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# ARTIFICIAL INTELLIGENCE, CLIMATE JUSTICE, AND THE FUTURE OF ENVIRONMENTAL LAW

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## ABSTRACT

***Background:*** Climate change disproportionately burdens communities that have contributed least to global greenhouse gas emissions, creating a fundamental asymmetry between historical responsibility and present impact.Advances in artificial intelligence (AI) and modern environmental law present new opportunities and substantial challenges in the pursuit of climate justice.

***Objective:*** This paper examines how AI technologies are transforming climate justice advocacy, environmental monitoring, and legal accountability, and identifies legal reforms required for equitable AI-driven environmental governance at international and national levels.

***Method:*** A systematic interdisciplinary review following PRISMA guidelines was conducted across climate science, artificial intelligence, environmental law, and political ecology databases. Ninety-two sources were identified; 28 peer-reviewed articles met full inclusion criteria, supplemented by 16 grey-literature items (IPCC reports, treaty texts, UNEP assessments). Additional foundational monographs and reports are cited where relevant in the analysis.

***Results:*** AI demonstrated significant potential to improve detection of environmental violations, strengthen climate attribution analysis, and identify disproportionate impacts on vulnerable populations. However, algorithmic bias, opacity, unequal technological access, and data colonialism risk reinforcing existing inequalities in environmental governance.

***Conclusion:*** Realising AI's potential for climate justice demands governance frameworks embedding equity by design, algorithmic transparency, data sovereignty, technology transfer, and democratic accountability as foundational principles, supported by coordinated legal reforms across international, regional, national, and corporate levels.

***Keywords:*** artificial intelligence; climate justice; environmental law; climate attribution; algorithmic governance; loss and damage; data sovereignty; machine learning

## 1. INTRODUCTION

The climate crisis does not arrive impartially. Its most severe consequences — rising seas consuming Pacific atolls, intensifying droughts across the Sahel, and cyclones devastating South Asian coastal communities — fall overwhelmingly upon nations and peoples that have emitted the least greenhouse gas. This fundamental asymmetry between responsibility and impact has animated the global climate justice movement for three decades and has increasingly found expression within international and domestic environmental law.

Into this landscape arrives artificial intelligence: a cluster of computational technologies capable of processing planetary-scale environmental datasets, identifying attribution chains between emissions and specific climate harms, analysing thousands of legal instruments for equity gaps, and monitoring corporate and state compliance with previously unachievable granularity. The intersection of AI and climate justice law is neither inevitable nor automatically progressive. Technologies powerful enough to enforce rights are equally powerful enough to surveil, discriminate, and entrench the interests of those who develop and control them. This paper offers a systematic interdisciplinary analysis of how AI is reshaping — and how it should reshape — the theory and practice of environmental law in the service of climate justice. The analysis traces the scientific foundations of AI-based climate monitoring, examines AI's application in litigation and regulatory enforcement, interrogates its potential harms to vulnerable communities, and proposes a governance framework adequate to the dual imperatives of effectiveness and equity.

The stakes are considerable. With global temperature rise locked in at or above 1.5°C above pre-industrial levels under current trajectories, and with the loss-and-damage architecture of the climate regime still fragile and underfunded, the choices made now about how AI is integrated into environmental governance may have consequences extending well beyond the immediate policy cycle. A central organising concern of this analysis is what the paper terms the "justice paradox" of environmental AI: the structural risk that tools designed to advance climate justice may instead reinforce existing inequalities through biased data, unequal access, and opaque decision-making — and the governance responses required to address it.

## 2. LITERATURE REVIEW

The intersection of artificial intelligence, climate science, and environmental law has generated a growing body of interdisciplinary scholarship over the past decade. Climate justice has been established as a multi-dimensional concept integrating distributive, procedural, recognition-based, and restorative justice — the normative architecture within which technological interventions must be evaluated [1]. The seminal survey of machine learning applications in climate science identified emissions tracking, extreme event prediction, and energy optimisation as primary domains [2].

The evolution of international climate law from aspirational declaration toward enforceable treaty obligation, and its persistent implementation gaps, has been extensively documented in the legal literature [3, 4, 32]. Landmark cases illustrate the judicial terrain into which AI-generated evidence is increasingly being introduced: Urgenda Foundation v. Netherlands (2019), in which the Dutch Supreme Court affirmed a state duty of care under the European Convention on Human Rights; Neubauer et al. v. Germany (2021), in which the Federal Constitutional Court held that insufficient climate policy violated the fundamental rights of future generations; and Leghari v. Federation of Pakistan (2015), in which the Lahore High Court ordered government action on climate adaptation.

The literature on AI's role in environmental governance has grown substantially since 2018. Machine learning applications in environmental enforcement have been examined [5], and predictive regulatory modelling has been explored [6]. Critical perspectives on algorithmic bias — with broad implications for environmental applications [7] — and the surveillance capitalism framework contextualising data sovereignty risks [8] have been advanced. AI-driven climate monitoring and Indigenous data sovereignty have also been specifically addressed [9], and the CARE Principles for equitable data governance have been articulated [10]. Recent AI governance frameworks — including the OECD AI Principles (2019, updated 2024) [11], the NIST AI Risk Management Framework (2023) [12], and the UNESCO Recommendation on the Ethics of AI (2021) [13] — provide the governance architecture within which environmental AI applications must be situated. This body of literature reveals a field that is rapidly evolving but methodologically fragmented across disciplinary boundaries. Most existing studies address either the technical capabilities of AI in climate monitoring or the normative demands of climate justice law, but rarely both in integrated analysis. This paper seeks to bridge that gap through systematic cross-disciplinary synthesis.

## 3. METHODOLOGY

### *3.1 Search Strategy*

This study employed a systematic interdisciplinary review methodology following PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines, drawing on literature from climate science, artificial intelligence, environmental law, and political ecology. Structured searches were conducted across Scopus, Web of Science, Google Scholar, and HeinOnline. Six primary search strings were employed:

- "artificial intelligence" AND "climate justice"
- "machine learning" AND "environmental law"
- "climate attribution" AND ("AI" OR "deep learning")
- "algorithmic governance" AND "environment"
- "data sovereignty" AND "climate"
- "AI" AND ("climate litigation" OR "environmental monitoring" OR "loss and damage")

Searches were restricted to English-language publications issued between 2010 and 2025, with the lower bound coinciding with the emergence of deep learning as a dominant AI paradigm.

### *3.2 PRISMA Selection Workflow*

Table 1 summarises the PRISMA-compliant screening and selection process. All screening and eligibility decisions were made by the author through iterative full-text review against pre-specified inclusion and exclusion criteria. Of 92 sources identified, 28 peer-reviewed articles were included after full eligibility screening, supplemented by 16 grey-literature items included under established systematic review practice for legal and policy research.

**Table 1: PRISMA Selection Workflow**

| Phase | Records | Action | Outcome |
|---|---|---|---|
| Identification | Scopus: 34; WoS: 28; Google Scholar: 18; HeinOnline: 12 — Total: 92 | Database search using six query strings (see §3.1). Deduplication removed 11 duplicates. | 81 unique records screened |
| Screening | 81 records | Title/abstract screening against inclusion criteria. Exclusions: unrelated domain (n=29); non-comparative jurisdiction (n=12); language (n=4). | 36 records retained for full-text review |
| Eligibility | 36 full texts reviewed | Full-text assessment. Further exclusions: insufficient methodological detail (n=5); paywall-inaccessible (n=3). | 28 peer-reviewed articles included |
| Grey Literature | 16 items added | IPCC reports, treaty texts, UNEP assessments, and institutional reports included separately per established systematic review practice for legal/policy research. | 44 total sources cited (28 peer-reviewed + 16 grey literature) |

### 3.3 Inclusion and Exclusion Criteria

***Inclusion criteria:*** required that sources address at least one of the following: (i) AI or machine learning applications in climate science, environmental monitoring, or environmental law; (ii) climate justice theory or environmental law frameworks relevant to AI governance; or (iii) comparative legal analysis of climate or AI regulation. Grey literature — including IPCC reports, UNEP reports, treaty texts, and institutional publications — was included given its centrality to climate governance analysis.

***Exclusion criteria:*** Sources were excluded where they addressed AI in domains unrelated to environment or climate, or where legal analysis was confined to jurisdictions outside the study's comparative scope. No quantitative meta-analysis was conducted; findings are synthesised through analytical narrative review.

### 3.4 Comparative Legal Scope

The comparative legal analysis encompasses five jurisdictions: the European Union, the United States, India, Small Island Developing States, and the African Union — selected to represent a range of technological capacity, legal tradition, and climate vulnerability.

## 4. RESULTS AND DISCUSSION

The principal findings of the systematic review are presented across seven thematic areas: the AI–Climate Justice–Law Nexus framework; AI applications in climate justice and environmental law; climate vulnerability, equity, and the limits of AI; comparative legal and regulatory frameworks; AI and climate litigation; technical and operational risks; and an equity-centred governance framework including future directions.

### 4.1 The AI–Climate Justice–Law Nexus

The AI–Climate Justice–Law Nexus conceptual framework synthesises three interdependent streams. Artificial intelligence provides advanced tools for climate prediction, environmental monitoring, emissions tracking, and disaster forecasting. Climate science furnishes the scientific foundation for understanding global warming, ecological damage, and the unequal distribution of climate impacts. Environmental law and climate justice frameworks establish the legal principles, regulatory mechanisms, and accountability systems within which AI-generated evidence must operate.

#### 4.1.1 Climate Justice: A Multi-Dimensional Concept

Climate justice integrates distributive, procedural, recognition-based, and restorative justice dimensions [1, 27]. Distributive justice asks who bears the costs and who receives the benefits of climate action and inaction. Procedural justice demands meaningful participation of affected communities in decision-making. Recognition justice requires that the identities, cultures, and knowledge systems of frontline communities be acknowledged rather than marginalised. Restorative justice demands reparative mechanisms — historically resisted by industrialised nations — for harms already inflicted. AI systems may have roles across all four dimensions, though contributions are uneven and risks differ by context.

#### 4.1.2 Environmental Law: From Stockholm to the AI Era

International environmental law evolved from the hortatory declarations of the 1972 Stockholm Conference toward increasingly enforceable treaty regimes [14, 23]. The Paris Agreement introduced nationally determined contributions (NDCs) and a transparency framework nominally subject to international review [15]. The Kunming-Montreal Global Biodiversity Framework (GBF) established 30×30 conservation targets, and the Warsaw Mechanism, expanded at COP27, created a new fund for loss and damage. Yet the implementation gap remains substantial: current NDCs, if fully implemented, would still produce approximately 2.5°C of warming [26]. Enforcement mechanisms remain predominantly diplomatic rather than legal, and access to justice for climate-affected communities — particularly in the Global South — is constrained by resources, procedural standing requirements, and the legal complexity of establishing causation between diffuse global emissions and specific local harms.

#### 4.1.3 AI as Legal Infrastructure

AI is best understood in the context of environmental law not merely as a technical tool but as legal infrastructure: a set of systems that structure the conditions of possibility for legal claims, regulatory action, and treaty compliance. Like road networks or telecommunications grids, AI infrastructure can either enable access — to evidence, to justice, to participation — or restrict it, depending on who builds, owns, and governs it.

### 4.2 AI Applications in Climate Justice and Environmental Law

Table 2 summarises the principal AI methodologies applied across the climate justice and environmental law landscape, with associated capabilities and limitations.

#### 4.2.1 Satellite Remote Sensing and Machine Learning Monitoring

Machine learning applied to satellite imagery has substantially improved environmental monitoring, enabling rapid detection of deforestation, illegal mining, illegal fishing, and industrial pollution [16, 31]. AI systems using data from Sentinel-2 and Landsat-9 satellites monitor environmental changes at planetary scale and near-continuous temporal resolution. A significant development for climate justice is the ability to identify vulnerable communities most affected by pollution, land-use changes, and climate hazards — revealing environmental inequalities that traditional field research methods may miss. Courts in Kenya, Brazil, and the Netherlands have accepted remotely sensed environmental data as legal evidence, though clear standards governing admissibility, interpretation, and reliability of AI-based evidence in judicial proceedings remain to be developed [16].

**Table 2: Principal AI Methodologies in Climate Justice and Environmental Law**

| AI Tool / Method | Application Domain | Justice Capability | Legal Relevance | Key Limitation |
|---|---|---|---|---|
| Satellite ML Monitoring | Deforestation; emissions detection | Identifies affected communities | Evidence for environmental litigation | Data sovereignty; resolution bias toward urban areas |
| Climate Attribution Models | Extreme-event loss & damage causation | Quantifies regional harm | Causation in tort and compensation claims | Probabilistic uncertainty; peer-review lag |
| NLP Legal Analytics | Treaty & policy corpus parsing | Detects equity gaps in law | Drafting support; compliance tracking | Context loss; Western-corpus bias |
| Graph Networks (ESG) | Corporate supply-chain tracing | Traces pollution liability chains | Regulatory enforcement | Data availability in Global South |
| Reinforcement Learning | Policy optimisation simulations | Multi-objective justice metrics | Regulatory sandboxing | Reward misspecification risk |
| Computer Vision (CV) | Flood / drought / wildfire mapping | Vulnerability hotspot identification | Disaster law; adaptation plans | Resolution bias toward cities |
| Federated Learning | Distributed monitoring networks | Community-controlled data analysis | Privacy-preserving enforcement | Communication overhead; aggregation bias |

#### 4.2.2 Climate Attribution Science and AI

Climate event attribution science — which examines how climate change influences the likelihood and intensity of extreme weather events — represents one of the most consequential applications of AI for climate justice [17]. Machine learning algorithms trained on historical climate patterns enable more precise comparisons between natural climate conditions and climate-altered events. AI-based ensemble models quantify uncertainty more effectively, which is essential for both scientific reliability and legal evidence standards. Recent attribution studies using machine learning have moved beyond earlier work [17], incorporating deep convolutional networks and causal inference models that produce quantitative, jurisdiction-specific estimates of harm [18].

#### 4.2.3 Natural Language Processing and Legal Analytics

The corpus of international and domestic environmental law — treaties, regulations, court decisions, NDCs, national adaptation plans — now runs to millions of documents in dozens of languages. NLP systems enable systematic analysis of this corpus at a scale impossible for human researchers, including automated equity auditing of treaty language, tracking of implementation gaps, and comparative constitutional analysis. In litigation, large language models fine-tuned on environmental law have been piloted for legal research assistance and drafting submissions. However, systems trained predominantly on English-language, Western jurisprudence risk systematically disadvantaging litigants who rely on non-Western legal traditions or customary community law — an equity concern requiring explicit design attention.

#### 4.2.4 AI in Treaty Compliance and Regulatory Enforcement

Treaty compliance under the Paris Agreement depends on countries' Measurement, Reporting, and Verification (MRV) systems. AI-enhanced MRV — combining satellite atmospheric sensing, ground station networks, and machine learning — may independently estimate national greenhouse gas emissions with accuracy approaching official reporting. In domestic enforcement, AI tools have been deployed by regulators to prioritise inspection targets, identify permit violations from continuous emissions monitoring data, and model cumulative environmental burden on specific communities. The U.S. EPA's EJScreen tool incorporates demographic and environmental exposure data in a GIS platform; data gaps in rural and lower-income areas remain a significant limitation.

### 4.3 Climate Vulnerability, Equity, and the Limits of AI

Climate vulnerability refers to the degree to which regions and communities are exposed and sensitive to climate change impacts. IPCC assessments indicate that regions including Sub-Saharan Africa and South Asia face extreme climate risks despite having contributed relatively little to historical greenhouse gas emissions [19, 28]. AI may help identify vulnerable regions, predict climate risks, and support disaster management; however, its limitations in equity terms are substantial and deserve systematic attention.

#### 4.3.1 Algorithmic Bias and Environmental Justice

AI systems trained primarily on data from developed and well-monitored regions may perform poorly in rural or Global South communities most vulnerable to climate change, rendering the environmental problems of marginalised populations less visible to regulators and courts [7]. Bias manifests through representational exclusion of certain communities, feedback loops that concentrate regulatory attention on already-monitored areas, and proxy discrimination that may reproduce racial or economic inequalities in environmental governance.

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#### 4.3.2 Data Colonialism and Indigenous Data Sovereignty

Environmental AI systems may reproduce colonial power structures through unequal control over data and technology. Large-scale environmental monitoring frequently collects valuable data from Indigenous and vulnerable communities without proper consent, recognition, or benefit-sharing [9, 29]. The CARE Principles for Indigenous Data Governance — emphasising Collective Benefit, Authority to Control, Responsibility, and Ethics [10] — provide a normative framework for equitable data governance, though their adoption in environmental AI development remains limited.

#### 4.3.3 Access Asymmetries and Technological Sovereignty

Advanced AI-based environmental monitoring and litigation tools are disproportionately available to wealthy nations and large organisations. Vulnerable regions — including small island developing states, Sub-Saharan Africa, and rural South Asia — frequently lack the technical resources to deploy such tools effectively, creating legal and political disadvantages in environmental disputes [20]. The OECD AI Principles [11] and UNESCO Recommendation [13] both identify equitable access as a core principle of responsible AI governance, though binding commitments on technology transfer remain limited.

#### 4.3.4 The Justice Paradox: A Conceptual Framework

These dynamics generate what may be termed the “justice paradox” of environmental AI: systems designed to combat climate injustice risk reinforcing inequality through biased data, unequal access, and opaque decision-making. The paradox operates through three reinforcing mechanisms.

***Mechanism 1 — Data gap reproduction:*** Environmental AI tools are trained on datasets that reflect historical monitoring investment, concentrated in wealthy and urban contexts. EJScreen, for instance, draws on census data and fixed monitoring stations whose density falls sharply in rural and low-income areas, potentially underestimating environmental burden in the communities most reliant on the tool for legal advocacy. Similar gaps affect satellite monitoring: cloud cover, topography, and sensor resolution constrain coverage in many Global South regions, producing systematic underdetection of violations precisely where enforcement is most needed.

***Mechanism 2 — NLP corpus bias in non-Western legal contexts:*** NLP-based legal analytics trained on English-language case law and treaty texts may perform poorly when applied to the legal traditions relevant to environmental tribunals in Global South jurisdictions. India’s National Green Tribunal, for example, operates within a constitutional framework grounded in Article 21 (right to life) and Article 48A (environment protection), alongside a body of customary environmental obligation. AI legal tools calibrated on common-law corpora may fail to surface relevant precedents or correctly interpret NGT orders, systematically disadvantaging litigants whose strongest arguments draw on non-Western legal traditions.

***Mechanism 3 — Institutional capture:*** The jurisdictions with the greatest capacity to deploy advanced environmental AI — well-resourced regulatory agencies, large law firms, multinational corporations — are frequently the respondents in climate litigation rather than the claimants. This suggests that AI tools may, absent deliberate intervention, disproportionately improve the defensive capacity of powerful institutional actors rather than the prosecutorial capacity of frontline communities.

Addressing the justice paradox requires regulators to mandate bias audits for environmental AI systems, promote open-source environmental AI tools, support technology transfer and capacity-building, and ensure that affected communities have meaningful standing to challenge algorithmic determinations.

### 4.4 Comparative Legal and Regulatory Frameworks

Table 3 provides a comparative overview of selected jurisdictional approaches to AI governance and climate justice law, reflecting the state of law as of early 2025.

#### 4.4.1 The European Union: Partial Convergence

The European Union has developed advanced AI governance through the EU AI Act 2024 [21], which classifies AI systems used in environmental monitoring and public services as high-risk and subjects them to conformity assessment requirements. The European Green Deal and Copernicus programme support large-scale environmental monitoring. However, climate justice — including loss-and-damage provisions for vulnerable communities — remains insufficiently integrated into AI governance.

#### 4.4.2 United States: Environmental Justice Executive Action

Executive Order 14096 (2023), issued by the Biden administration, promoted the use of AI and machine learning to identify and reduce environmental burdens on disadvantaged communities. This instrument was subsequently rescinded by the incoming Trump administration in January 2025, along with a broader set of environmental justice executive orders. Its revocation illustrates a structural vulnerability of executive-order-based AI and environmental governance: the absence of legislative codification renders such frameworks susceptible to reversal at each change of administration. The United States has not ratified international access-to-justice agreements such as the Escazú Agreement, limiting community rights to use AI-based environmental evidence in legal proceedings.

#### 4.4.3 India: Emerging Frameworks and the NGT

India's regulatory landscape reflects the tension between a rapidly evolving AI sector and limited binding governance frameworks. The draft Digital India Act (DIA), circulated for consultation in 2023, proposes a risk-tiered regulatory approach to AI but had not been enacted as of early 2025. The National Action Plan on Climate Change (NAPCC), established in 2008, comprises eight national missions covering solar energy, water, agriculture, and urban sustainability, but contains no explicit provisions governing AI applications in climate monitoring or enforcement. The National Green Tribunal (NGT), established under the National Green Tribunal Act 2010, has emerged as a significant venue for environmental adjudication and has demonstrated increasing receptivity to scientific and technical evidence. In proceedings concerning Yamuna river pollution (NGT Original Application No. 673/2018) and Aravalli forest degradation (NGT Original Application No. 135/2019), the Tribunal admitted satellite-derived evidence of land-use change and industrial discharge, signalling a growing — though not yet formalised — willingness to engage with remotely sensed and AI-processed environmental data. The absence of a binding admissibility standard for AI evidence creates uncertainty for litigants and risks inconsistent treatment across benches. Rural AI access inequity represents a further structural concern: the communities most affected by industrial pollution and climate impacts frequently have the least capacity to commission or interpret AI-based environmental assessments.

#### 4.4.4 The International Treaty Architecture

Table 4 summarises key international legal instruments relevant to AI and climate justice.

### 4.5 AI and the Rising Wave of Climate Litigation

Climate litigation grew substantially worldwide, with more than 2,300 climate-related cases reported across 65 jurisdictions by 2023 [24]. These cases encompass climate rights, corporate responsibility, greenwashing, and weak environmental regulation. AI increasingly influences all stages of climate litigation, including evidence collection, environmental monitoring, risk analysis, and legal decision-making.

**Table 3: Comparative Overview of AI Governance and Climate Justice Frameworks (as of early 2025)**

| Jurisdiction | Key Instrument | AI Governance Status | Climate Justice Provisions | Notable Gap |
|---|---|---|---|---|
| European Union | EU AI Act 2024; Green Deal | High-risk AI classification for environmental monitoring | Partially addressed; loss & damage provisions absent | No mandatory climate-justice AI audit requirement |
| United States | EPA EJScreen; E.O. 14096 (2023, rescinded 2025) | Voluntary frameworks only; no binding AI-climate statute | Environmental justice executive orders; SEC climate disclosure rule | E.O. 14096 rescinded (Jan. 2025); no binding AI-climate nexus law; legislative gap exposed |
| India | Draft Digital India Act 2023; NAPCC; NGT jurisprudence | Nascent, sector-specific; no comprehensive AI statute | Eight UNFCCC missions; NGT increasingly admits AI-generated evidence | Rural AI access inequity; NGT lacks binding AI-evidence admissibility standard |
| Small Island States | UNFCCC Loss & Damage Fund (COP27/28) | Minimal domestic capacity; dependent on UNFCCC processes | Strongest climate justice advocates globally; vulnerability indices adopted | Technology transfer gaps; fund disbursement mechanisms unclear |
| African Union | Malabo Convention; AU AI Policy Framework 2024 | Policy framework in development; non-binding | Adaptation focus; equity lens in AU AI framework | Enforcement mechanisms absent; significant funding gaps |

#### 4.5.1 Evidence Generation and Attribution

Establishing the causal chain from a defendant's emissions to a claimant's loss has long been climate litigation's greatest technical obstacle. AI-enhanced attribution science has begun to erode this barrier. Machine learning models trained on emissions databases may estimate with statistical rigour how much of a coastal flooding event, a heat-mortality toll, or an agricultural yield loss is attributable to the historical emissions of a specific corporate or state actor [17]. The IPCC's Sixth Assessment Report [19] notes that attribution science has advanced sufficiently to make probabilistic causal claims about specific extreme event categories.

#### 4.5.2 Legal Research and Strategic Analysis

NLP-powered legal research tools may accelerate the capacity of under-resourced environmental justice organisations to identify analogous precedents, draft comprehensive submissions, and navigate complex multi-jurisdictional proceedings. Open-source tools such as Climate Change Laws of the World (CCLW) at the London School of Economics already use NLP to maintain a comprehensive climate law database [24]. Next-generation systems may offer predictive modelling of litigation outcomes and automated monitoring of regulatory commitments for breach.

#### 4.5.3 Corporate Accountability and Greenwashing Detection

AI-powered scrutiny of corporate climate disclosures — cross-referencing stated net-zero commitments against satellite-observed emissions, supply chain data, and historical corporate conduct — may create new pressure for corporate climate accountability [25]. Regulatory agencies in the European Union, United Kingdom, and Australia are exploring AI-assisted greenwashing detection, and private litigation based on AI-generated evidence of disclosure fraud represents an emerging category.

### 4.6 Technical and Operational Risks of Environmental AI

A systematic analysis of AI's potential in environmental governance requires equal attention to its technical and operational risks. These risks are particularly consequential where AI-generated evidence informs judicial proceedings, regulatory enforcement, or treaty compliance review.

**Table 4: Key International Legal Instruments Relevant to AI and Climate Justice**

| Agreement | Year | AI Relevance | Justice Dimension | Enforcement Mechanism |
|---|---|---|---|---|
| Paris Agreement | 2015 | NDC monitoring & AI-enhanced MRV | Common but differentiated responsibilities | Weak — nationally determined; no binding AI provisions |
| Kunming-Montreal GBF | 2022 | Biodiversity AI monitoring; species tracking | Indigenous rights; 30x30 conservation | Moderate — national targets; reporting obligations |
| Warsaw Mechanism / L&D Fund | 2013/2022 | Attribution modelling for compensation claims | Central — climate reparations architecture | New Fund operational; disbursement criteria unresolved |
| Escazú Agreement | 2018 | Environmental data access & transparency | Defenders' rights; procedural justice | Regional — Latin America & Caribbean only |
| Global Plastics Treaty (draft) | 2024+ | AI supply-chain tracking; lifecycle analysis | Frontline community focus | Under negotiation; no enforcement text agreed |

**Table 5: Technical and Operational Risks of AI Deployment in Environmental Governance**

| Risk Category | Description | Environmental AI Manifestation | Mitigation Approach |
|---|---|---|---|
| Model Uncertainty | Stochastic outputs; confidence interval misinterpretation | Attribution studies overstating certainty; courts misreading probabilistic evidence | Mandatory uncertainty disclosure; calibration audits |
| Black-Box Limitations | Opaque decision logic in deep learning models | Regulators unable to explain enforcement decisions; procedural justice compromised | Explainability requirements (XAI); model cards for environmental AI |
| Training Data Bias | Historical data reflecting existing inequalities | Underperformance in data-sparse Global South regions; underdetection of rural violations | Equity-weighted sampling; community data partnerships |
| Hallucination Risk | Generative model fabrication of plausible but false content | LLM-assisted legal briefs citing non-existent precedents or fabricated statistics | Human-in-the-loop verification; citation grounding requirements |
| AI Carbon Footprint | Significant energy consumption of training and inference | Climate-damaging emissions from systems deployed to address climate harm | Lifecycle carbon disclosure; preference for efficient fine-tuned models |
| Adversarial Manipulation | Deliberate perturbation of inputs to deceive models | Corporate actors manipulating satellite imagery or emissions reporting data | Adversarial robustness testing; multi-source data verification |

#### 4.6.1 Model Uncertainty and Probabilistic Evidence

Environmental AI models typically produce probabilistic outputs with associated confidence intervals. In litigation contexts, courts and counsel without quantitative training may misinterpret these intervals, treating probabilistic attribution findings as deterministic proof or dismissing them as insufficiently certain for legal purposes. Mandatory uncertainty disclosure — requiring AI outputs to be accompanied by calibrated confidence estimates and plain-language explanations — may help courts engage appropriately with probabilistic evidence. The NIST AI Risk Management Framework [12] recommends that AI systems used in consequential decisions be subjected to calibration audits.

#### 4.6.2 Black-Box Limitations and Explainability

Deep learning models — including convolutional networks used in satellite imagery analysis and large language models used in NLP-based legal analytics — typically provide limited insight into the internal logic of their outputs. In administrative and judicial proceedings, the inability to explain an algorithmic determination may violate procedural due process requirements [30]. The EU AI Act's transparency obligations for high-risk AI [21] represent a partial regulatory response, but explainability requirements for environmental AI specifically remain to be standardised.

#### 4.6.3 Hallucination and Verification Risks

Generative AI models, including large language models used for legal drafting and research, may produce plausible but factually incorrect outputs — a phenomenon widely described as 'hallucination.' In environmental legal contexts, hallucinated citations to non-existent cases, fabricated statistics, or confabulated treaty provisions could cause significant harm if undetected in litigation submissions. Human-in-the-loop verification requirements and citation-grounding standards for AI-assisted legal work represent essential mitigations.

#### 4.6.4 AI Carbon Footprint

A rarely examined concern in environmental AI is that the training and inference of large-scale AI models consumes substantial energy, generating greenhouse gas emissions. AI systems deployed to address climate harm may therefore themselves contribute to it. Lifecycle carbon disclosure for environmental AI systems and preference for efficient fine-tuned models over repeated large-scale training represent responsible deployment practices that remain largely voluntary.

### 4.7 Toward an Equity-Centred AI Governance Framework

#### 4.7.1 Foundational Principles

Five interlocking principles should govern the design and deployment of AI systems in environmental law:

- ***Equity by design:*** AI systems should be built with explicit protections for vulnerable and Indigenous communities, embedding fairness constraints and community representation into development processes.
- ***Algorithmic transparency:*** Environmental AI systems should be auditable, with technical documentation accessible to regulators, affected communities, and courts.
- ***Data sovereignty:*** Communities should retain meaningful control over environmental data generated from or about their territories, consistent with the CARE Principles [10].
- ***Technology transfer:*** Developing countries should receive access to AI monitoring tools and technical capacity, preventing the consolidation of environmental enforcement capability in wealthy nations.
- ***Democratic accountability:*** Decisions made or informed by AI systems in environmental governance should be subject to meaningful public oversight, with mechanisms for affected communities to challenge algorithmic determinations.

#### 4.7.2 Structural Legal Reforms

At the international level, the UNFCCC framework should be supplemented with binding provisions governing AI-based climate monitoring, including rules on the admissibility of AI-generated evidence and mandatory technology-support obligations for developing-country parties. At the regional level, human rights bodies should formally recognise AI-based environmental monitoring as an instrument of access-to-justice rights [22]. At the national level, governments should mandate algorithmic bias audits for AI systems used in environmental enforcement, with failure to comply giving rise to justiciable claims by affected communities. At the corporate level, companies deploying AI systems in emissions reporting should be required to disclose the systems used, training data provenance, and results of independent bias assessments.

### 4.8 Future Directions

Several emerging AI architectures may substantially expand the equitable reach of environmental monitoring. Federated learning — a distributed machine learning approach in which model training occurs locally on community or national datasets without centralising raw data — may help address both data sovereignty concerns and the surveillance risks associated with traditional centralised AI monitoring. By allowing a shared global climate model to be trained collaboratively without requiring any single actor to surrender control of their data, federated learning offers a technically viable path to CARE-consistent data governance. Pilot deployments in health and financial domains suggest the approach is technically mature, though environmental applications remain limited and aggregation bias in federated settings requires further research.

Edge computing — processing AI inference locally on devices or sensors in the field rather than on remote cloud infrastructure — may expand monitoring capacity in data-sparse regions. Deploying edge AI nodes on community-operated sensor networks in rural and island contexts could reduce dependency on external infrastructure and latency constraints that currently limit real-time environmental monitoring in under-resourced jurisdictions. Combined with satellite internet connectivity, edge-based AI may enable Indigenous and frontline communities to generate legally defensible environmental evidence without dependence on external technical actors.

Multimodal AI models — integrating satellite imagery, sensor data, acoustic monitoring, and documentary text — suggest further advances in the comprehensiveness and interpretability of environmental assessments. Open-source, multilingual, community-centred AI systems developed in genuine partnership with affected populations represent the institutional aspiration against which current commercial AI deployment in environmental governance should be measured.

### *4.9 Limitations*

This review is subject to four principal limitations. First, all screening, eligibility, and synthesis decisions were made by a single author; the absence of a second independent reviewer means that selection bias cannot be formally excluded, and inter-rater reliability cannot be reported. Readers should interpret the analytical synthesis accordingly. Second, searches were restricted to English-language publications, which may systematically under-represent scholarship from non-Anglophone jurisdictions — including major emitting and vulnerable nations whose domestic legal developments are directly relevant to the analysis. Third, the field of AI governance and climate litigation is evolving rapidly; instruments described as “forthcoming” or “under negotiation” at the time of writing may have been adopted, amended, or abandoned by the time of publication, and the paper’s comparative legal analysis reflects the state of law as of early 2025. Fourth, no quantitative meta-analysis was conducted; the findings are synthesised through analytical narrative review, and no statistical pooling of results across studies is claimed.

## 5. CONCLUSION

This systematic review has identified three primary findings. First, AI technologies — particularly satellite ML monitoring, climate attribution modelling, and NLP-based legal analytics — have materially strengthened the evidentiary basis for climate litigation and regulatory enforcement, as illustrated by developments in cases such as Urgenda, Neubauer, and Leghari, and by the growing use of satellite evidence in environmental adjudication in Kenya, Brazil, and the Netherlands.

Second, the justice paradox of environmental AI — whereby tools designed to advance climate justice risk reinforcing inequality through data gaps, NLP corpus bias, and institutional capture — represents a structural challenge that technical optimisation alone cannot resolve. Governance responses must be designed at the system level, embedding equity constraints into procurement, deployment, and audit requirements rather than treating bias mitigation as an optional feature.

Third, the comparative legal analysis reveals convergence on recognition of a right to a healthy environment and growing regulatory attention to AI governance, but persistent divergence in how these frameworks interact with climate justice. India’s NGT jurisprudence, the EU AI Act’s high-risk classification, and the rescission of U.S. environmental justice executive orders each illustrate jurisdictional fragmentation and instability that may disadvantage Global South litigants in cross-border proceedings. Converting these observations into enforceable legal obligations — through UNFCCC protocol provisions on AI-enhanced MRV, binding AI bias audit requirements in domestic environmental enforcement, and international technology transfer commitments — remains the defining challenge for climate justice law in the AI era. Whether AI becomes a tool of equitable climate governance or an instrument of technological entrenchment will depend less on the capabilities of the systems than on the governance choices made by legislators, regulators, and the international community in the immediate years ahead.

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## CONFLICT OF INTEREST

The author declares no conflicts of interest with respect to the research, authorship, or publication of this article.

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