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A critical review of trusted environmental intelligence using cloud, blockchain, and generative AI

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Abstract
Environmental Intelligence (EI) has become a crucial field for tackling complex ecological issues of the Anthropocene. It utilises large datasets to guide policy, conservation, and sustainable development. The combination of Cloud Computing, Blockchain Technology, and Generative Artificial Intelligence (GenAI) introduces a new concept called "Trusted Environmental Intelligence," a system aimed at ensuring data integrity, transparency, and meaningful insights. This review critically evaluates the promises and actual limitations of this technological mix. It shows that, while these technologies offer significant potential for scalable processing, immutable data records, and advanced synthetic modelling, they also face serious problems, including high energy use, governance issues, algorithmic bias, and the challenge of balancing decentralisation with regulation. By examining current research and identifying key gaps, this article argues that building truly trusted EI is more of a social and technical challenge than just a technological one, requiring a shift from quick fixes to a framework rooted in critical data studies and environmental justice.

Keywords: Environmental Intelligence, Trusted Environmental Intelligence, Cloud Computing, Blockchain Technology, Generative Artificial Intelligence (GenAI)

Introduction

The rising climate crisis, combined with unprecedented rates of biodiversity loss and pollution, has made traditional environmental monitoring and governance models less effective. The large volume, speed, and variety of environmental data from satellites, IoT sensors, and citizen science efforts demand advanced analytical methods [1]. This has led to the emergence of Environmental Intelligence (EI), an interdisciplinary field that integrates environmental science with data science, artificial intelligence, and high-performance computing to generate practical insights [2].

In recent years, a compelling narrative has emerged within both academic literature and industry discourse: the convergence of three foundational technologies, Cloud, Blockchain, and Generative AI, can create a new generation of "Trusted Environmental Intelligence" systems [3]. The premise is alluring. Cloud computing provides virtually unlimited scalability and storage needed to manage planetary-scale datasets [4]. Blockchain technology offers an immutable, decentralised ledger that ensures verifiable provenance and transparency for environmental data and carbon credits, thereby addressing greenwashing [5]. Generative AI, with its ability to synthesise data, develop predictive models, and generate innovative scenarios, holds the potential to simulate complex environmental systems and enhance decision-making [6].

However, this technological triumvirate is often presented with an air of solutionism, where technological capability is conflated with practical efficacy and ethical neutrality [7]. This review critically examines this convergence. It goes beyond descriptive accounts of each technology's features to question the foundational assumptions underpinning the notion of "trust" in environmental intelligence. How is trust being redefined? What are the epistemological, political, and material costs of building such systems?

The objective of this article is threefold. First, to synthesise and critically analyse the existing literature on the application of cloud, blockchain, and generative AI within environmental contexts. Second, to identify significant, often overlooked tensions and contradictions—such as the energy footprint of blockchain-based environmental monitoring and the inherent biases in AI models trained on Western-centric data. Third, to propose a research agenda that prioritises socio-technical integration, environmental justice, and critical reflexivity over technological determinism.

The Cloud as Foundational Infrastructure: Scale, Access, and Centralisation

The rise of cloud computing has arguably become the most important factor enabling modern Environmental Intelligence. Before its widespread adoption, environmental modelling faced limitations due to on-premise supercomputers and fragmented data storage [8]. Cloud platforms, mainly Amazon Web Services (AWS), Microsoft Azure, and Google Cloud Platform, now provide flexible, on-demand computing resources and petabyte-scale storage to host and process data from sources such as the European Space Agency's Copernicus program and NASA's Earth Observing System [9].

1. Democratisation or Aggregation?

One of the main promises of cloud-based EI is democratisation. By offering access to high-performance computing with a pay-as-you-go model, cloud platforms supposedly lower barriers for researchers and institutions in the Global South, who have historically been marginalised in global environmental research [10]. Public cloud data archives, such as the AWS Earth data repository, host large, open datasets, enabling collaborative analysis that extends beyond institutional boundaries [11].

However, this narrative of democratisation hides a deeper trend of data concentration and corporate centralisation. A few multinational corporations now control the essential infrastructure for global environmental science [12]. This creates a significant power imbalance. When private entities own the infrastructure for monitoring planetary health, questions about data sovereignty, pricing strategies, and long-term access stability arise. Research shows that dependence on proprietary cloud services can lock institutions into specific systems, leading to vendor lock-in that conflicts with the open-science principles often promoted by the environmental community [13].

2. The Latency and Autonomy Problem

Another critical limitation is the cloud computing architecture itself. Centralised data processing introduces latency that can be problematic for time-sensitive environmental applications, such as real-time flood forecasting or wildfire detection [14]. The need to transmit raw data from remote sensors (e.g., in rainforests or deep oceans) to a centralised cloud data centre for processing is both bandwidth-intensive and slow.

This has sparked interest in edge and fog computing paradigms, where processing occurs closer to the data source [15]. A critical review of the literature reveals a growing tension: while cloud computing is praised for its centralized strength, the future of effective EI may depend on distributed architectures that challenge its dominance. Table 1 summarizes the key characteristics and tensions related to cloud computing in EI.

Table 1: Contrasting Perspectives on Cloud Computing in Environmental Intelligence

Dimension	Promised Benefit	Critical Tension / Limitation
Scalability	Handles planetary-scale datasets (e.g., satellite imagery) [9].	Resource-intensive; cost can become prohibitive for long-term projects [12].
Accessibility	Democratizes access to high-performance computing and data [11].	Creates vendor lock-in; centralises power in a few corporate entities [13].
Data Processing	Enables complex, global-scale models and analytics [8].	Introduces latency; unsuitable for real-time applications without edge integration [14].
Data Storage	Provides durable, centralised data lakes and archives [4].	Raises concerns about data sovereignty, privacy, and long-term archival funding [10].

The cloud, therefore, acts as a necessary but incomplete foundation. Its centralization challenges the idea of a decentralized, trusted system. This paradox paves the way for blockchain, which is often seen as a technological solution to the concentration of power.

Blockchain for Immutable Provenance: Transparency or Greenwashing?

Blockchain technology has been praised as a revolutionary way to build trust in environmental markets and supply chains. Its primary feature, an immutable, distributed ledger, offers a robust solution to the common problem of data integrity in environmental governance [16]. From carbon credit markets to sustainable supply chain certification, supporters assert that blockchain can provide transparent, verifiable information needed to prevent fraud and greenwashing [17].

1. Trust through Disintermediation

The core idea is that blockchain replaces trust in central authorities (e.g., certification bodies, government agencies) with cryptographic verification and consensus mechanisms [18]. In the context of EI, this is most clearly applied to carbon offset markets. Traditional carbon credits have faced issues such as double-counting, questionable additionality, and a lack of transparency [19]. Blockchain-based registries aim to establish a single source of truth, where each credit is tokenised, its lifecycle is permanently recorded, and its retirement is clearly visible to all participants [20].

Similarly, in supply chain monitoring for commodities like timber, palm oil, and seafood, blockchain can create an unchangeable record of custody [21]. When used with IoT sensors, data from a logger can be cryptographically protected for a retailer, providing consumers and regulators with unmatched visibility into a product's environmental impact [22].

2. The Paradox of Immutability and the Oracle Problem

Despite these promises, a critical analysis reveals fundamental challenges. The most notable is the "oracle problem." A blockchain's reliability depends on the accuracy of the data entered into it [23]. Although the ledger itself is immutable, the process of transferring off-chain environmental data (e.g., sensor readings, manual certifications) onto-chain introduces a major vulnerability. If an IoT sensor is faulty, compromised, or if a human actor submits fraudulent data, the blockchain permanently records that false information. The technology guarantees data integrity after entry but cannot verify the accuracy of the initial data point. As one critical commentary notes, blockchain can turn a lie into an immutable truth [24].

Another major tension lies in how these systems are governed. Many environmental blockchain projects use public, permissionless networks (like Ethereum) to enhance transparency [25]. However, these networks often rely on energy-intensive consensus mechanisms such as Proof-of-Work (PoW), which have a large carbon footprint—a contradiction for a technology designed to promote environmental sustainability [26]. Although a shift to more energy-efficient models, such as Proof-of-Stake (PoS), is underway, the long-standing association with high energy use and the ongoing presence of PoW chains raise important questions about whether the technology truly benefits the environment [27].

Furthermore, the promise of decentralisation often conflicts with practical governance needs. Who has the authority to update a smart contract when a new environmental regulation is enacted? Who resolves disputes over a disputed carbon credit? The literature indicates that many operational blockchain EI systems are, in practice, not fully decentralised but are instead governed by consortia of powerful actors, mimicking the centralised structures they aim to replace [28].

Generative AI: Synthesis, Simulation, and the Spectre of Synthetic Ecology

The latest and arguably most disruptive addition to the EI toolkit is Generative Artificial Intelligence (GenAI). Unlike traditional AI models that classify or predict, GenAI models such as large language models (LLMs) and generative adversarial networks (GANs) are designed to create new content [29]. In environmental science, this ability supports advanced simulation, data enhancement, and scenario planning [30].

1. Augmenting Data Scarcity and Modelling Complexity

One of the ongoing challenges in environmental modelling is data scarcity, especially in remote or under-resourced regions [31]. GenAI, using techniques such as GANs, can generate synthetic environmental data that reflects the statistical properties of real-world observations. This can help expand limited training datasets for machine learning models, improving their robustness for applications such as predicting deforestation patterns or species distribution [32]. LLMs are also being explored to analyse and synthesise unstructured environmental knowledge from millions of scientific papers, policy documents, and indigenous knowledge repositories, creating intelligent tools for environmental managers [33].

Furthermore, GenAI's ability to create complex simulations introduces a new approach to predictive modelling. Instead of relying on a single deterministic model, GenAI can generate multiple plausible future scenarios based on different climate policies or intervention strategies [34]. This probabilistic method provides decision-makers with a deeper understanding of uncertainty and risk, moving beyond the "single forecast" model that has often limited climate adaptation planning [35].

2. Critical Concerns: Hallucinations, Bias, and the Black Box

Despite its potential, integrating GenAI into EI involves significant risks. The most well-known problem is "hallucination", the tendency of generative models to confidently produce outputs that are factually incorrect, nonsensical, or entirely fabricated [36]. In fields like environmental science, where decisions can be life-or-death, a hallucinated flood prediction or a fabricated ecological trend could be disastrous. The literature on trust in AI highlights that the opacity of these models (the "black box" problem) makes it extremely hard to verify their outputs for accuracy [37].

Another significant concern is algorithmic bias. GenAI models are trained on extensive collections of text and data scraped from the internet, which are primarily dominated by English-language, Western, and Global North perspectives [38]. This skews their outputs. When applied to environmental issues in the Global South, such models may overlook local ecological knowledge, socio-economic contexts, or specific climatic conditions, thereby unknowingly reinforcing colonial patterns of knowledge production [39]. A generative model trained to suggest reforestation strategies might favour commercially profitable timber species from a Western database over indigenous, biodiverse species recommended by local communities.

Furthermore, the computational cost of training and running large GenAI models is immense. The carbon footprint of training a single large language model can be equivalent to the lifetime emissions of several automobiles [40]. This creates a stark ethical contradiction: using a high-emission technology to address an environmental problem. Table 2 outlines the critical trade-offs involved in deploying GenAI in environmental settings.

Table 2: The Generative AI Trade-off in Environmental Intelligence

Application Area	Potential & Promise	Critical Risks & Drawbacks
Data Augmentation	Fills gaps in sparse environmental datasets [32].	Risk of generating synthetic data that reinforces existing biases or creates unrealistic patterns [38].
Scenario Modelling	Generates multiple, nuanced future scenarios for policy planning [34].	"Hallucinations" can produce inaccurate or dangerous predictions [36].
Knowledge Synthesis	Automates review of vast scientific and policy literature [33].	Opacity makes auditing for accuracy and bias difficult; it may exclude non-digital indigenous knowledge [39].
Foundation Models	Provides a base for versatile environmental applications [30].	Massive energy consumption and carbon footprint; it entrenches corporate control of foundational AI [40].

The Convergence: Towards a Trusted EI Framework

The true promise of this technological era is not in any single technology but in its convergence. Several frameworks suggest integrating cloud, blockchain, and GenAI into a cohesive "Trusted Environmental Intelligence" stack [41]. In such an architecture, cloud infrastructure provides the computational backbone, blockchain ensures data provenance and transactional integrity, and GenAI serves as the intelligent layer for analysis and synthesis [42].

1. Proposed Architectures and Use Cases

A typical architecture, as described in recent white papers and research articles, functions as follows: environmental data from IoT sensors and satellite feeds is collected and pre-processed either at the edge or in the cloud. This data is then hashed and logged on a blockchain to create an unchangeable audit trail, establishing trust in its origin and history [43]. Smart contracts automate processes such as issuing carbon credits based on verified data thresholds. Finally, GenAI models are deployed on cloud infrastructure to analyse this trusted dataset, develop predictive models, and generate human-readable reports and insights for stakeholders [44].

Potential use cases for such an integrated system are compelling. In sustainable agriculture, a system could combine soil sensors (IoT), an immutable record of farming practices (blockchain), and AI-generated yield predictions and market intelligence (GenAI) to create a trusted ecosystem for premium, verifiable "green" produce [45]. In climate finance, a platform could use blockchain-verified satellite imagery to trigger parametric insurance payouts via smart contracts, with GenAI providing risk assessment and post-event analysis [46].

2. The Integration Gap and Fragmentation

However, the literature on this integration remains mostly conceptual. There is a notable gap between the proposed architectures and actual large-scale deployments. Early adopter projects often face challenges with interoperability. Seamless integration of cloud APIs, blockchain protocols, and AI model pipelines is complex and frequently results in fragmented, pilot-scale systems that struggle to scale [47].

A critical review reveals that most "integrated" solutions are actually isolated, with each technology operating independently. For instance, a blockchain project might record data that is then analysed by a separate, non-integrated AI model. Genuine convergence, where the AI model's training data and decision-making are governed by the principles of immutability and transparency enforced by blockchain, remains an ideal rather than a current reality [48]. Moreover, the socio-technical integration—how such systems fit within existing regulatory frameworks, institutional practices, and community governance structures is often neglected. The belief that technology alone can create "trust" overlooks the complex social processes involved in building, maintaining, and sometimes breaking trust. Trust is not a technical result; it is a social relationship [49].

Critical Synthesis and Future Directions

This review has explored the landscape of cloud, blockchain, and generative AI in environmental intelligence, highlighting a field full of high promise and significant, often overlooked, contradictions. A critical review of the literature identifies several key areas that require urgent attention from researchers, policymakers, and practitioners.

1. The Energy-Environmental Paradox

A key theme is the paradoxical relationship between these technologies and their environmental impact. The technologies deployed to address environmental issues are themselves significant sources of carbon emissions and e-waste [50]. The data centres that power the cloud account for a growing share of global electricity consumption [51]. Blockchain's historical energy intensity, although reduced by PoS, still raises concerns about the overall environmental benefits of blockchain-based environmental markets [52]. The substantial computational demands of Genai represent a new and rapidly expanding area of energy consumption [40].

Future research should go beyond net-zero rhetoric and focus on thorough life-cycle assessments (LCAs) of integrated EI systems. A key question is: When does the environmental benefit of a trusted EI system outweigh its operational footprint? This is not only a technical optimisation issue but also a fundamental concern of environmental ethics.

2. Governance, Equity, and Environmental Justice

The centralisation of cloud infrastructure and the capital-intensive nature of GenAI development risk creating a new digital divide in environmental science. The institutions and nations capable of building and deploying these advanced EI systems will be the ones already holding significant power, potentially marginalising community-based monitoring and indigenous knowledge systems that are essential for holistic environmental stewardship [53]. The concept of' trust" must be examined from an environmental justice perspective: Trust for whom? Whose data is being protected, and whose knowledge is being marginalised?

Future work should focus on creating governance frameworks that encourage fair access and participation. This includes exploring the potential of decentralized autonomous organizations (DAOs) for community-led environmental monitoring [54]. However, it also requires critically assessing DAOs, as they can replicate existing power structures if not designed with inclusivity in mind [55].

3. From Technological Solutionism to Socio-Technical Systems

A persistent critique from this review is the tendency toward technological solutionism, the belief that complex social and environmental issues have simple technological solutions [7]. The convergence of cloud, blockchain, and AI is often presented as a cure-all for failures in environmental governance. This viewpoint hides the deeper political, economic, and cultural causes of environmental damage.

A crucial step forward requires a paradigm shift from creating technology-centred systems to designing socio-technical ones. This involves integrating social sciences and humanities into the development process from the beginning. It means asking not just "Can we build it?" but also "What are the possible unintended effects? Who could be harmed? How can we include mechanisms for accountability, contestation, and redress?" [56]. Table 3 presents a proposed framework for a vital research agenda.

Table 3: A Critical Research Agenda for Trusted Environmental Intelligence

Critical Lens	Key Research Questions	Required Disciplinary Integration
Environmental Justice	Who benefits from these systems? Whose knowledge is validated/excluded? How do systems address historical inequities?	Environmental humanities, political ecology, and post-colonial studies.
Energy & Materiality	What is the full life-cycle environmental cost? Can net-positive outcomes be reliably achieved?	Industrial ecology, energy systems engineering, and critical infrastructure studies.
Governance & Sovereignty	How are decisions made? How do systems interact with existing laws? How is data sovereignty protected?	Law, political science, public policy, science and technology studies (STS).
Epistemology & Trust	How does algorithmic transparency (or opacity) shape trust? How is "truth" defined and enforced?	Philosophy of science, sociology of knowledge, and critical data studies.

Conclusion

The convergence of cloud computing, blockchain technology, and generative artificial intelligence marks a pivotal moment for Environmental Intelligence. The available capabilities, unmatched computational power, immutable data origins, and advanced synthetic modelling are truly transformative and hold great potential for improving our understanding and response to global environmental crises. As this review demonstrates, these technologies can establish a foundation for more transparent carbon markets, stronger supply chain oversight, and more detailed climate scenario planning.

However, uncritically accepting this convergence as the way to achieve "trusted" EI overlooks the complex challenges involved. The hope of decentralisation through blockchain is complicated by the centralising tendencies of cloud infrastructure and corporate-controlled AI. The aim of transparency is undermined by the opacity of "black box" AI models and the ongoing oracle problem. The pursuit of environmental sustainability paradoxically conflicts with the large energy and material footprint of the technologies used. This review argues that the greatest risk is not technological failure but the success of a narrow, solutionist vision that equates technological capability with trustworthiness. True trust in environmental intelligence cannot be achieved solely through cryptographic proofs and algorithms; it is fundamentally a socio-technical construct. It requires transparent governance, equitable access, meaningful stakeholder participation, and deep, critical engagement with the political and ethical dimensions of environmental data.

Therefore, the path forward must involve careful, critical, and interdisciplinary integration. It requires moving beyond the hype cycle to thoughtfully evaluate the real-world impacts of these systems through the perspectives of environmental justice, energy materiality, and democratic governance. The question is no longer whether we can build trusted environmental intelligence systems using cloud, blockchain, and GenAI, but whether we should and if so, for which stakeholders, under what conditions, and with what safeguards. The answers to these questions will ultimately determine whether this technological convergence becomes a tool for genuine ecological stewardship or merely a sophisticated form of digital greenwashing.

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