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A Scalable Framework for Predictive Environmental Monitoring and Decision Support

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Abstract: This article introduces a comprehensive AI-driven framework designed to transform environmental monitoring and climate resilience through real-time data analysis, predictive modeling, and policy simulation. By integrating satellite imagery, sensor networks, and advanced machine learning techniques, the system addresses critical gaps in current climate monitoring approaches, particularly regarding fragmentation, lack of adaptive feedback loops, and insufficient implementation in vulnerable regions. The framework's modular architecture, comprising data integration, AI analytics, edge computing, and policy visualization components, enables flexible deployment across diverse environmental contexts while maintaining system coherence. Case studies across wildfire prediction, urban cooling optimization, and flood detection demonstrate its practical impact and versatility. Technical innovations, including the Fusion Transformer architecture, ClimateGAN simulations, and bias mitigation strategies, enhance performance while addressing ethical considerations. Comprehensive evaluation confirms significant improvements over existing approaches while maintaining functionality on resource-constrained devices. The framework represents a significant advancement in democratizing access to sophisticated environmental monitoring tools while ensuring algorithmic fairness, responsible deployment in marginalized regions, and transparent decision support for effective climate governance.

Keywords: Environmental Monitoring, Artificial Intelligence, Climate Resilience, Edge Computing, Ethical AI.

INTRODUCTION

Climate change represents one of the most pressing global challenges of the 21st century, requiring scalable and data-driven interventions across multiple sectors. The acceleration of environmental monitoring capabilities has created unprecedented opportunities for data-driven climate action. Over the past decade, the volume of environmental datasets has expanded dramatically through advances in remote sensing, sensor networks, and citizen science initiatives. This growth has enabled more comprehensive monitoring of Earth systems, yet human capacity for analysis and timely response remains constrained by cognitive and institutional limitations that prevent full utilization of these rich data resources (Olawade, D. B. *et al.,* 2024).

Artificial intelligence offers significant potential to accelerate climate action through emissions forecasting, which enables the prediction of carbon outputs with high spatiotemporal resolution that traditional methods cannot achieve. These predictive capabilities extend beyond simple trend analysis to incorporate complex interactions between economic activity, energy systems, and natural carbon cycles. The application of AI to disaster early warning systems represents another promising direction, with recent advances enabling the anticipation of extreme weather events before they can be detected by traditional monitoring systems (Dhanikonda, S. R. *et al.,* 2025).

In the realm of resource management, AI systems demonstrate the capacity for smart energy and resource optimization by dynamically balancing consumption patterns in real-time. These systems leverage reinforcement learning techniques to adapt to changing conditions across power grids, water distribution networks, and transportation systems. Perhaps most significantly for long-term climate governance, AI enables sophisticated policy simulation and decision support by modeling intervention outcomes before implementation (Olawade, D. B. *et al.,* 2024).

This paper outlines a novel, modular framework for deploying AI across climate-sensitive sectors, enabling coordinated and evidence-based climate resilience strategies. The framework builds upon recent advances in environmental informatics while addressing critical gaps in existing systems, particularly regarding interoperability, accessibility, and ethical implementation. By integrating edge computing techniques with cloud-based analytics, the proposed architecture enables deployment across diverse contexts—from data-rich urban centers to remote regions with limited connectivity (Dhanikonda, S. R. *et al.,* 2025).

Related Work

The application of AI in climate science has evolved rapidly, with significant advances in downscaling climate models and interpreting satellite imagery. Research published in Frontiers in Environmental Science demonstrates how

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convolutional neural networks can extract fine-grained deforestation patterns from medium-resolution satellite imagery with detection accuracies reaching 87% for areas as small as 0.5 hectares—a substantial improvement over traditional remote sensing approaches that typically require minimum detectable areas of 2-5 hectares (Lin, W., Li, T., & Li, X. 2025). Complementary work in IEEE Transactions on Geoscience and Remote Sensing shows how transformer architectures can integrate multimodal data to improve seasonal precipitation forecasting, reducing mean absolute percentage error by 24% compared to conventional statistical downscaling methods across diverse climate regions (Dhanikonda, S. R. *et al.,* 2025).

However, significant gaps remain in existing systems. The fragmentation between data sources and models represents a persistent challenge, as climate data remains siloed across institutions with incompatible formats, inconsistent metadata, and restrictive access policies. According to a comprehensive review of environmental data management practices, fewer than 30% of climate datasets conform to FAIR (Findable, Accessible, Interoperable, Reusable) principles, severely limiting integration possibilities across domains (Lin, W., Li, T., & Li, X. 2025). This fragmentation is compounded by the lack of real-time adaptive feedback loops in most current systems. While Earth observation technologies now provide near-continuous monitoring of many environmental parameters, most analytical models operate on historical data without continuous learning capabilities, creating significant delays between data acquisition and actionable insights. Studies of early warning systems for climate-related disasters indicate that model retraining typically occurs at quarterly or annual intervals, preventing adaptation to rapidly evolving conditions (Dhanikonda, S. R. *et al.,* 2025).

Perhaps most concerning is the insufficient implementation of advanced climate technologies in vulnerable, low-resource regions. The digital divide significantly limits deployment where climate monitoring is most needed, with high-resolution Earth observation data coverage showing an inverse correlation with climate vulnerability indices across multiple regions. Analysis of technological deployment patterns reveals that nations with the highest climate risk often have the lowest density of advanced monitoring infrastructure, creating a paradoxical situation where the most vulnerable populations have the least access to early warning and adaptive management tools (Lin, W., Li, T., & Li, X. 2025). These limitations highlight the need for a unified, open architecture supporting modular AI services that can be adapted to diverse contexts and constraints, particularly focusing on accessibility, low computational requirements, and robust performance under data-sparse conditions (Dhanikonda, S. R. *et al.,* 2025).

Table 1: Barriers to Effective Environmental Monitoring Systems (Dhanikonda, S. R. *et al.*, 2025; Lin, W., Li, T., & Li, X. 2025)

Challenge	Impact	Prevalence
Data fragmentation	Limited integration	High
Lack of real-time feedback	Delayed insights	Medium
Insufficient implementation in vulnerable regions	Inequitable protection	High
Non-compliance with FAIR principles	Poor interoperability	Very high

FRAMEWORK ARCHITECTURE

The proposed framework consists of four integrated components designed to function both independently and as a cohesive system. This modular approach enables flexible deployment across diverse environmental contexts while maintaining system coherence. According to research published in Ecological Solutions and Evidence, modular environmental monitoring frameworks demonstrate significantly greater adaptability to changing data availability compared to monolithic systems (Warner, E. *et al.*, 2025).

The data integration layer aggregates and normalizes inputs from multiple sources, creating a unified information ecosystem from previously disparate data streams. This layer processes information from Earth observation platforms, ground-based sensor networks, social media signals, and administrative datasets. Raw data undergoes automated quality control, gap-filling, and cross-validation before being prepared for model ingestion (Dhanikonda, S. R. *et al.,* 2025).

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The core analytical component, the AI Engine, employs ensemble learning models tailored to specific environmental monitoring tasks. For emissions tracking, transformer models process satellite-derived measurements alongside economic indicators. Urban heat island detection leverages CNN architectures to identify thermal anomalies in metropolitan regions. Deforestation monitoring employs time-series analysis of vegetation indices using LSTM networks. For flood and drought prediction, the system implements hybrid models combining physical constraints with statistical learning (Warner, E. *et al.*, 2025).

To ensure functionality in remote or low-bandwidth regions, the framework includes optimized deployment for edge computing. Model compression techniques reduce memory requirements with minimal accuracy loss, enabling deployment on devices with limited computational resources. Asynchronous inference allows operation during intermittent connectivity, while prioritization algorithms ensure critical alerts transmit even under severe bandwidth constraints (Dhanikonda, S. R. *et al.*, 2025).

The visualization and simulation interface, implemented as a Policy Dashboard, translates technical outputs into actionable insights for decision-makers. This component features interactive scenario modeling for policy interventions, cost-benefit visualization for adaptation strategies, multi-stakeholder collaboration tools, and automated report generation capabilities (Warner, E. *et al.*, 2025).

Table 2: Modular Architecture of Environmental Monitoring Framework (Dhanikonda, S. R. *et al.*, 2025; Warner, E. *et al.*, 2025)

Component	Primary Function	Key Technologies
Data Integration Layer	Data aggregation	Automated QC, gap-filling
AI Engine	Analytical processing	Transformers, CNNs, LSTMs
Edge Deployment	Resource-constrained operation	Model compression, async inference
Policy Dashboard	Decision support	Interactive visualization, scenario modeling

CASE STUDIES

The framework has been deployed across three distinct climate challenges, demonstrating its versatility and impact across diverse geographical and socioeconomic contexts. These implementations validate the system's effectiveness in addressing critical environmental monitoring needs while adapting to varying resource constraints (Ogunwumi, O. T., & Matindike, R 2025).

Wildfire Prediction (California, Australia)

Researchers trained hybrid CNN-RNN models on 10 years of MODIS satellite data, integrating vegetation indices, meteorological variables, and historical fire patterns. The system achieved high accuracy in predicting high-risk ignition zones 72 hours in advance—a critical window for evacuation planning and resource allocation. This represents a significant improvement over previous early warning systems that typically provided only 24-48 hours of advance notice with lower spatial precision (Leal Filho, W. *et al.*, 2022).

Local municipalities now use these predictions to optimize fire department staffing and pre-position equipment during high-risk periods. In the 2024 fire season, the system helped authorities issue targeted evacuation orders earlier than would have been possible with traditional methods, potentially reducing evacuation congestion and improving public safety outcomes (Ogunwumi, O. T., & Matindike, R 2025).

Urban Cooling Optimization (Smart Cities)

The framework deployed deep reinforcement learning algorithms to model green space placement and energy grid modulation in urban environments. Using a digital twin of Barcelona as a testbed, simulations demonstrated potential reductions in urban heat island effects through optimized placement of green infrastructure and adaptive building systems. This approach allowed planners to evaluate hundreds of potential intervention scenarios before committing to specific infrastructure investments (Leal Filho, W. *et al.*, 2022).

City planners have incorporated these insights into Barcelona's 2026-2030 climate resilience plan, prioritizing interventions in neighborhoods identified as most vulnerable to heat stress. The approach is now being adapted for implementation in Mexico City and Jakarta, with calibration adjustments to account for different urban

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morphologies and climate conditions (Ogunwumi, O. T., & Matindike, R 2025).

Flood Detection in Sub-Saharan Africa

In partnership with local NGOs, researchers deployed mobile-optimized models on low-power devices (Raspberry Pi) to enable real-time flood monitoring in regions with limited infrastructure. The system processes satellite data alongside river gauge measurements to predict river swell 48-72 hours in advance, delivering alerts via SMS to vulnerable communities. This approach overcomes critical infrastructure limitations that have historically prevented effective early warning systems in flood-prone regions (Leal Filho, W. *et al.*, 2022). Initial deployments in Mozambique and Malawi have demonstrated the system's ability to function effectively despite challenging connectivity and power constraints. Community feedback indicates substantial improvement in preparedness for flood events compared to previous early warning mechanisms, with particularly strong performance in remote areas previously underserved by conventional monitoring networks (Ogunwumi, O. T., & Matindike, R 2025).

Table 3: Real-World Applications of AI Environmental Monitoring (Ogunwumi, O. T., & Matindike, R 2025; Leal Filho, W. *et al.*, 2022)

Application	Region	Lead Time	Implementation Challenge
Wildfire Prediction	California, Australia	72 hours	Resource allocation
Urban Cooling	Barcelona	Planning phase	Infrastructure investment
Flood Detection	Mozambique, Malawi	48-72 hours	Connectivity, power

TECHNICAL INNOVATIONS

The development of this framework required several novel technical approaches to address the unique challenges of environmental monitoring. These innovations represent significant advances in applied AI for climate science, addressing longstanding limitations in existing environmental modeling approaches (Magazzino, C. 2024).

Fusion Transformer

Researchers designed a new neural architecture called the Fusion Transformer, which combines temporal and spatial attention mechanisms to process environmental time series data. This approach allows the model to simultaneously capture long-range temporal dependencies in climate patterns, spatial correlations across geographic regions, and cross-variable interactions between different environmental metrics. As documented in BMC Environmental Sciences, this architectural innovation enables more holistic analysis of complex environmental systems by preserving relationships across multiple dimensions that traditional models typically process in isolation (Olawade, D. B. *et al.*, 2024).

The architecture outperforms standard transformers on geospatial forecasting tasks while maintaining computational efficiency. This performance improvement stems from the model's ability to learn joint representations that capture how environmental variables evolve across both space and time, rather than treating these dimensions separately. The Fusion Transformer architecture has demonstrated particular strength in identifying precursor patterns for extreme weather events, where subtle interactions between multiple variables often provide early indications of developing conditions (Magazzino, C. 2024).

Climate GAN

The framework introduces ClimateGAN, a generative adversarial network specifically designed for simulating potential outcomes under different climate policy scenarios. Unlike traditional simulation approaches that rely on simplified physical models, ClimateGAN learns complex relationships from historical data while incorporating known physical constraints. This hybrid approach maintains scientific validity while capturing emergent behaviors that purely physical models often miss, particularly in coupled human-natural systems where social responses can significantly alter environmental trajectories (Olawade, D. B. *et al.*, 2024).

This approach enables high-resolution visualization of climate impacts, helping stakeholders understand potential futures under different intervention strategies. The model generates synthetic but physically realistic scenarios for sea level rise impacts on coastal

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infrastructure, agricultural productivity under changing precipitation patterns, and energy demand shifts with varying temperature extremes. According to evaluation studies published in the Journal of Environmental Informatics, these visualizations have proven particularly effective for communicating complex climate risks to non-technical stakeholders, bridging an important gap between scientific understanding and public engagement (Magazzino, C. 2024).

Bias Mitigation

Recognizing the potential for algorithmic bias in environmental monitoring, the framework incorporates a systematic approach to ensuring equity across predictions. Fairness metrics track performance across different geographic regions and socioeconomic groups, providing continuous assessment of how model accuracy varies across diverse contexts. Active learning techniques prioritize data collection in historically underrepresented areas, systematically addressing data gaps that might otherwise lead to lower performance in marginalized communities. Uncertainty quantification highlights regions where predictions may be less reliable, ensuring that decision-makers understand the varying confidence levels associated with different forecasts (Olawade, D. B. *et al.,* 2024).

This framework ensures that AI-driven climate solutions avoid perpetuating existing inequalities in climate vulnerability and response capacity. Research in environmental data science has shown that without explicit attention to equity concerns, environmental monitoring systems tend to perform best in data-rich regions that already benefit from extensive infrastructure, potentially exacerbating rather than alleviating environmental justice disparities. The bias mitigation approaches incorporated into this framework represent a deliberate effort to counter these tendencies and ensure more equitable distribution of benefits from advanced climate monitoring (Magazzino, C. 2024).

Table 4: Novel AI Architectures for Environmental Monitoring (Magazzino, C. 2024; Olawade, D. B. *et al.*, 2024)

Innovation	Function	Key Advantage
Fusion Transformer	Multimodal time series processing	Joint spatiotemporal representation
ClimateGAN	Policy scenario simulation	Realistic visualization of outcomes
Bias Mitigation Framework	Equity assurance	Balanced performance across regions

RESULTS & EVALUATION

Comprehensive evaluation across multiple metrics demonstrates significant improvements over existing approaches for environmental monitoring and prediction. These performance gains validate the framework's effectiveness across diverse application domains while highlighting its particular strengths in resource-constrained deployment scenarios (Chauhan, B. V.*et al.*, 2024).

Mean Absolute Error decreased substantially for emissions predictions compared to statistical baselines, representing a notable advancement in the accuracy of carbon tracking capabilities. This improvement enables more precise attribution of emissions sources and more effective targeting of mitigation efforts. As documented in Environmental Science and Artificial Intelligence, the enhanced predictive accuracy stems primarily from the framework's ability to integrate heterogeneous data streams and capture complex non-linear relationships that traditional statistical approaches often miss ((Khan, S.*et al.,* 2024).

Recall improved considerably for extreme weather event classification, with particularly strong performance for flash flooding and rapid-onset drought conditions. This enhancement in detection sensitivity translates directly to longer lead times for early warning systems, providing vulnerable communities with critical additional hours for preparation and evacuation when necessary. Performance analysis published in comprehensive review studies indicates that the most substantial improvements occur for rapidly developing phenomena that traditional monitoring approaches often detect too late for effective intervention (Chauhan, B. V.*et al.,* 2024).

F1 scores for deforestation detection increased while reducing false positives in indigenous territories. This balanced improvement in both precision and recall addresses a persistent challenge in remote sensing applications, where

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increased sensitivity typically comes at the cost of higher false alarm rates. The framework's ability to maintain high detection rates while simultaneously reducing false positives has particular significance for monitoring activities in culturally sensitive regions, where false accusations of environmental degradation can create social conflicts and undermine trust in monitoring systems ((Khan, S.*et al.*, 2024).

Performance testing on edge devices confirmed that critical functionality remains intact even on hardware with less than 2 GB of RAM, enabling deployment in resource-constrained environments. This capability represents a significant advance in the democratization of environmental monitoring technology, making sophisticated analytical capabilities accessible in regions where computational infrastructure remains limited. According to field testing documented in systematic evaluation studies, edge-optimized models maintain high performance metrics while reducing power consumption compared to cloud-dependent alternatives (Chauhan, B. V.*et al.*, 2024).

The simulation engine has been incorporated into three pilot programs for carbon offset evaluation, providing data-driven insights for climate finance allocation. These implementations demonstrate the framework's practical utility beyond monitoring and prediction, extending into decision support for climate governance mechanisms. Initial results suggest that AI-informed carbon offset verification can significantly reduce verification costs while improving the reliability of offset certifications, addressing a critical bottleneck in scaling climate finance mechanisms (Khan, S.*et al.*, 2024).

ETHICAL AND SOCIETAL IMPLICATIONS

The development and deployment of AI for climate action raises important ethical considerations that must be addressed proactively. As environmental monitoring systems become increasingly automated and influential in decision-making processes, their ethical dimensions require systematic attention to ensure equitable outcomes (Choudhary, C. *et al.*, 2023).

Algorithmic Fairness

Environmental AI systems must avoid reproducing historical inequities in climate vulnerability. The framework incorporates ongoing fairness audits that evaluate prediction quality across different communities, with particular attention to historically marginalized populations. When disparities are detected, model retraining prioritizes improving performance for underserved groups. Research published in the International Journal of Advanced Research in Science, Communication and Technology has demonstrated that without explicit fairness controls, AI systems tend to perform better in regions with extensive historical data, which often correlates with economic advantage and existing technological infrastructure (Abbot, J., & Guijt, I. 1998). The fairness audit process implemented in this framework quantifies performance gaps across different demographic and geographic contexts, creating accountability mechanisms that help prevent the reinforcement of existing inequities. This approach recognizes that seemingly neutral technical choices in model development can have significant distributional implications for how environmental benefits and burdens are allocated across different communities (Choudhary, C. *et al.*, 2023).

Responsible AI for Marginalized Regions

Deployment in vulnerable regions requires careful attention to local contexts and needs. The framework development included extensive stakeholder consultation with communities in potential deployment areas, ensuring that the system design accommodates local knowledge systems and governance structures. This participatory approach helps prevent technological colonialism while maximizing local relevance and adoption. According to field studies documented by the International Institute for Environment and Development, environmental monitoring systems developed without meaningful community engagement often fail to address local priorities and may undermine existing knowledge systems that have evolved over generations (Abbot, J., & Guijt, I. 1998). The framework explicitly incorporates mechanisms for integrating indigenous and local knowledge alongside scientific data, recognizing that effective environmental governance requires bridging diverse knowledge traditions. This approach has proven particularly valuable in regions where traditional ecological knowledge contains insights about environmental changes that may not be captured in conventional scientific monitoring (Choudhary, C. *et al.*, 2023).

Transparency and Explainability

For AI to effectively support policy decisions, stakeholders must understand both the capabilities and limitations of the underlying models. The

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framework includes gradient-based explanation methods that visualize the factors influencing specific predictions, helping decision-makers assess reliability and appropriateness for different contexts. Research in environmental governance emphasizes that black-box systems, regardless of their technical performance, face significant adoption barriers in policy contexts where accountability and justifiability of decisions are essential (Abbot, J., & Guijt, I. 1998). The explanation methods implemented in this framework allow users to trace how specific input factors influence predictions, providing necessary transparency for high-stakes environmental decisions. This capability also facilitates error detection and system improvement by enabling domain experts to identify when models are relying on spurious correlations rather than causally meaningful relationships (Choudhary, C. *et al.*, 2023). By making AI systems more interpretable to both technical and non-technical stakeholders, these explainability tools help build trust and enable more effective human-AI collaboration in addressing complex environmental challenges.

CONCLUSION

This framework demonstrates the transformative potential of artificial intelligence for climate resilience, bridging critical gaps between environmental monitoring and actionable decision support. By addressing longstanding challenges of data fragmentation, computational constraints, and ethical implementation, the system enables more democratized access to sophisticated climate analytics across diverse contexts. The modular architecture ensures adaptability to varying environmental conditions and resource constraints, while technical innovations in multimodal data processing and simulation capabilities provide unprecedented insights for climate governance. Case studies across different geographical regions and climate challenges validate the framework's practical utility, from wildfire prediction to flood monitoring in resource-constrained environments. Particularly noteworthy is the system's commitment to ethical principles through algorithmic fairness controls, participatory development approaches, and transparency mechanisms that build trust among diverse stakeholders. As climate impacts intensify globally, this framework offers a scalable approach to environmental monitoring that balances technical sophistication with equitable implementation, providing essential tools for evidence-based climate action at local, regional, and global scales.

REFERENCES

1. Olawade, D. B., Wada, O. Z., Ige, A. O., Egbewole, B. I., Olojo, A., & Oladapo, B. I. "Artificial intelligence in environmental monitoring: Advancements, challenges, and future directions." *Hygiene and Environmental Health Advances* 12 (2024): 100114.
2. Dhanikonda, S. R. *et al.*, "Transformers-Based Multimodal Deep Learning for Real-Time Forecasting, D. & Adaptive Climate Resilience Strategies." *International Journal of Computational and Experimental Science and Engineering*, (2025). https://ijcesen.com/index.php/ijcesen/article/view/1349
3. Lin, W., Li, T., & Li, X. "Deep learning-based object detection for environmental monitoring using big data." *Frontiers in Environmental Science* 13 (2025): 1566224.
4. Warner, E., Giuliani, L. M., Campbell, G. A., Smith, P., Seddon, N., Seddon, D., & Smith, A. C. "Integrated above-and below-ground ecological monitoring for nature-based solutions." *Ecological Solutions and Evidence* 6.2 (2025): e70043.
5. Ogunwumi, O. T., & Matindike, R. "AI Applications in Environmental Monitoring: Case Studies on Deforestation and Pollution Assessment." *AI and Ecological Change for Sustainable Development*. IGI Global Scientific Publishing, (2025). 65-100.
6. Leal Filho, W., Wall, T., Mucova, S. A. R., Nagy, G. J., Balogun, A. L., Luetz, J. M., ... & Gandhi, O. "Deploying artificial intelligence for climate change adaptation." *Technological Forecasting and Social Change* 180 (2022): 121662.
7. Magazzino, C. “The impact of deep learning on environmental science." *BMC Environmental Science* 1.1 (2024): 4.
8. Chauhan, B. V., Vedrtnam, A., Wyche, K. P., & Verma, S. "Review on Artificial Intelligence in the Environmental Monitoring." *Prospects of Artificial Intelligence in the Environment* (2025): 29-60.
9. Khan, S., Mazhar, T., Khan, M. A., Shahzad, T., Ahmad, W., Bibi, A., ... & Hamam, H. "Comparative analysis of deep neural network architectures for renewable energy forecasting: enhancing accuracy with meteorological and time-based features." *Discover Sustainability* 5.1 (2024): 533.

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10. Choudhary, C., Mishra, S. P., Dubey, D. K., Pathak, A. K., & Pandey, M. "Legal and Ethical Dimensions of AI Applications in Environmental Monitoring and Conservation." *International Journal of Advanced Research in Science, Communication and Technology* 3.2 (2023): 8-16.
11. Abbot, J., & Guijt, I. *Changing views on change: participatory approaches to monitoring the environment*. No. 2. IIED, (1998).

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