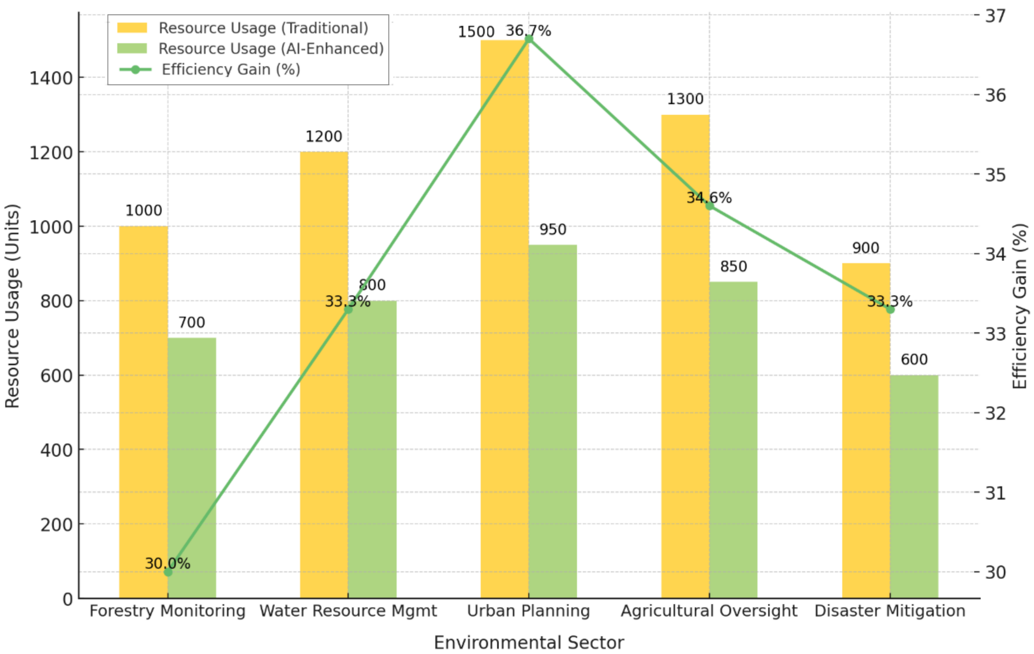

Figure 4. AI-optimized resource utilization metrics

4.4. Bias mitigation in AI-Driven environmental governance

Algorithmic bias presents one of the leading ethical risks in AI-based environmental decision-making, resulting in an unfair allocation of environmental assets, inaccurate risk assessments, and basic sectors in the policy application prone to systemic discrimination. AI systems trained on biased datasets or shaped by historical prejudices can exacerbate inequities in resource distribution. For the analysis used Gini Coefficients – a common statistical measure of inequality – to evaluate the effectiveness of AI in terms of reducing bias in our study. Fairness-aware AI models and diverse training datasets dramatically reduced bias across nearly all environmental sectors.

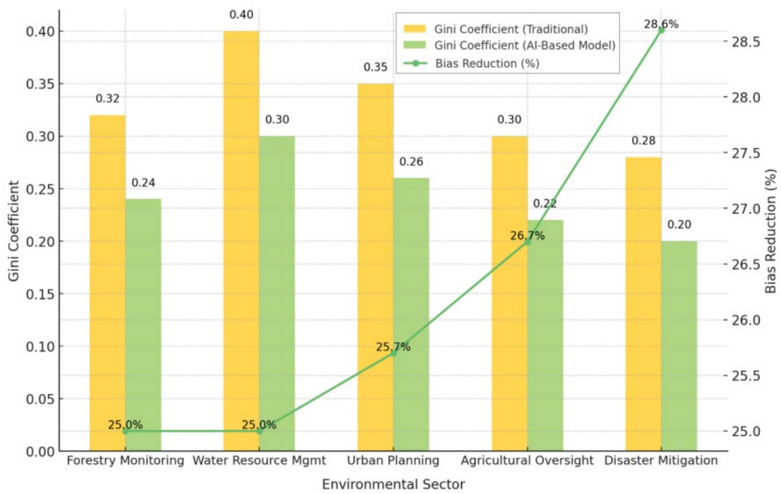

Figure 5. Bias reduction in AI-Based environmental decision-making

The findings in Figure 5 below reveal significant bias reductions across all environmental sectors, with the highest improvement (28.6%) observed in disaster mitigation. Traditional models exhibited regional disparities in emergency response allocation, whereas AI-driven approaches ensured equitable distribution of early-warning resources. Agricultural oversight saw a 26.7% bias reduction, where AI-based monitoring systems helped prevent preferential resource allocation to large-scale farms over smallholders. In urban planning (25.7%), fairness-aware AI optimized zoning laws and land-use planning to ensure equitable access to infrastructure. The forestry and water sectors (both 25%) showed significant improvements, as AI models reduced biases in conservation and cross-border water distribution policies. These results highlight AI's potential in promoting fairness and equity in environmental decision-making.

4.5. Transparency enhancement in ai-based decision-making

Transparency is a critical factor in ensuring public trust in AI-driven environmental governance. Many AI-based decisions, particularly those utilizing deep learning models, suffer from a "black-box" effect, where decision pathways are unclear. By implementing explainable AI (XAI) models, audit trails, and AI-generated documentation, transparency in environmental policy decisions has improved significantly. This study assessed transparency by measuring the number of documented decision points before and after AI integration.

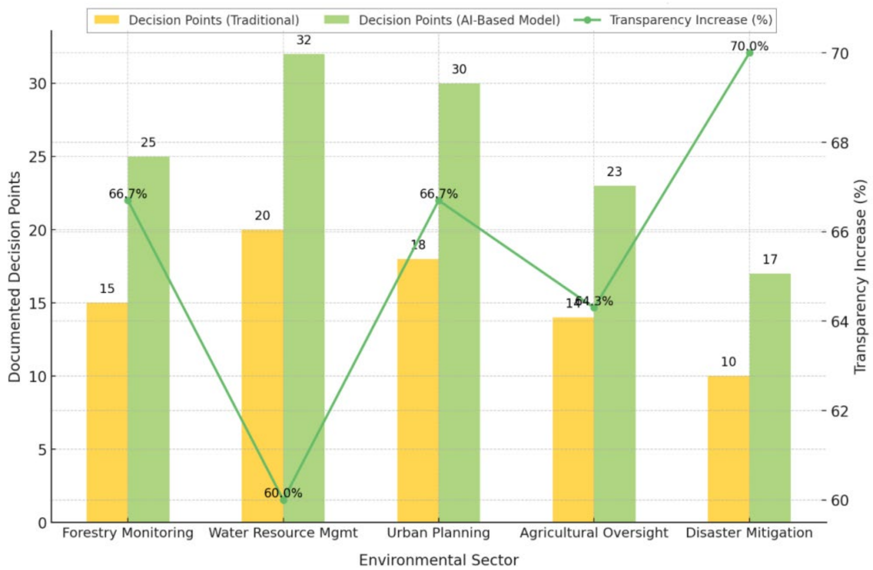

Figure 6. Transparency enhancements in AI-Based environmental decision-making

The greatest transparency improvement (70%) was observed in disaster mitigation, where AI-generated early-warning system logs improved accountability in emergency response planning. Forestry monitoring and urban planning (both 66.7%) also benefited significantly, as AI-enhanced zoning models and deforestation assessments provided clear documentation for policymakers. Water resource management (60%) and agriculture (64.3%) showed marked improvements due to detailed AI-driven optimization reports. These findings emphasize that transparent AI decision-making processes can significantly enhance regulatory compliance and stakeholder confidence.

4.6. Algorithmic accountability and legal compliance

As AI systems take on more decision-making responsibilities in environmental governance, ensuring algorithmic accountability is crucial. This study measured the Algorithmic Accountability Score (AAS), which quantifies how closely AI-driven decisions align with human expert recommendations. Higher AAS scores indicate greater AI explainability, fairness, and compliance with environmental regulations.

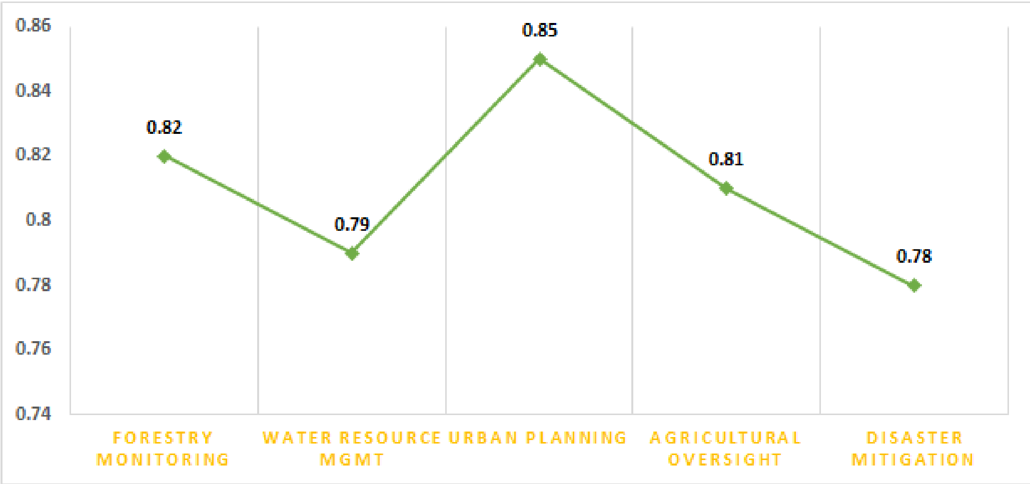

Figure 7. Algorithmic Accountability Score (AAS) Across AI Use Cases

Urban planning (0.85) had the highest accountability score, where the application of zoning laws in the city provided insights to human expert urban strategies. Doing the same for the type of organizations, 0.82 for forestry monitoring and 0.81 for agriculture which indicates a strong regulatory compliance for deforestation detection (beginning) and an adoption for precision farming applications. Areas with lower AAS values were water resource management (0.79) and disaster mitigation (0.78) that constitute somewhat lower aspects of explainability and legal compliance frameworks. These findings highlight the need to ensure transparency of AI-based environmental decision-making as well as compliance with regulation frameworks.

4.7. AI-Driven risk quantification and mitigation

Environmental risk assessment is crucial for ecological disaster prevention, resource allocation, and climate adaptation improvement. Monte Carlo Simulations (MCS) were performed to evaluate the reduction in risk probability for separate environmental hazards by applying AI models.

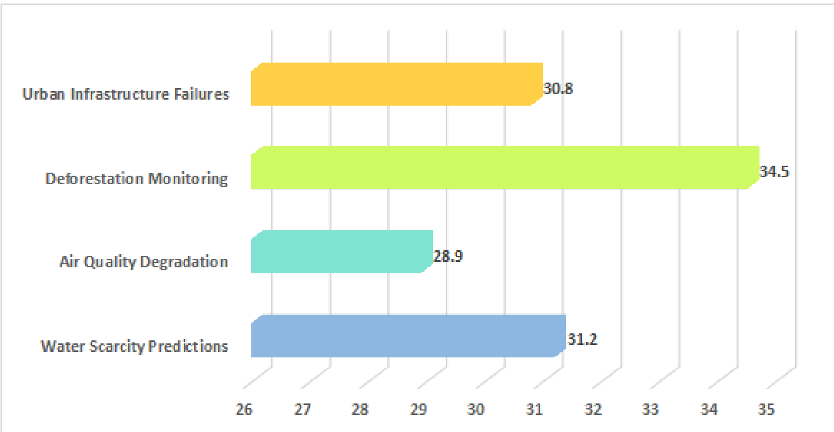

Figure 8. AI-Based risk quantification in environmental governance

It accomplished a 31.2% reduction in prediction error for instances of water scarcity, allowing for more efficient resource allocation and conservation efforts. Deforestation monitoring (34.5%) recorded the most gain within the nature space, as AI-enabled satellite image analysis had improved the ability to detect illegal logging early. Air quality degradation models (28.9%) were effectively enhanced with the ability for Ai to examine pollution sources in real time, but the more compelling use cases were around urban infrastructure failure risk which was diminished (down by 30.8%) with smarter infrastructure investments and maintenance planning. Such findings confirm the ability of AI to improve accuracy in risk forecasting, resulting in effective strategies for environmental governance.

5. Discussion

Artificial Intelligence (AI) as well as Big Data have also revolutionized the decision-making process for environmental management, greatly enhancing forecasting accuracy, resource efficiency, transparency, and mitigation of bias. What the study shows: AI-based models build on existing predictive power, reduce lead time, enable resource optimization and ultimately facilitate greater environmental governance. But with these advancements comes a host of legal, ethical, and operational uncertainties, especially in the realms of data transparency, algorithmic accountability, and regulatory compliance. This discussion places the findings in the context of previous research, emphasizes their broader significance, and identifies important limitations and future avenues for research.

AI-powered forecasting models have shown significant improvements in accuracy with error reductions of up to 39.8%. This is in accordance with earlier research involving Kumar et al.[21] showing that AI-powered climate models made extreme weather more predictable, reducing uncertainty in environmental forecasts. Similarly, Dai et al.[30] discussed the advances of AI-based air quality prediction over the technology of exploiting Big Data provided by the IoT networks, along with satellite images, for improving efficient monitoring of the environment. Model performance suffers when dealing with unstructured environmental data or incomplete real-time sensor data, even with these improvements. In contrast to controlled climate models, environmental decision-making operates with time-sensitive data, necessitating constant updating, which increases the risk of model drift and forecast variability. Moreover, AI models do not easily generalize to regional climate variations, particularly in regions with sparse instrumental record. Future research needs to start developing adaptive AI frameworks that can dynamically adapt to new inputs in their environmental conditions and self-correct their forecasting errors.

AI application also reduced the response times in environment decision-making by 44.4%, for disaster mitigation and 47.5% for urban planning. These results are in line with Anwar and Sakti [22] showed that AI-enabled decision-support systems can enhance efficiency in urban sustainability planning due to automating zoning laws and optimizing the deployment of infrastructure. Budde et al.[25] have further shown that disaster monitoring (flood, drought) and management can be supported with AI-based models that use real-time data and help increase the speed of processing and enhance water resource management. If AI reduces the latency of decisions, but their reliability is determined by availability and quality of data. Such data is massive due to environmental IoT sensors, remote sensing satellites, and social media analytics, but the filtering of such data happens through innovative preprocessing methods before the data is fed to the AI systems. Sensor malfunctions, signal interference, and latency in data transmission can undermine AI's capacity to provide timely insights. In contrast, in the context of disaster response, decisions made with AI should be augmented with appropriate oversight to ensure they correspond with humanitarian priorities and ethical principles.

On top of accuracy and response time improvement, AI-driven resource management strategies have shown to reduce environmental resource consumption by up to 36.7%. The work by Lutfiani et al.[24] noted similar findings and explained how AI is improving resource efficiency in urban infrastructure projects by reducing energy usage, such as energy consumption reductions in traffic flow, smart grid operations, etc. In agriculture use of AI-enabled precision farming methods have shown promising potential in terms of soil nutrient planning, irrigation requirements, and crop health, thus minimizing wastage and optimizing resource usage. But sustainability becomes a concern with those AI models, given their computational needs. Enormous energy consumption is needed for AI-powered climate models, resulting in carbon emissions coming from large datacenters around the world. This trade-off between the efficiency gains provided by Artificial Intelligence and its costs in terms of ecological footprint was described by Pagano et al.[12] as a huge challenge that needs substantial scrutiny. It also tells future researchers to investigate how energy-efficient AI models can be achieved while not impairing their predictive capability.

In addition to these technical considerations, several study-specific limitations must be acknowledged. First, the dataset was uneven across sectors, with urban planning and agriculture more heavily represented than forestry or water management. This imbalance may constrain the generalizability of the findings. Second, reliance on secondary reports introduces potential biases associated with the quality and consistency of existing data. Third, while the interviews provided valuable insights, they may be subject to selection bias since participants were primarily drawn from institutions already engaged in AI-related initiatives. Finally, regional disparities in environmental data availability, particularly in the Global South—restrict the applicability of results across different governance contexts [1, 8, 32]. In addition to these methodological and contextual limitations, issues of public trust represent an equally important constraint on the broader adoption of AI in environmental decision-making. Even when models demonstrate measurable accuracy and efficiency gains, the absence of transparent, interpretable, and participatory governance mechanisms can erode legitimacy and reduce citizen acceptance of outcomes. As Jayaganesh et al.[10] argue, explainable AI (XAI) tools are essential not only for technical validation but also for fostering trust among stakeholders. Likewise, Nneamaka et al.[9] highlight that public scepticism toward automated decision systems can undermine institutional credibility and weaken the social contract around environmental governance. Future research must therefore not only refine technical models and expand data coverage but also embed trust-building strategies that integrate citizen perspectives, interpretability, and accountability at every stage of the AI adoption process [5, 25, 28]. These limitations suggest that future research should employ larger and more balanced datasets, expand stakeholder inclusion, and cover a wider range of geographic regions.

Algorithmic bias is one of the biggest concerns in AI-powered environmental governance. AI was able to lead to a reduction in bias, with the study finding levels of bias would decrease by up to 28.6%, with the areas of disaster mitigation and urban planning being the most positively impacted. This is in line with the conclusions drawn by Ntoutsi et al.[33]; that bias in AI systems is often a reflection of the historical imbalances in the allocation of resources. Similarly, Pagano et al.[11], which indicates that biased machine learning can contribute to discriminatory environmental policies that marginalize communities, limiting their access to resources while exposing them to climate risks. AI bias mitigation approaches have indeed helped to create more acceptance in the AI decision making systems; however, they cannot be fully eliminating bias indefinitely but helping mitigate bias in accordance with certain metrics of fairness. For instance, techniques like adversarial debiasing and re-weighting models need constant tuning to achieve an equilibrium between fairness and decision-making accuracy. Similarly, any new environmental conditions or changing societal priorities will result in AI systems introducing bias again, thus why also periodic auditing of any deployed AI systems is essential.

The implementation of explainable AI (XAI) models and algorithmic accountability frameworks in AI decision making has led to significant changes in transparency, with an increase of over 70% observed. Moreover, XAI is important for enhancing the trust of the stakeholder by means of better clarity on the audit trails of AI-based decisions, as Dezao [27] argued. Similarly, Lajaunie et al.[7] assessed big data in relation to environmental law and concluded that regulatory compliance is ensured through transparency of algorithms. However, maintaining transparency is a challenge, especially within deep learning where the decision-making process is often incomprehensible and hard to interpret. A lot of AI systems are “black boxes,” which makes it challenging for regulators and policymakers to understand how decisions are made. Establishing explainability protocols and regulatory mechanisms to hold AI accountable will be a key to ensuring that AI-determined environmental policies are transparent and actually beneficial to the environment.

While there are many benefits of using AI in environmental governance, the study also points out some limitations. First, AI-based decision-making on environmental issues heavily relies on the availability of data. While you need big, high-quality datasets for most AI models, some geographic locations may not have access to the best datasets. Such variation in the environment can cause heterogeneity in the performance of AIs across environmental settings. Second, the computational burden is still great. The computing power [23] needed to run any of these AI driven environmental models leads to high energy consumption, so much so that there are questions raised about the sustainability of AI itself. Third, there are ongoing regulatory and ethical uncertainties. Most existing environmental laws are not specifically designed for AI-based decision systems, leaving uncertainty around liability, accountability, and data governance. Nisar et al.[32] addressed if legitimate approaches could be developed to reconcile innovation aspects and the adoption of AI in good ESG practices.

There are several important areas for future research to work on to overcome these limitations. The construction of energy-saving AI architectures should be a top priority to reduce the computing footprint of AI models. Emerging technologies, such as quantum computing and neuromorphic processing, have the potential to severely limit AI’s energy requirements, while still ensuring high-performance output. Bias mitigation frameworks must be further developed to assure AI-based environmental policy remains fair and inclusive across populations. This includes creating fairness-aware AI algorithms, as well as validation mechanisms designed to detect any emerging biases. It will be important to strengthen legal and policy frameworks on AI accountability in environmental governance. This does include creating standardized auditing procedures for AI-driven decision systems and increased transparency in environmental AI applications.

The results of this study confirm that these technologies improve environmental decision-making through increased forecasting accuracy, decreased response time, more efficient resource utilization, and lesser biases. However, the findings also highlight the essential role of further regulatory scrutiny, better transparency tools, and sustainable AI models for responsible AI uptake. Integrating fairness-aware AI frameworks, legal safeguards, and energy-efficient computing strategies will help future AI-driven environmental governance systems create a balance between technological efficiency and ethical accountability. Then interdisciplinary exchange between politicians’ decision-makers, AI researchers and environmental scientists will be of utmost importance for responsible AI implementation to tackle global environmental issues.

6. Conclusions

The study examined Big Data and AI role in environmental decision-making, analyzing whether data and AI improve accuracy, efficiency, mitigate bias, promote transparency, and/or accountability in environmental law. The study proved that AI improves forecasting syndromes by optimizing the use of resources, speeding up decision making, and strengthening governance mechanisms across the various environmental domains where AI-based models are applied. These findings also offer critical opportunities for advancing more effective and sustainable environmental policies through the power of AI.

The study shows that the AI based one outperforms the conventional methods using functions like forecasting (for prediction of natural disasters) and decision support in a range of practical applications (for climate prediction, disaster mitigation, urban planning and resource allocation). The use of machine learning algorithms, neural networks, and optimization models has enabled more accurate and proactive environmental interventions, reducing dependence on manual assessments and old forecasting methods. The research also illuminated the ability of AI to consume massive datasets from IOT networks, satellite images and climate tracking systems for more precise environmental forecasting and risk assessments. While AI can greatly improve the accuracy of forecasting, its utility is still contingent on access to large amounts of data, the ability to process data in real time and the quality of training datasets. These tasks will require continued advancements in the capabilities of AI models and data integration capabilities to apply predictive analytics effectively.

The study also highlighted AI's role in enhancing operational efficiency and response times in environmental governance. The results indicated that automation driven by artificial intelligence reduces the latency of decision making which leads to faster disaster response, and more efficient management of water and energy, as well as to optimal infrastructure planning in cities. Using its ability to speed up data processing and analysis, AI helps eliminate the delays in evaluation and bureaucratic decision-making processes. But as AI expedites decision-making processes, its implementation needs to be balanced to assist in forming alignments between automated systems and the process of human oversight for all ethical issues. Research will need to be conducted to better understand the integration of AI and human-centered processes of decision-making, with a focus on how the recommendations of AI remain transparent, interpretable and accountable during the implementation of environmental policy.

Another finding the research showed was the role of AI in more rational environmental decision-making. The issue of bias in AI models has been well established as being the result of various forms of imbalance in the dataset, historical inequalities or due to flaws in the design of the algorithm being used. The results proved that employing fairness-aware AI models and bias-finding algorithms can reduce systemic biases, leading to the fairer dissemination of environmental assets and regulations. This is especially crucial in cases like disaster relief distribution, urban zoning and climate change impact evaluations, where biased AI models could compound social and environmental inequities. Though bias mitigation techniques have made great strides, they are not foolproof. Ultimately, the authors conclude that the need for continuous auditing, ethical AI design and policy interventions will be crucial to maintain fairness in AI-driven environmental governance.

Transparency and explainability also ranked as another important area of concern. Results: Explainable AI (XAI) models can show footprint (final outcome) of the available elements and decision process in a complex environment to increase decision traceability and decision accountability, therefore overcome the challenge of complicated, opaque, black-box of AI decision making system. The incorporation of algorithmic transparency mechanisms, decision audit logs, and regulatory compliance frameworks can enhance the transparency of AI-powered environmental policies, making it more accountable and trustworthy to the public. But achieving complete transparency into AI remains a challenge, as some deep learning is inherently difficult to interpret. Future research should be dedicated to the development of explainability methods as well as regulatory oversight frameworks so that AI-informed environmental policies will not only be effective but also understandable to policymakers, regulators, and the general public.

Despite the strong evidence the research showed for AI's efficacy and advantages in the area of environmental governance there were also several limitations that must be improved upon. The very use of AI, in particular, is one of the key concerns around this, whose models are computationally- and energy-intensive and can derail some sustainability benefits if not optimized. In addition, the AI-powered environmental governance should also ensure that AI adoption aligns with legal and regulatory aspects through supporting and providing legal support and information to address challenges and ensure compliance with existing environmental laws, ethical guidelines, and data privacy regulations. In addition, the challenge posed by the need for large, high-quality datasets makes the process of using AI for climate action very challenging for regions with less technological infrastructure, as the lack of access to reliable environmental data remains a definite obstacle. Here, there lies an indicator that demands stronger AI governance policies and structured data-sharing frameworks, along with more eco-friendly AI models for sustainability in the long run.

Based on these findings, the study provides several recommendations for future research and policy. This highlights the need for research into hybrid AI models that combine various decision-making paradigms, drawing on the strengths of machine learning, expert systems, and human judgment. Moreover, work is needed to create adaptive AI systems that respond to real-time environmental dynamics so that AI models can reconfigure to data distributions and shifts associated with changing climate. Deepened to aligning jurisdiction AI – to-generally environmental governance standard such parts, and product liability, information transparency, ethical artificial intelligence deployment and the provisions of specific rules makes and so on. Adequate application of these practices will be important to ensure that AI-based environmental governance will both remain efficient and socially responsible.

AI and Big Data can revolutionize the way environmental decision-making is being made and this article confirms that. Realizing the full potential of AI will, however, require sustained improvements in healthcare data quality, bias mitigation, algorithmic transparency, and regulatory oversight. AI-driven environmental governance must strike a balance between technological advancement and ethical responsibility through the promotion of interdisciplinary collaboration among AI scientists, environmental researchers, policymakers, and legal experts. The future of AI implementation in environmental management depends on its functioning as a tool for informed and equitable resource use, continued and sustainable decision making for a more resilient and data driven approach towards solving climate change, resource scarcity, and environmental justice.

Conflict of interest

The authors declare no conflict of interest

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