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Article

Algorithmic Sustainability: Governance Conditions for AI-Driven Environmental Decision-Making

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Abstract

Environmental governance is no longer shaped only by expert judgement or statutory procedure. In recent years, algorithmic systems have begun to mediate how data are interpreted, to shape the scoring of risk, and to influence the way policy priorities are established. These systems now affect regulatory analysis. They also inform climate adaptation modelling and guide decisions on land use while supporting sustainability monitoring. Although artificial intelligence (AI) is often presented as a means to improve environmental outcomes, its deployment introduces lifecycle emissions while raising concerns about institutional opacity and exposing risks related to public legitimacy that remain insufficiently embedded in current governance frameworks. This article advances the concept of algorithmic sustainability and treats it as a condition of governance rather than a technical attribute of computational tools. Drawing on a structured qualitative synthesis of interdisciplinary research, the study identifies three conditions required for sustainable AI use in environmental decision systems. One concerns lifecycle carbon integrity. Another addresses institutional accountability. A third focuses on alignment with public value. These conditions are translated into a tiered Environmental AI Impact Assessment model (EAIA) designed to support regulatory oversight while remaining institutionally feasible. By separating computing-related effects from operational consequences and from wider systemic implications, the framework clarifies how algorithmic applications may improve environmental performance while still generating rebound pressures that threaten broader sustainability goals.

Keywords: algorithmic sustainability; AI governance; environmental policy; lifecycle impacts; climate ethics; contestability

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1. Introduction

In recent years, algorithmic systems have increasingly shaped environmental governance by mediating the interpretation of data, the evaluation of risks, and the setting of regulatory priorities. Across areas such as climate-risk modelling, biodiversity monitoring, pollution forecasting, and land-use classification, algorithmic systems increasingly influence the empirical evidence used in environmental regulation. A closer examination of current regulatory practice suggests that artificial intelligence (hereinafter referred to as AI) systems increasingly shape the analytical foundations of public decisions. This change is part of a broader digital transformation in public administration. Studies on how governments use AI show that they are increasingly relying on algorithmic tools to help with regulatory analysis, provide public services, and coordinate enforcement activities [1–3]. These systems promise stronger predictive capacity together with administrative efficiency. At the same time, they reconfigure accountability relationships and alter how institutional authority is exercised [4,5].

In environmental matters, these questions are highly significant. Decisions are often made even when the science is not fully settled, and the risks to ecosystems may only become clear over long periods of time. There are also ongoing disagreements about who benefits and who bears the costs. Sustainability research therefore argues that new technologies must be assessed within the wider socio-technical systems they transform, rather than in isolation. Instead, we need to look at how they fit into wider social and technical systems [6,7]. Algorithmic mediation becomes embedded in the governance architecture that shapes ecological trajectories. The main question is changing. It is no longer just about whether AI can improve environmental decisions. Instead, we now need to ask: under what kinds of rules, oversight, and governance can AI stay truly aligned with sustainability goals?

AI is often described as a tool that can speed up progress on sustainability, especially when it is used for monitoring, optimization, or prediction. But when we look at AI in relation to the UN Sustainable Development Goals, we see a mixed picture: there are real opportunities, but also serious, system-wide risks [8]. Emerging evidence nevertheless shows that the environmental implications of AI extend well beyond efficiency gains. Kaack et al. distinguish three layers of climate effect associated with AI deployment. One originates in computing infrastructure [3]. Another appears at the level of immediate applications. A further layer emerges through structural change at the system scale. Computing emissions stem from data centers, together with model training and hardware production. Immediate impacts may improve resource allocation or reduce waste in specific contexts. System-level dynamics, however, can generate rebound pressures that offset efficiency gains, particularly when reduced costs stimulate additional demand or trigger infrastructural expansion.

Altogether, these trends suggest a bigger structural change. Other analyses show that algorithmic systems are becoming built-in parts of our social and technical infrastructure, instead of just staying as separate tools for analysis [9]. As institutional adoption deepens, path dependency may emerge alongside technological lock-in. Institutional economics suggests that once governance infrastructures become embedded, sunk investments and adaptation costs can restrict future regulatory flexibility [10]. Such findings complicate narratives that portray AI deployment as environmentally neutral. Sustainability needs to be evaluated not just in terms of a product's life cycle, but also the infrastructure it relies on and its broader impacts on society and the environment. Recent research also shows that AI is becoming a core part of our digital infrastructure. As institutional reliance on AI deepens, these systems increasingly function as infrastructure, creating potential path dependencies and forms of technological lock-in within environmental governance [9].

Environmental governance isn't just a technical task. It takes place in a space where public accountability, fairness in how benefits and burdens are shared, and democratic trust all matter.

When AI systems help shape environmental decisions, they unavoidably affect how public values are understood and applied in real situations. Studies on AI in government show that these systems can change how transparent decisions are and have important impacts on fairness and accountability. They also influence who gets to take part in decision-making and how that participation works [11]. Where algorithmic tools mediate environmental decisions, for example, in the allocation of conservation resources or in the prioritization of enforcement, distributive outcomes may shift in subtle but consequential ways. That said, research on the ethics of algorithmic governance further shows that optimization criteria often contain implicit normative assumptions [12]. In practical terms, this means that algorithmic design choices can carry distributive consequences that are not always visible at the point of deployment.

These concerns become particularly important when we consider how we manage climate issues. Coeckelbergh (2020) argues that when AI is used for climate action, it should be evaluated not only on its environmental effectiveness, but also on whether it is fair and respects people's political voice and participation. Put simply, AI for climate action must be both environmentally effective and politically just [13]. Related analysis by Bartmann (2022) shows that AI-enabled behavioral interventions, including climate nudging, may raise autonomy concerns when institutional safeguards remain weak. Regulatory legitimacy ultimately depends on the presence of procedural safeguards [14]. Black (2008) emphasizes that accountability in complex regulatory environments

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requires structured oversight together with meaningful contestability. Without such safeguards, algorithmic mediation may gradually erode democratic trust [5].

These governance concerns are increasingly reflected in international standards. The UNESCO Recommendation on the Ethics of Artificial Intelligence (2021) frames environmental stewardship and transparency as obligations grounded in human rights protection. The OECD Principles on Artificial Intelligence (2019) similarly emphasize accountability expectations for public-sector AI systems. Algorithmic sustainability, therefore depends on alignment with public value governance principles rather than on performance metrics alone [15,16].

Even when governance rules are clear, putting them into practice still depends on how strong institutions are. Using AI in government needs good digital systems and people with the right skills—but in reality, many institutions are not yet ready [2]. Empirical assessments continue to reveal uneven administrative readiness for effective algorithmic oversight [2]. Research on knowledge systems indicates that sustainability governance depends on information flows that remain credible, legitimate, and salient to decision makers [17]. When AI helps interpret environmental data, its results become very important. So, we must make sure these results can be checked and reviewed.

In reality, this change creates new pressure on public audit offices. Traditional auditing methods were not built to check how models are tested, where the data comes from, or whether the algorithms are biased [18]. Technical work on trustworthiness metrics provides partial evaluation tools [19]. Institutional context is still the key to effective governance. Things become more complex because institutions are diverse and often operate across multiple levels. Ostrom (2009) shows that sustainability governance depends on nested institutions working together. So, algorithmic systems should be part of a broader governance framework, not used as stand-alone technical tools [20].

Many AI ethics frameworks set out useful principles and basic governance ideas. However, they are usually not tailored to specific sectors and are only loosely linked to environmental impacts or to whether institutions can actually apply them. Research on sustainability transitions shows that deep, system-wide change is needed instead [7]. Yet this research rarely treats algorithmic mediation as a basic part of how environmental governance works.

The gap is more conceptual than technical. Current approaches do not fully connect the environmental impacts of AI over its lifecycle with the institutional accountability needed when AI influences environmental decisions, nor do they consistently ensure alignment with public values. Without this integration, it is difficult to assess claims about “sustainable AI” from a governance perspective. In practice, the governance implications of AI are often clearer in theory than in actual implementation.

This article asks: How can AI systems used in environmental governance be designed to preserve lifecycle carbon integrity, ensure institutional accountability, and remain aligned with public values? To answer this, the article introduces the concept of algorithmic sustainability as a governance condition and puts it into practice through a tiered Environmental AI Impact Assessment (EAIA) framework.

Unlike most responsible AI frameworks, which focus on ethical principles such as fairness or transparency, algorithmic sustainability directly links lifecycle environmental impacts with institutional governance requirements. This approach places AI within the wider ecological and regulatory systems that shape sustainability outcomes.

The rest of the article is structured as follows. Section 2 develops the theoretical foundation by drawing on lifecycle impact research, institutional economics, public value theory, and regulatory governance scholarship. Section 3 explains the methodology used to construct the framework. Section 4 sets out the governance conditions associated with algorithmic sustainability. Section 5 introduces the EAIA model and discusses its regulatory use and institutional feasibility. Section 6 examines the resulting policy implications. Section 7 concludes by outlining directions for future research and implications for governance practice.

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2. Theoretical Foundations

2.1. Lifecycle Environmental Impacts of Artificial Intelligence

We can't judge the environmental impact of AI just by how well it works. Research shows that AI affects the environment over time and at many different levels of the systems it is part of [8]. Kaack et al. (2022) provide one of the most comprehensive analytical approaches for examining greenhouse gas emissions associated with AI [3]. Their framework separates impact into three analytically distinct layers that operate at different points in the lifecycle. One layer originates in the computing infrastructure that supports AI. Energy use in data centers, the training of large models, hardware production, and the expansion of digital infrastructure all contribute to this footprint [21]. Even though hardware keeps getting more efficient, training large models still uses a lot of energy. A second layer shows up when we look at how these models are actually used. In certain areas, like transport management or energy optimization, predictive systems can help reduce waste and make operations run more efficiently.

A further layer appears through broader system responses. Behavioral adjustments, demand expansion following efficiency gains, and wider economic shifts associated with digitalization may offset earlier improvements. Within environmental governance, these dynamics are particularly consequential because algorithmic systems can reshape incentives, alter regulatory focus, or redirect investment flows. As Kaack et al. (2022) note, long-term climate consequences depend less on technical capability than on the conditions under which deployment occurs [3]. Seen from a lifecycle perspective, the assumption that AI is inherently sustainable becomes difficult to maintain. Environmental performance depends instead on the institutional and regulatory settings that shape how these systems are introduced and scaled.

2.2. Artificial Intelligence as Infrastructure: Implications for Path Dependency and Carbon Lock-In

Beyond questions of emissions accounting, artificial intelligence increasingly operates as part of infrastructural architecture rather than as a discrete analytical tool. Robbins and van Wynsberghe (2022) argue that AI is becoming embedded within socio-technical arrangements in ways that can generate path dependency and forms of technological lock-in, dynamics that are widely recognized in infrastructure transitions research [9,22]. Once algorithmic systems are built into regulatory processes, they can start to shape how governance develops over time. This usually happens slowly and can be hard to notice while it is going on. This hidden, infrastructure-like role is especially important in environmental areas. Public agencies already use AI to monitor forest changes, classify species, estimate environmental risks, and set enforcement priorities. As this reliance grows, everyday administrative work may become locked into proprietary platforms, centralized data systems, or model designs that are hard for outsiders to question or review.

Lock-in usually doesn't come from just one thing. Institutions normally change step by step, not through one big decision. Over time, they become committed to certain paths because of (a) Money already invested, (b) experience and routines they have built up, and (c) costs of changing rules and regulations

Network effects (where something becomes more valuable as more people use it) can also make it harder to move away from existing systems. As this continues, governments and organizations may find that they have fewer realistic policy options when new environmental problems appear. If the core infrastructure depends heavily on high-carbon energy or resource-intensive supply chains, expanding it can also indirectly increase emissions.

In reality, these changes are usually not sudden or surprising. When we look at AI in this way—as part of long-lasting infrastructure—we can't judge its sustainability just by looking at single tools or applications. Instead, governance needs to plan for how AI will become deeply embedded in institutions over the long term, rather than assuming we can readily reverse its adoption later without serious consequences.

2.3. Public Values and Democratic Legitimacy in Algorithmic Governance

Environmental governance cannot be treated as a purely technical exercise in optimization. It operates within a field shaped by distributive justice, political accountability, and public legitimacy. Research in public administration shows that algorithmic systems can influence core public values, including transparency, equity, participation, and accountability [11]. In other words, the question is not simply whether these systems work, but whose values they end up expressing in practice. When artificial intelligence mediates environmental decisions, for instance, in determining eligibility for subsidies, delineating environmental risk zones, or directing enforcement activity. It may alter how costs and benefits are distributed. Distortions in training data, limited visibility into scoring processes, or poorly aligned optimization objectives can produce inequitable outcomes even when efficiency improves.

Ethical scholarship has also drawn attention to tensions between efficiency and autonomy. Coeckelbergh (2020) argues that AI applied in climate governance must be assessed not only in terms of environmental performance but also in relation to freedom and global justice. Related work by Bartmann (2022) indicates that behavior-shaping systems, including climate nudging applications, can raise concerns about autonomy when institutional safeguards remain weak[13,14].

International guidance increasingly reflects these risks. The UNESCO Recommendation on the Ethics of Artificial Intelligence (2021) frames environmental stewardship and human rights protection as governance obligations[15]. The OECD Principles on Artificial Intelligence (2019) similarly emphasize accountability expectations in public-sector deployment [16]. Together, these frameworks suggest that ethical oversight must remain institutionally grounded rather than delegated to technical design alone. In environmental policy settings, the legitimacy threshold is especially high. Decisions concerning land use, climate adaptation, or resource allocation often involve contested trade-offs. Under such conditions, algorithmic mediation must satisfy demanding standards of procedural fairness and public contestability.

2.4. Institutional Capacity and Regulatory Oversight

Even when normative commitments are clearly articulated, effective governance depends on institutional capacity. The responsible integration of artificial intelligence requires organizational readiness that many public authorities have not yet developed. Evidence from studies of public administration indicates uneven preparedness for algorithmic oversight and limited formalization of audit procedures [2].

The difficulty is compounded by technical complexity. Paolanti et al. (2024) propose quantitative approaches for assessing trustworthiness, focusing on robustness, algorithmic interpretability, and bias detection [19]. Yet the application of such metrics presupposes technical expertise that regulatory bodies do not consistently possess. Public audit institutions are therefore encountering new responsibilities. Genaro-Moya et al. (2025) observe that AI-enabled decision systems introduce challenges that extend beyond conventional financial review, including questions of model validation, data provenance, and algorithmic transparency [18]. Established auditing practices were not designed with these requirements in mind. Institutional feasibility thus becomes central to any sustainability claim. In practice, governance failures rarely arise from a lack of principles; they more often emerge from limited institutional capacity to apply them. Technical efficiency alone does not ensure responsible deployment if oversight bodies lack the capacity to scrutinize system behavior or to enforce procedural safeguards.

2.5. Toward Algorithmic Sustainability as a Governance Condition

Taken together, these strands of scholarship point to a common conclusion. Sustainability in AI-mediated environmental governance cannot be reduced to performance indicators or to isolated ethical commitments. What is required is a governance condition that brings environmental impact, infrastructural embedding, public legitimacy, and institutional capacity into a single evaluative frame. This approach goes beyond existing tools that treat environmental, social, and institutional issues separately or as late-stage add-ons. Those who often look at environmental, social, and institutional issues separately, or treat them as add-ons at the end of the process. Instead, we are suggesting a governance approach where environmental impact, infrastructure, public trust, and institutional capacity are all seen as tightly linked parts of one shared framework. The goal is not just to tack on environmental or ethical checks to AI systems, but to ask a deeper question: given these four dimensions together, is AI actually governable in this specific context at all?

The concept of algorithmic sustainability, as developed here, is intended to capture this integration. It reframes sustainability not as a technological aspiration but as a property that emerges from governance arrangements. The synthesis process converged on three interdependent governance conditions for AI-mediated environmental decision systems: (1) lifecycle carbon integrity, (2) institutional accountability, and (3) public value alignment. These conditions are analytically distinct yet mutually reinforcing and provide the conceptual backbone for the framework developed in the rest of the article.

The following section explains the methodological approach used to construct and examine this governance framework.

3. Methodology

3.1. Research Design and Analytical Orientation

The study adopts a qualitative framework-development approach grounded in structured interdisciplinary synthesis. The purpose is not to test empirical hypotheses but to integrate conceptual insights drawn from several bodies of scholarship that address artificial intelligence within environmental governance. This orientation is appropriate when theoretical knowledge exists but remains distributed across disciplinary boundaries. Research on lifecycle environmental impacts of artificial intelligence, governance theory, institutional economics, and public-sector algorithmic accountability has progressed largely in parallel. Yet the relationships between these strands have rarely been examined within a unified analytical structure. In practice, researchers often encounter fragments of the same problem dispersed across different literatures. Framework development therefore becomes an integrative exercise rather than an experimental one [23]. The objective is to identify conceptual connections that allow governance conditions to be articulated with greater clarity. Earlier work on institutional analysis and sustainability transitions has demonstrated the value of such integrative approaches when complex socio-technical systems are under examination [7,20].

The research design unfolds through a sequence of analytical stages. The process begins with structured identification of relevant literature across several domains of scholarship. The material is then examined through thematic coding that focuses on governance-relevant dimensions. Finally, insights are synthesized across disciplinary boundaries to derive operational conditions capable of guiding regulatory evaluation. This analytical orientation is consistent with the knowledge-systems integration perspective described by Cash et al. (2003), which emphasizes that sustainability governance depends simultaneously on credibility, salience, and legitimacy [17]. In other words, knowledge must not only be technically sound; it must also be meaningful to decision-makers and trusted by those affected by policy outcomes.

3.2. Literature Identification and Selection Criteria

The study does not employ a quantitative systematic review. Instead, a purposive selection strategy was used to assemble a corpus of influential peer-reviewed scholarship and widely recognized governance frameworks. The goal was conceptual saturation across governance dimensions rather than exhaustive bibliometric coverage.

Sources were selected according to several guiding considerations. Priority was given to publications indexed in major academic databases such as Scopus or Web of Science. Each selected work needed to contribute substantively to at least one of the analytical domains relevant to algorithmic environmental governance. In most cases, publications dated from the period between 2016 and 2025, reflecting the recent acceleration of artificial intelligence deployment within public administration and environmental management. Authoritative intergovernmental governance frameworks were included when they shaped global policy expectations. The resulting corpus spans several areas of scholarship. Climate and lifecycle analyses of artificial intelligence provide insight into energy demand, infrastructure expansion, and potential rebound effects associated with digital technologies [3,24,25]. Research on socio-technical transitions and infrastructural lock-in highlights the structural consequences of embedding technologies within institutional systems [6,9].

Institutional economics and governance theory contribute analytical perspectives on regulatory accountability, oversight mechanisms, and institutional evolution [10,20]. A growing body of scholarship examining artificial intelligence in public administration further addresses issues of transparency, algorithmic accountability, and administrative integration [1,11]. Technical work on trustworthiness and algorithmic auditing introduces methods for evaluating system robustness and governance risks [18,19,26]. Finally, global policy frameworks provide normative guidance for responsible AI deployment within public institutions [15,16]. Taken together, these sources create a multi-domain analytical base capable of supporting cross-disciplinary synthesis without extending beyond governance-relevant scholarship.

3.3. Analytical Coding Framework

In order to examine conceptual relationships across the selected literature, the study employed deductive thematic coding. Initial reading revealed several recurring governance concerns that appeared consistently across disciplinary boundaries. These concerns were translated into analytical categories that guided the coding process. Three macro-dimensions emerged as particularly central to the governance of AI-mediated environmental decision systems. The first concerns environmental impact integrity across the technological lifecycle. The second relates to institutional accountability within public decision systems. The third addresses the alignment of algorithmic decision processes with public values and democratic legitimacy. Each dimension was further operationalized through sub-themes reflecting patterns identified in the literature.

The resulting coding structure is summarized in Table 1, which illustrates how governance themes identified in the literature were organized into analytical dimensions.

Table 1. Coding Structure for Governance Synthesis.

Macro-Dimension	Sub-Themes	Representative Sources
Lifecycle Carbon Integrity	Computing emissions; embodied hardware impact; rebound and system effects	[3,24,25]
Infrastructural Embedding	Path dependency; institutional lock-in; socio-technical transitions	[6,9]
Institutional Accountability	Auditability; regulatory oversight; accountability relationships	[4,5,18]
Public Value Alignment	Transparency; equity; autonomy; procedural legitimacy	[11–13]
Institutional Capacity	Administrative readiness; governance maturity; audit competence	[1,27]

Each source was examined in relation to these categories. The coding process did not aim to quantify theme frequency. Instead, attention was directed toward identifying conceptual convergence across different areas of scholarship. At several points it became clear that ideas developed independently within separate disciplines were describing closely related governance concerns.

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3.4. Cross-Domain Synthesis and Condition Derivation

After thematic coding, the study proceeded to structured comparative synthesis. The purpose was to determine whether recurring governance concerns could be translated into a smaller number of analytically coherent conditions. This stage involved several analytical steps. First, overlapping risk dimensions were identified across the coded literature. Next, categories that proved conceptually redundant were consolidated. The remaining themes were then examined for conceptual independence and institutional relevance.

During this process some categories initially treated as distinct were later integrated into broader governance conditions. For example, trustworthiness metrics proposed in technical literature [19] were initially considered as a separate analytical dimension. Closer examination suggested that such metrics have limited practical significance unless embedded within institutional oversight arrangements [4]. Consequently, these considerations were incorporated into the broader dimension of institutional accountability. A similar adjustment occurred in relation to infrastructural lock-in. Research on digital infrastructure and technological path dependency [9]. revealed systemic environmental implications extending beyond operational emissions. These insights were therefore incorporated into lifecycle carbon integrity and institutional feasibility considerations rather than retained as a separate category. Through iterative refinement, three interdependent governance conditions emerged

- Lifecycle carbon integrity
- Institutional accountability
- Public value alignment

These conditions were retained only when they satisfied several methodological criteria. Each needed to represent a conceptually distinct analytical dimension. Each also required grounding in established scholarship. Finally, the condition had to possess practical relevance for regulatory institutions responsible for overseeing AI-mediated environmental decisions. In practice, the aim was to avoid conceptual inflation. A governance framework becomes less useful if it expands indefinitely.

3.5. Constructing the Environmental AI Impact Assessment (EAIA)

The final stage of analysis translated governance conditions into an operational instrument termed the Environmental AI Impact Assessment (EAIA). The objective was not to produce a universal compliance checklist but to design a governance architecture that could realistically function within institutional settings. The development of EAIA was guided by the principle of proportional regulation described in governance scholarship [5,16]. This principle recognizes that oversight intensity should correspond to the scale of potential systemic impact.

The operational design therefore followed a backward-mapping approach. Categories of environmental decision systems were first identified according to the scale of their ecological and distributive implications. Governance obligations were then calibrated relative to these potential impacts. In practical terms, this approach reflects a simple observation: regulatory capacity is always finite. Governance frameworks that assume unlimited institutional resources rarely function effectively. The EAIA therefore operates as a tiered structure that aligns governance expectations with institutional feasibility.

3.6. Scope and Analytical Limitations

The study is conceptual and normative rather than empirical. Its validity rests on several foundations. First, the framework draws on convergent insights from high-impact interdisciplinary scholarship. Second, the analytical structure maintains internal logical coherence across governance dimensions. Third, the proposed conditions remain consistent with intergovernmental policy frameworks addressing artificial intelligence governance. The framework does not evaluate specific technologies, companies, or jurisdictions. This limitation is deliberate. By avoiding jurisdiction-specific legal analysis, the study maintains broader applicability across governance contexts.

Nevertheless, certain limitations remain. The analysis relies primarily on secondary scholarship rather than on primary empirical observation. Lifecycle emissions measurement standards also continue to evolve, which may influence future environmental assessments of digital infrastructure. In addition, institutional capacity varies significantly across regulatory systems, potentially affecting implementation. Future research should therefore examine how the Environmental AI Impact Assessment framework performs when applied within specific environmental regulatory settings. Empirical application would allow evaluation of its practical effectiveness and reveal potential adjustments required for different governance environments.

4. Governance Conditions of Algorithmic Sustainability

4.1. From Technical Robustness to Governance Conditions

Sustainability in AI-mediated environmental decision-making cannot be understood purely as a matter of technical performance. Technical metrics such as accuracy or robustness are necessary but insufficient: they capture only a narrow part of the conditions under which environmental decisions are produced. Much of the literature on responsible AI now provides formal guidance on fairness, transparency, and accountability [12,28]. These contributions have significantly shaped the ethics of algorithmic systems. Nevertheless, sustainability is often treated within this literature as an ethical aspiration rather than as a condition embedded within institutional governance.

Environmental governance unfolds within socio-technical regimes structured by regulatory authority, institutional arrangements, and political legitimacy [6,7]. Artificial intelligence introduced into these regimes inevitably alters the way knowledge is produced, risks are categorized, and policy priorities are formulated. In practice, algorithmic systems do not simply optimize decisions; they reshape the informational foundations on which decisions are based. The sustainability of such systems, therefore, depends less on algorithmic design alone than on the institutional architecture through which they are deployed and supervised.

For this reason, the concept of algorithmic sustainability is defined in this study as a governance condition requiring the simultaneous presence of several interdependent institutional safeguards. Building on the earlier synthesis, the analysis now treats the three dimensions identified—lifecycle carbon integrity, institutional accountability, and public value alignment—as explicit governance conditions. Sustainability is understood to arise only when these conditions are present simultaneously. None of these conditions can secure sustainability on its own. When one dimension is absent, the stability of the entire governance arrangement becomes uncertain.

4.2. Lifecycle Carbon Integrity

Lifecycle carbon integrity refers to the requirement that artificial intelligence systems introduced into environmental governance remain consistent with long-term ecological objectives throughout their technological lifecycle. This perspective recognizes that environmental impacts arise not only from the direct operation of AI systems but also from the infrastructure and systemic transformations that accompany their deployment.

4.2.1. Computational and Embodied Impacts

Artificial intelligence systems depend on large-scale digital infrastructure. Data centers, model training processes, and global hardware supply chains collectively generate substantial energy demand. Empirical research has demonstrated that training complex machine-learning models can involve considerable carbon emissions [25]. Subsequent studies examining the environmental footprint of artificial intelligence highlight additional lifecycle effects linked to hardware manufacturing and infrastructure expansion [24].

Kaack et al. (2022) provide a widely cited analytical framework distinguishing several categories of climate impact associated with AI deployment [3]. Their work differentiates computing-related

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emissions from immediate application effects and broader system-level responses. This layered perspective clarifies that the environmental implications of AI extend well beyond computational efficiency alone.

Lifecycle carbon integrity therefore requires transparent accounting of the environmental footprint associated with algorithmic systems. At minimum, governance arrangements must require disclosure of energy consumption during model training and inference, emissions embedded in hardware production, and the intensity of operational deployment. Without such transparency, claims of sustainability remain difficult to verify.

4.2.2. Immediate Environmental Effects

Artificial intelligence may contribute to environmental management through enhanced monitoring, predictive modelling, or improved allocation of regulatory resources. In certain contexts, these capabilities can reduce waste or improve operational efficiency. Yet such improvements must be assessed against appropriate baselines and within the broader trajectory of emissions reduction. Research on digital sustainability emphasizes that the environmental performance of software systems evolves throughout their lifecycle rather than remaining fixed at deployment (Kunkel et al., 2022). Environmental assessment must therefore be iterative. What appears efficient at one stage of technological development may become inefficient as usage patterns expand or infrastructure requirements increase.

4.2.3. System-Level and Rebound Dynamics

Long-term environmental consequences frequently arise through indirect system responses rather than through immediate technological effects. Efficiency gains may reduce operational costs and encourage increased activity, thereby offsetting anticipated environmental benefits. Kaack et al. (2022) describe such rebound dynamics as a central challenge in evaluating the climate implications of artificial intelligence [3].

From the perspective of socio-technical transitions theory, the introduction of digital optimization tools may also reshape broader economic and institutional structures [6]. If algorithmic optimization accelerates resource extraction or intensifies monitoring practices without structural reform, environmental outcomes may deteriorate rather than improve.

Based on this narrative, lifecycle carbon integrity cannot be ensured solely through performance metrics. It also requires governance arrangements that can identify indirect effects and assess system-wide changes. Sustainability is therefore not an automatic result of optimization; it is a quality that must be examined and verified through institutional processes.

4.3. Institutional Accountability

Environmental lifecycle analysis alone cannot secure sustainable governance. Effective oversight also requires institutional arrangements capable of evaluating and enforcing regulatory standards. Institutional accountability refers to the structured capacity of public authorities to supervise algorithmic systems and ensure compliance with established legal norms.

4.3.1. Accountability Relationships

Accountability operates through a relational structure in which decision-makers must justify their actions to a forum capable of evaluation and sanction [4]. When algorithmic systems mediate environmental decisions, these relationships can become less visible. Responsibility may appear to shift toward automated processes even when human institutions remain ultimately accountable. Research on regulatory governance emphasizes that legitimacy in complex regulatory systems depends on structured oversight mechanisms capable of questioning and reviewing decisions [5]. If algorithmic systems operate without such oversight, the authority of environmental governance institutions may gradually weaken. Institutional accountability therefore requires explicit allocation of responsibility for algorithmic decisions, the establishment of review forums, and the practical ability to question and sanction system behavior.

4.3.2. Auditability and Oversight Mechanisms

Public audit institutions increasingly encounter algorithmic decision systems within regulatory processes. Studies of emerging audit practices indicate that AI-enabled systems introduce new challenges extending beyond conventional financial auditing, including evaluation of training data, validation procedures, and potential algorithmic bias [18].

Technical evaluation tools provide partial support for such oversight. Work on trustworthy artificial intelligence proposes metrics related to robustness, interpretability, and bias detection [19,26]. Yet technical metrics alone cannot ensure effective governance. Without institutional authority to interpret and enforce these assessments, such metrics remain advisory rather than binding. In practice, accountability requires the integration of technical evaluation within formal oversight procedures. Possible mechanisms include independent algorithmic audits, documentation requirements for model development, and periodic reassessment of system performance.

4.3.3. Institutional Capacity and Feasibility

Oversight mechanisms are effective only when supported by adequate administrative capacity. Studies examining artificial intelligence adoption in the public sector highlight persistent challenges related to organizational readiness, digital infrastructure, and workforce expertise [1]. These limitations can restrict the ability of institutions to supervise complex algorithmic systems.

Institutional economics further suggests that governance frameworks must align with enforcement capacity if regulatory commitments are to remain credible [10]. High-impact AI systems introduced without corresponding oversight capabilities risk creating governance gaps in which responsibility exists formally but cannot be exercised in practice. Institutional feasibility is integral to accountability. Oversight mechanisms are effective only when supported by sufficient administrative capacity; otherwise, responsibility remains formal but unenforceable.

4.4. Public Value Alignment

Environmental governance inevitably involves normative judgement. Decisions regarding land use, conservation priorities, or enforcement allocation produce distributive consequences that extend beyond technical optimization. Artificial intelligence systems that influence these decisions must therefore remain aligned with public values and democratic legitimacy.

4.4.1. Transparency and Interpretability

Research on artificial intelligence in public governance emphasizes the importance of transparency for maintaining institutional trust [11]. When algorithmic systems influence environmental outcomes, affected stakeholders must be able to understand how decisions are produced. Scholarship examining algorithmic ethics demonstrates that opaque models may conceal biases or embed assumptions that remain invisible to decision-makers [12,29]. Public value alignment therefore requires interpretability proportional to the significance of the decision being made.

4.4.2. Justice and Autonomy

Environmental governance also raises questions of justice and political agency. Decisions about climate mitigation or conservation policy frequently involve the distribution of costs and benefits among communities. Ethical analyses of artificial intelligence emphasize that technological interventions should respect both distributive justice and individual autonomy [13]. Related work examining behavioral interventions suggests that AI-driven nudging systems may raise concerns regarding autonomy when deployed without adequate safeguards [14]. Environmental AI systems must therefore incorporate protections that prevent discrimination or coercive influence.

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4.4.3. Normative Standards and International Principles

Global governance frameworks increasingly reflect these ethical concerns. The UNESCO Recommendation on the Ethics of Artificial Intelligence (2021) emphasizes environmental stewardship, transparency, and human rights protection as core governance principles [15]. The OECD Principles on Artificial Intelligence (2019) similarly stress accountability and responsible oversight in public-sector AI deployment [16]. Together, these frameworks signal a broader shift in policy thinking. Artificial intelligence systems are no longer evaluated solely in terms of technical capability; they are assessed in relation to the public values that democratic institutions seek to uphold.

4.5. Interdependence of Governance Conditions

The governance conditions identified above operate in an interdependent manner. None can secure sustainability in isolation. Lifecycle carbon integrity without institutional accountability leaves environmental claims unenforced. Institutional accountability without public value alignment risks technocratic governance detached from legitimacy. Public value alignment without environmental integrity may legitimize environmentally harmful systems. The interdependence of these conditions mirrors insights from social-ecological systems research, which stresses that sustainable governance emerges from interactions across multiple institutional layers rather than from isolated interventions [20].

Table 2. Interdependent Governance Conditions.

Condition	Core Risk if Absent	Governance Consequence
Lifecycle Carbon Integrity	Hidden emissions and rebound dynamics	Unsustainable environmental trajectory
Institutional Accountability	Opaque decision systems	Regulatory capture or governance failure
Public Value Alignment	Legitimacy deficit	Erosion of democratic trust

Algorithmic sustainability therefore functions less as a technical attribute than as a governance architecture. It situates artificial intelligence systems within institutional ecosystems and ecological constraints rather than treating them as isolated optimization tools.

The following section translates these governance conditions into the operational structure of the Environmental AI Impact Assessment framework.

5. The Environmental AI Impact Assessment (EAIA)

5.1. From Governance Conditions to an Operational Instrument

The preceding analysis established that algorithmic sustainability depends on three governance conditions: lifecycle carbon integrity, institutional accountability, and alignment with public values. Conceptual principles alone, however, rarely influence administrative practice unless they are translated into operational decision tools. Environmental governance has long relied on such instruments. Environmental Impact Assessments (EIAs) and Strategic Environmental Assessments (SEAs), for example, connect scientific knowledge with regulatory judgment before projects are implemented. AI-mediated environmental decision systems increasingly operate within similar institutional contexts. When algorithmic models influence land classification, biodiversity monitoring, or enforcement prioritization, their role extends beyond analytical support and begins to shape regulatory outcomes. Governance frameworks must therefore anticipate systemic consequences before technological deployment becomes embedded in administrative routines.

The Environmental AI Impact Assessment (EAIA) is proposed as an institutional instrument for this purpose. Rather than focusing on computational performance alone, the EAIA evaluates whether

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AI systems used in environmental governance satisfy the three conditions of algorithmic sustainability identified in Section 4. The framework follows a proportional governance logic consistent with regulatory scholarship [5,16]. Oversight intensity increases as the environmental and distributive consequences of algorithmic decisions expand. Experience in environmental regulation suggests that assessment mechanisms are most effective when applied early in the policy cycle. For this reason, the EAIA highlights pre-deployment evaluation rather than retrospective correction. 5.2. Proportional Governance Logic

Because AI applications in environmental governance vary widely in their potential ecological and distributive impacts, the EAIA adopts a three-tier proportional structure in which oversight intensity increases with systemic consequence. Some systems perform internal administrative tasks with minimal external impact, whereas others shape policy outcomes by influencing how environmental risks are classified or how regulatory resources are distributed.

Regulatory proportionality doctrine suggests that oversight requirements should correspond to the scale of potential impact [5]. Excessive regulation of low-impact systems may produce administrative inefficiency, while insufficient oversight of high-impact applications can generate environmental or governance risks. The EAIA therefore adopts a three-tier classification structure reflecting increasing systemic influence. Tier assignment considers both environmental consequence and governance implications, recognizing that algorithmic interventions often reshape ecological outcomes and institutional decision processes simultaneously [6,7].

5.2. Tier Classification Framework

Tier classification occurs before deployment and remains adaptable across jurisdictions. The structure of this classification framework and the corresponding oversight intensity are summarized in Table 3.

Table 3. EAIA Tier Classification Structure.

Tier	Environmental Impact	Governance/Distributive Impact	Oversight Intensity
Tier I	Minimal or indirect environmental consequence	Limited distributive impact	Basic documentation and disclosure
Tier II	Moderate environmental influence	Noticeable policy or allocation effects	Lifecycle review and internal audit
Tier III	High systemic environmental consequence	Significant distributive or regulatory implications	Full lifecycle assessment, independent audit, periodic reassessment

Illustratively, internal administrative data tools generally fall within Tier I because their environmental and distributive effects are limited. Predictive pollution monitoring models affecting inspection scheduling may correspond to Tier II. Systems determining conservation zoning or enforcement priorities typically fall within Tier III because of their systemic environmental implications. The framework intentionally avoids reference to particular jurisdictions or technologies in order to maintain legal neutrality and broad applicability.

5.3. Operational Criteria by Governance Condition

To support institutional evaluation, the EAIA translates each governance condition into practical assessment criteria. These criteria guide administrative scrutiny without prescribing specific technological solutions.

5.3.1. Lifecycle Carbon Integrity

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Lifecycle carbon integrity concerns the environmental impacts associated with computational infrastructure supporting artificial intelligence systems. Evaluation considers energy consumption during model training and inference, the energy sourcing of data centers, and hardware lifecycle emissions. Hardware production and replacement cycles can generate substantial embodied carbon. The assessment therefore includes expected operational lifespan and replacement frequency. Indirect environmental effects must also be considered. Efficiency improvements achieved through algorithmic optimization can reduce costs and stimulate additional activity, potentially offsetting environmental gains. For this reason, lifecycle evaluation includes rebound dynamics and broader system-level effects.

Finally, environmental performance is examined relative to an appropriate baseline scenario to determine whether algorithmic deployment produces a net ecological benefit. This approach aligns with lifecycle analyses of digital technologies [3,25] and with systems-oriented sustainability research [20]. Therefore, Tier III systems require independent verification of lifecycle accounting.

5.3.2. Institutional Accountability

Institutional accountability examines whether public authorities maintain sufficient oversight when environmental decisions are made using algorithmic systems. Responsibility for operating these systems must be clearly assigned within administrative structures so that decision-making authority remains identifiable. Effective oversight also requires auditability. Documentation of data sources, model validation procedures, and system updates enables external scrutiny and regulatory review. Without such records, lines of accountability can become unclear. Institutional evaluation also considers whether appropriate oversight bodies exist and whether procedures allow for regular reassessment of system performance. These mechanisms ensure that algorithmic decisions remain subject to review as environmental and governance conditions evolve. The criteria reflect accountability theory [4], regulatory governance scholarship (Black, 2008), and emerging research on algorithmic auditing [18,26]. Tier III systems require independent audit structures rather than internal review alone.

5.3.3. Public Value Alignment

Environmental governance involves normative judgments concerning the distribution of ecological resources and regulatory obligations. AI systems that influence these decisions must remain consistent with principles of transparency, fairness, and democratic legitimacy. Transparency assessment examines whether the objectives and reasoning guiding algorithmic decisions can be communicated in accessible terms. Evaluation also considers potential distributive impacts, recognizing that algorithmic models may reproduce historical inequalities if data limitations or optimization choices are left unexamined. Procedural safeguards are equally important. Individuals or communities affected by algorithmic decisions should retain the ability to contest outcomes, and human oversight must remain available for review. Assessment also considers alignment with international governance standards such as the UNESCO Recommendation on the Ethics of Artificial Intelligence (2021) and the OECD Principles on Artificial Intelligence (2019) [15,16]. These criteria draw on public value research [11], algorithmic ethics scholarship [12,29], and climate justice analysis [13]. The analytical relationship between the three governance conditions and their associated evaluation criteria within the Environmental AI Impact Assessment framework is illustrated in Figure 1.

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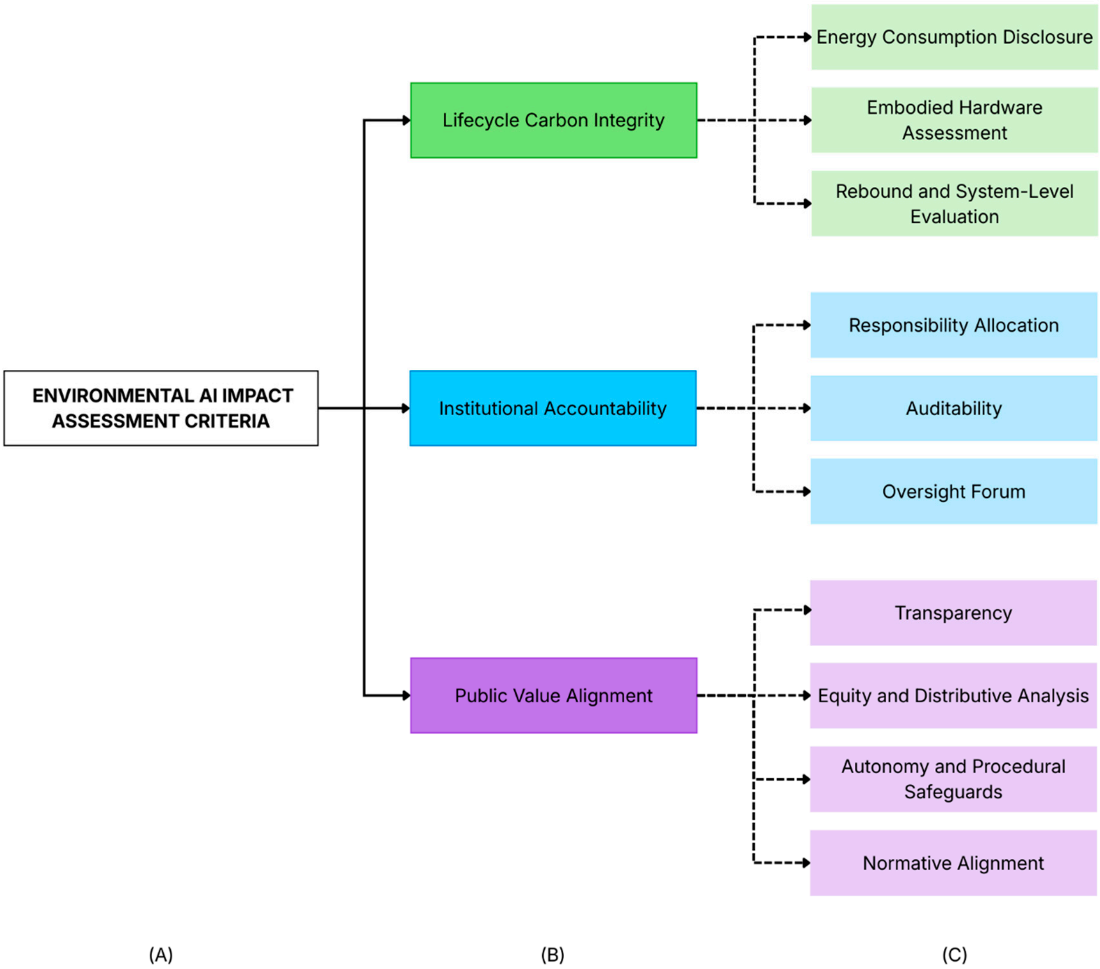

Figure 1. Relationship between governance conditions and Environmental AI Impact Assessment (EAIA) criteria.

5.4. Integrating the EAIA Within Institutional Practice

Governance frameworks rarely succeed unless they are embedded within existing institutional procedures. Institutional economics underlines that regulatory instruments must correspond to enforcement capacity if they are to influence performance [10]. The EAIA may therefore be incorporated within environmental permitting systems, digital governance strategies, or the mandates of public audit institutions. Each pathway allows algorithmic oversight to become part of routine administrative practice. Administrative readiness varies widely across jurisdictions. Studies of public-sector AI governance reveal substantial differences in institutional capacity and digital maturity [1,30,31]. For this reason, the EAIA is designed as a scalable framework: low-impact systems require limited documentation, whereas high-impact deployments may involve more intensive oversight and inter-agency coordination. Experience from environmental regulation suggests that gradual institutional integration often proves more effective than abrupt regulatory expansion.

5.5. Reflexive Governance and Adaptive Review

Environmental governance operates under conditions of uncertainty and evolving knowledge. Reflexive governance theory features adaptive oversight mechanisms capable of responding to changing circumstances [32]. The EAIA incorporates periodic reassessment cycles through which algorithmic systems may be reclassified if environmental consequences evolve or if substantial model retraining alters decision actions. Review may also be triggered when new environmental evidence emerges or when regulatory priorities shift. Such adaptive oversight reduces the risk that digital infrastructures become rigid elements of administrative practice. Without periodic review,

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technological dependence may deepen and create forms of institutional lock-in [9]. The operational workflow of this governance instrument is illustrated in Figure 2.

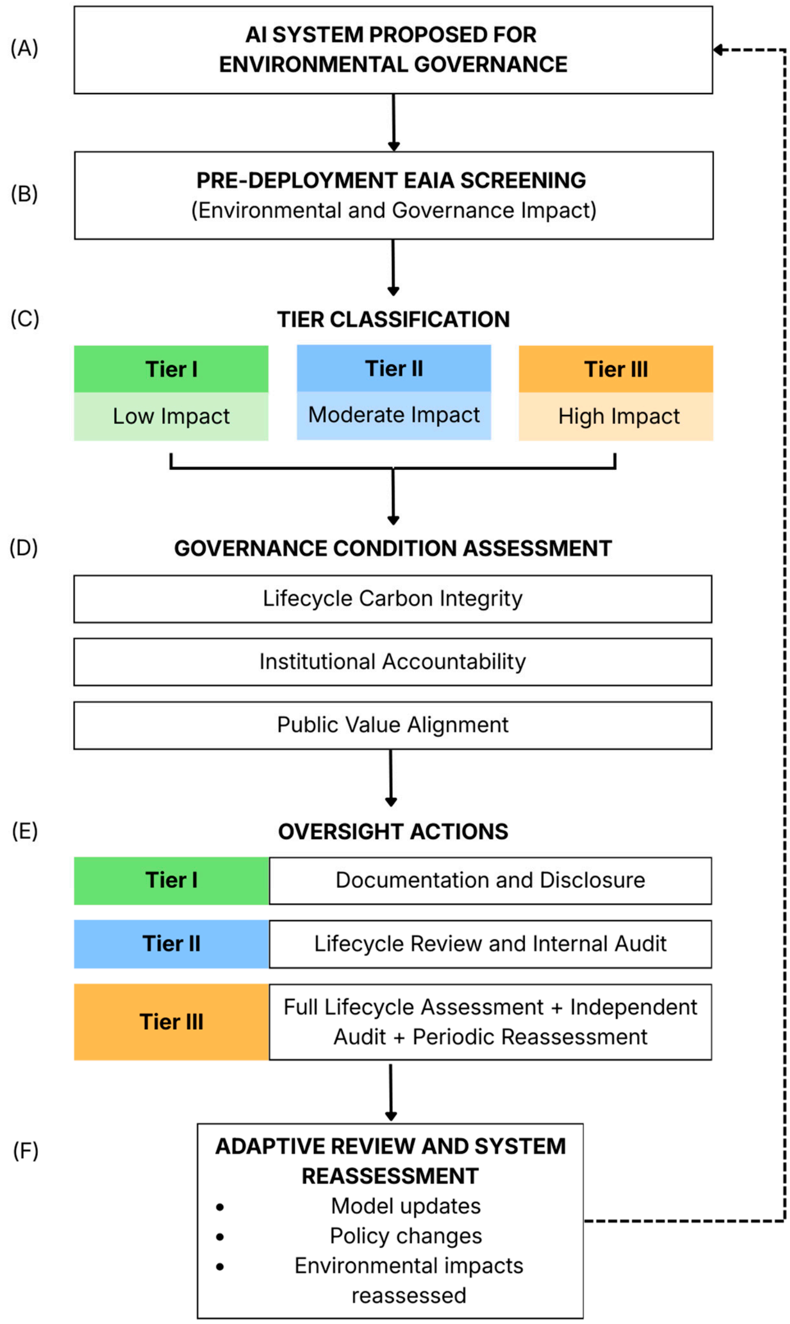

Figure 2. Environmental AI Impact Assessment (EAIA) governance workflow. AI systems proposed for environmental governance undergo pre-deployment screening and are classified into three proportional governance tiers based on environmental and governance impact. Each tier is evaluated against three governance conditions: lifecycle carbon integrity, institutional accountability, and public value alignment. With oversight intensity increasing with systemic impact. Adaptive review mechanisms allow periodic reassessment as models, policies, or environmental conditions evolve.

5.6. Distinction from Existing Responsible AI Frameworks

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Existing responsible-AI frameworks focus primarily on ethical principles such as fairness, transparency, and robustness. EAIA extends this orientation by integrating explicit lifecycle carbon accounting, proportional oversight tiers, and institutional feasibility into a single governance instrument tailored to environmental decision systems [28,33]. Yet these approaches typically focus on algorithmic behavior rather than on the environmental and institutional contexts in which systems operate. By situating AI within environmental governance systems, the framework aligns AI evaluation with sustainability transitions scholarship [7]. Algorithmic sustainability thus shifts from a set of normative principles toward an operational governance architecture capable of guiding real-world environmental decision-making. Taken together, EAIA moves beyond checking whether an AI system is only fair, transparent, or technically robust in the abstract. It asks how these systems fit into real environmental institutions, with their specific rules, constraints, and responsibilities over time. By linking lifecycle impacts, regulatory tiers, and institutional capacity, EAIA turns high-level principles into a practical way to judge if and how AI should be used in environmental governance.

Table 4. Distinction between general Responsible AI frameworks and the Environmental AI Impact Assessment (EAIA).

Dimension	Responsible AI Frameworks	Environmental AI Impact Assessment (EAIA)
Primary Focus	Ethical principles (fairness, transparency, robustness)	Governance conditions integrating environmental and institutional sustainability
Lifecycle Carbon Accounting	Rarely integrated	Explicitly required as core condition
Rebound / System-Level Effects	Typically absent	Integrated within lifecycle carbon integrity assessment
Proportional Oversight Logic	Often uniform guidance	Tiered, risk-based regulatory structure
Institutional Accountability	Frequently principle-based	Structured audit and oversight mechanisms
Administrative Feasibility	Often implicit	Explicit alignment with institutional capacity
Environmental Governance Integration	Limited	Designed specifically for environmental decision systems
Reflexive Reassessment	Not consistently defined	Mandatory periodic reassessment for high-impact systems

5.7. Illustrative Application of the Environmental AI Impact Assessment

To clarify operational implications, this subsection presents a hypothetical application of the Environmental AI Impact Assessment (EAIA) within a sustainable energy planning context. The scenario concerns an AI-based decision-support system used by a regional environmental authority to prioritize coastal sites for renewable energy infrastructure under a climate adaptation strategy. The proposed system influences long-term infrastructure siting, land-use allocation, and coastal ecosystem management. Because it carries both significant environmental consequences and distributive governance implications, it would be classified as Tier III under the EAIA proportional framework. Tier III designation triggers the highest level of oversight intensity.

5.7.1. Lifecycle Carbon Integrity Assessment

Under Tier III requirements, the authority would disclose:

- Estimated computational energy demand associated with model training and periodic retraining
- Data center sourcing information

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- Hardware lifecycle expectations and replacement frequency

In addition, a system-level evaluation would assess whether optimization logic could indirectly accelerate coastal infrastructure expansion in environmentally sensitive zones. A baseline comparison would determine whether the AI-supported approach produces net lifecycle environmental benefits relative to conventional planning processes.

5.7.2. Institutional Accountability Review Assessment

Tier III status would require:

- Clear designation of the accountable regulatory authority
- Documentation of data sources and model validation procedures
- Independent audit capacity for reviewing algorithmic outputs
- Scheduled reassessment intervals, particularly following major model updates

This ensures that algorithmic recommendations remain reviewable and contestable within established administrative structures.

5.7.3. Public Value Alignment Evaluation

Given the distributive implications of infrastructure siting, the authority would assess:

- Transparency of prioritization criteria
- Potential regional inequities in site allocation
- Mechanisms allowing affected communities to contest decisions

Human oversight provisions would remain mandatory for final siting approval.

6. Policy Implications and Governance Pathways

6.1. From Framework to Institutional Integration

The Environmental AI Impact Assessment (EAIA) is not intended as a standalone compliance mechanism. Its policy relevance depends on integration within existing environmental governance architectures. Environmental decision systems already operate within regulatory ecosystems that include environmental impact assessments, permitting regimes, sustainability reporting frameworks, and public audit oversight. Rather than creating a new regulatory layer, the EAIA is designed to operate within these established institutional processes.

According to regulatory scholarship, governance instruments are most likely to succeed when embedded in familiar administrative routines [5]. Institutional layering often proves more effective than institutional proliferation. Accordingly, the EAIA may be incorporated into environmental impact assessment procedures, digital governance oversight protocols, public audit mandates, or strategic sustainability planning frameworks. Such integration reduces administrative friction and improves feasibility.

6.2. Relevance to Sustainable Energy and Environmental Planning

Although the article does not focus on energy system modelling, its governance implications are directly relevant to sustainable energy planning. Artificial intelligence is increasingly used in renewable energy forecasting, grid optimization, infrastructure siting, emissions modelling, and resource allocation. Decisions supported by these systems can influence long-term investment pathways and infrastructure development.

Sustainability transitions research demonstrates that infrastructural decisions create durable path dependencies within socio-technical systems [6,7]. Algorithmic mediation of such decisions therefore has structural implications. Lifecycle carbon integrity is particularly relevant in this context. Machine learning systems used in energy planning rely on computational infrastructure that generates environmental impacts of its own. Although these impacts are generally small relative to

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physical infrastructure emissions, transparent evaluation remains necessary. The EAIA does not replace energy system analysis; it provides a governance layer ensuring that algorithmic tools used in environmental planning remain subject to environmental and institutional safeguards.

6.3. Institutional Capacity, Accountability, and Public Trust

Because institutional capacity for AI governance varies widely, the EAIA adopts a proportional structure that matches oversight requirements to available administrative resources. Research on public-sector AI adoption shows uneven levels of digital infrastructure, technical expertise, and regulatory readiness within government institutions [1]. These differences influence the feasibility of governance frameworks designed to oversee algorithmic decision systems.

The EAIA addresses this challenge through a proportional oversight structure. Systems with limited environmental or governance impact require basic documentation and internal review, while higher-impact deployments require lifecycle evaluation, accountability assessment, and, where appropriate, independent audit procedures. Differentiated oversight aligns governance requirements with administrative capacity while preserving safeguards for systems capable of producing significant environmental consequences. Institutional economics similarly underlines that regulatory instruments must correspond to enforcement capacity to avoid symbolic compliance [10].

Public audit institutions are likely to play an expanding role in this governance landscape. As algorithmic systems become embedded within administrative decision processes, traditional oversight models focused on financial compliance must adapt to evaluate digital decision infrastructures. Research highlights the growing importance of algorithmic oversight in public-sector auditing [18], including scrutiny of data provenance, model validation procedures, and system revision histories. The EAIA contributes to this evolving oversight architecture by providing structured evaluation criteria and documentation expectations for institutional review. Periodic reassessment helps ensure that environmental decision systems remain transparent and subject to governance scrutiny rather than becoming opaque administrative tools. Accountability mechanisms of this kind strengthen regulatory legitimacy by preserving the ability of public institutions to review algorithmic decisions [4].

Institutional oversight is also essential for sustaining public trust. Research on public values in AI governance stresses the importance of transparency, accountability, and procedural fairness [11,12]. Because environmental governance often involves distributive consequences, algorithmic systems influencing regulatory enforcement or resource allocation require clear communication of objectives and accessible decision criteria.

Public value alignment, therefore, requires mechanisms through which affected stakeholders can understand and contest algorithmic decisions when necessary. These safeguards align with international governance principles such as the UNESCO Recommendation on the Ethics of Artificial Intelligence (2021) and the OECD AI Principles (2019) [15,16]. The legitimacy of AI-mediated environmental governance depends not only on its technical performance but also on transparent, accountable institutional processes.

6.4. Preventing Infrastructural Lock-In and Technocratic Drift

As previously noted, the infrastructural embedding of AI can create lock-in and reduce the flexibility of environmental institutions. To counter this, the EAIA incorporates mechanisms for periodic reassessment and tier reclassification. Digital decision systems can gradually reshape regulatory practices, data standards, and administrative routines in ways that become difficult to reverse. Research on AI infrastructures warns that large-scale computational systems may produce unsustainable trajectories when governance oversight is weak [9]. Governance frameworks must therefore include mechanisms for reassessing algorithmic systems as technologies, environmental conditions, and policy priorities evolve. Reflexive governance scholarship highlights that sustainability challenges involve complex socio-technical systems requiring adaptive oversight rather than single optimal solutions [32]. The EAIA reflects this perspective through periodic

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reassessment cycles, review triggers following major model updates, and tier reclassification when environmental impacts change. Such mechanisms reduce the risk that algorithmic systems become entrenched components of governance infrastructure.

AI-mediated decision systems may also generate technocratic drift. Optimization metrics embedded within algorithmic models can gradually displace normative deliberation about environmental priorities. Yet environmental governance inevitably involves ethical and political judgments regarding the distribution of ecological resources and regulatory responsibilities. Scholars of technology ethics emphasize that climate governance must remain attentive to justice and political agency [13]. Behavioral optimization tools may raise similar concerns when safeguards for democratic oversight remain weak [14]. The EAIA does not seek to eliminate algorithmic decision tools. Instead, it ensures that algorithmic mediation remains embedded within accountable institutional processes. Human oversight remains essential, particularly for high-impact systems influencing land-use classification, conservation prioritization, or regulatory enforcement. By combining adaptive review with democratic safeguards, the framework aims to ensure that technological innovation supports rather than displaces environmental governance objectives.

6.5. International Governance and Policy Convergence

International governance frameworks increasingly recognize the environmental implications of artificial intelligence. The UNESCO Recommendation on the Ethics of Artificial Intelligence (2021) identifies environmental sustainability as a governance principle, while the OECD AI Principles (2019) emphasize accountability and robustness in public-sector deployment[15,16]. The EAIA contributes to this governance landscape by operationalizing sustainability criteria within AI deployment. Integration may occur through national AI strategies, environmental ministry policies, or digital governance guidelines. At the same time, governance diversity remains important. Polycentric governance research highlights the value of institutional diversity in managing complex environmental systems [20]. This tiered structure is compatible with polycentric governance arrangements, supporting adaptation across diverse institutional contexts.

6.6. Scope and Caution

The EAIA functions as a structured evaluative framework rather than a guarantee of sustainability outcomes. Implementation challenges remain, including limited technical expertise within public institutions, rapid technological evolution, and incomplete lifecycle emissions data. Empirical application of the framework across environmental governance settings will therefore be necessary to evaluate operational feasibility. Nevertheless, integrating lifecycle carbon integrity, institutional accountability, and public value alignment into environmental AI governance represents an important step toward ensuring that algorithmic systems contribute to long-term sustainability rather than undermining it.

7. Conclusions

Artificial intelligence (AI) is becoming progressively embedded within the institutional architecture of environmental governance. Its use increasingly shapes how environmental risks are interpreted, how regulatory priorities are established, and how resources are allocated across competing ecological objectives. These transformations extend beyond improvements in computational efficiency. What may appear at first glance as a technical enhancement can, over time, recalibrate institutional routines in ways that are not immediately visible. In practice, algorithmic systems influence the structure of accountability, the articulation of public values, and the trajectory of sustainability policies over time.

This study has argued that sustainability in AI-mediated environmental decision systems should be understood as a condition of governance rather than as a property of algorithmic performance. The analysis shows that technical performance alone cannot sustain environmental responsibility.

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Without attention to lifecycle impacts, institutional oversight, and public legitimacy, AI-mediated systems may undermine the very sustainability goals they are meant to support. In practice, the difficulty rarely lies in defining sustainability principles, but in ensuring that institutions are equipped to uphold them consistently. Through structured interdisciplinary synthesis, the analysis identified three governance conditions that repeatedly emerge across the literature on sustainability transitions, institutional economics, artificial intelligence ethics, and public administration. These conditions relate to lifecycle carbon integrity, institutional accountability, and alignment with public values. Each addresses a distinct dimension of algorithmic governance, yet their practical significance lies in their interaction.

Lifecycle carbon integrity ensures that artificial intelligence systems deployed for environmental objectives do not generate hidden computational or infrastructural emissions that offset intended ecological gains. Institutional accountability embeds algorithmic decision systems within formal oversight arrangements capable of review, contestation, and sanction. Public value alignment ensures that decisions influenced by artificial intelligence remain consistent with principles of transparency, fairness, and democratic legitimacy. Each dimension becomes fragile when detached from the others. Their effectiveness depends on their combined operation within institutional governance structures.

To translate these governance conditions into a practical analytical tool, the article introduced the Environmental AI Impact Assessment (EAIA). The EAIA functions as a proportional governance instrument designed to calibrate oversight intensity to the systemic impact of algorithmic decision systems. Rather than replacing environmental modelling or policy analysis, the framework provides an institutional layer of evaluation through which artificial intelligence systems can be assessed in relation to accountability, transparency, and environmental integrity. This study contributes at a conceptual level by bringing together strands of scholarship that are frequently treated in isolation: lifecycle environmental analysis of digital infrastructure, institutional governance theory, public administration research on algorithmic systems, and the ethics of artificial intelligence. Bringing these perspectives together reveals an important gap in existing responsible AI frameworks. While many current approaches emphasize fairness or transparency, they often pay insufficient attention to environmental lifecycle impacts and to the institutional feasibility of oversight mechanisms.

The analysis also highlights a broader insight. Algorithmic sustainability is not a technological feature embedded within code or model architecture. It emerges from the institutional conditions under which artificial intelligence is governed. As AI systems increasingly operate as infrastructural components of environmental planning, climate modelling, and resource management, governance structures will determine whether digital technologies reinforce or undermine sustainability transitions. Early integration of proportional oversight mechanisms may therefore reduce the risk of technological lock-in while strengthening the adaptive capacity of environmental institutions.

Limitations and Future Research

The framework is subject to important constraints that merit careful consideration. The framework proposed here remains conceptual and requires empirical application within specific governance contexts. Methods for measuring the lifecycle emissions of digital infrastructure are still evolving, and institutional capacity for algorithmic oversight varies widely across jurisdictions. Future research may therefore apply the Environmental AI Impact Assessment (EAIA) framework within concrete policy domains, such as land-use planning, climate risk modelling, or energy system governance, in order to evaluate its practical effectiveness and institutional feasibility.

Even so, the findings underline a central point that is sometimes overlooked in discussions of technological innovation. Environmental governance has always required institutional restraint as much as technical capability. Environmental sustainability cannot be delegated to algorithmic optimization alone. Without appropriate governance structures, artificial intelligence systems designed to advance sustainability may unintentionally introduce new environmental burdens, obscure accountability, or weaken public legitimacy. As digital infrastructures continue to expand within environmental governance, the relevant policy question is unlikely to be whether artificial intelligence should be used. A more consequential question concerns the conditions under which its use can remain compatible with ecological responsibility and democratic oversight. The concept of algorithmic sustainability developed in this study provides a structured starting point for addressing that challenge.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
EAIA	Environmental Artificial Intelligence Impact Assessment
EU	European Union
IPCC	Intergovernmental Panel on Climate Change
ITU	International Telecommunication Union
OECD	Organization for Economic Co-operation and Development
UN	United Nations
UNEP	United Nations Environment Programme
UNESCO	United Nations Educational, Scientific and Cultural Organization

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