Carlos Fernando Fillippo Rangel

Applications of AI for Sustainability: a case-study on biodiversity monitoring of the Colombian Amazon rainforest

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Supervisor: Prof. Dr. Vasilis Kostakis
Tutor: Dr. Christos Giotitsas

Presented by: Carlos Fernando Fillippo Rangel

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Abbreviations

AI	Artificial Intelligence
ACTO	Amazon Cooperation Treaty Organization
CNN	Convolutional Neural Network
EHRD	Environmental and Human Rights Defenders
GHG	Greenhouse Gas Emissions
IDEAM	Institute for Hydrology, Meteorology and Environmental Studies, Colombia
ML	Machine Learning
MoU	Memorandum of Understanding
OTCA	Amazon Cooperation Treaty Organization
SCAIS	Sustainability Criteria and Indicators for Artificial Intelligence Systems
SDG	Sustainable Development Goals
STES	Socio-Technical-Ecological Systems

1 Introduction

Artificial Intelligence (AI) and climate change are among the most pressing topics of the current decade, permeating diverse domains such as industry, media, policy, and academia. Both are broad topics with multiple intersections. Companies, scholars and policymakers agree on the potential contributions of AI to solve many environmental challenges (Rolnick et al. 2023; Suleyman and Bhaskar 2023). The optimism does not come without concern: scholars, journalists and activists have been making calls about the negative environmental impact of some of the largest and most widely used AI technologies, and how they can be—by design—unsustainable (Crawford 2021; Mezzadra and Neilson 2017; Strubell et al. 2019). As any other general-purpose technology, Artificial Intelligence is an encompassing term used to name a very diverse array of tools and methodologies, for which its relationship with sustainability is nuanced and deserves to be studied in detail by looking at current developments and implementations. Additionally, several authors agree on how the common understanding of sustainable technologies should not be limited to ecological terms, but also include other dimensions such as economic or social (Acemoglu and Johnson 2024; Ahlborg et al. 2019; Barocas et al. 2023; Crawford 2021; Rohde et al. 2024).

On the other hand, environment protection, climate change and sustainability are also broad umbrella terms, covering a vast number of issues globally. Complex interactions between multiple phenomena are the focus of work by scholars around the world to understand their causes and effects and, consequently, inform citizens, policymakers and companies' actions towards mitigation and adaptation. The specific subjects this dissertation addresses are biodiversity and deforestation, to shed light on how AI can be used to face issues central to the protection of forests and biodiversity. Hooper et al. (2012) have shown strong evidence on how biodiversity loss is a major driver of ecosystem change, while Fearnside (1999, 2021) has argued about biodiversity having significant intrinsic value for Earth because of its environmental functions and services.

This research project attempts to contribute to the discussion by documenting the case of Project Guacamaya: an ongoing partnership of private, public and non-for-profit organizations in Colombia that monitors biodiversity and deforestation in the Amazon Rainforest using multimodal AI-based data analysis. One major reason to dive deep into this project is its context: the global carbon and water cycles depend heavily on the ecosystemic services of the Amazon Forest. It is a major climate regulator and therefore requires rigorous monitoring in order to achieve international sustainability goals and mitigate climate change (Fearnside 2021; Ferreira 2024; Ponce de León et al. 2023). Moreover, the Amazon basin covers more than 7 million square kilometers over 9 different countries. Monitoring and conservation efforts require coordination across different politico-administrative regimes to be truly impactful. As will be discussed later, Project Guacamaya has promising features meant to overcome coordination, accessibility and scale challenges that are inescapable when dealing with such a massive ecosystem.

Case study methodology (Flyvbjerg 2006) is used to conduct the research, informed by the Sustainability Criteria and Indicators for Artificial Intelligence Systems (SCAIS) framework (Rohde et al. 2024), which is helpful to analyze the case as a socio-technical-ecological system. The multidimensional perspective enables identification of potential innovative, replicable or scalable attributes, as well as trade-offs, negative externalities or unsustainable practices.

1.1 The case of Project Guacamaya

Announced to the public in mid-2023, Project Guacamaya is the partnership between Microsoft, the CinfonIA lab of Universidad de Los Andes, Humboldt Institute, Sinchi Institute and Planet Labs. This initiative aims to contribute to the protection of the Amazon forest by means of permanent real-time monitoring of biodiversity, threat signalling and the generation of valuable data to inform policymaking. The design of the project is meant to consolidate a model of an integral broad understanding of the forest, through the multimodal analysis of data fed in real time, in addition to the combination of expertise coming from the different partners and their specialized knowledge (News Center Microsoft Latinoamérica 2023). More recently, in March 2025, Peruvian Ministry of Environment announced that it had joined the partnership, to expand the project to the Peruvian Amazon forest (Ministerio de Ambiente, Perú 2025).

The core of Guacamaya has initially been a model that captures three types of data: audio from microphone traps, images from camera traps and images from satellites. It is intended to process through machine learning large amounts of information that exceed the capacity of human operators, in search for signs of stress in species or potential deforestation activities. The data is owned and shared by Planet Labs, Humboldt, and Sinchi institutes, while Microsoft and CinfonIA are in charge of funding and developing the model(s) and platform. Since its inception, the platform is open source, so authorities and other researchers worldwide are able to use it (News Center Microsoft Latinoamérica 2023).

About the partners: Microsoft is a publicly listed multinational company, headquartered in the United States, with offices in Colombia. Specifically, its AI for Good Lab[1] is in

[1] https://www.microsoft.com/en-us/research/group/ai-for-good-research-lab/

charge of the project. CinfonIA[2] is the Centre for Research and Formation in Artificial Intelligence at Universidad de Los Andes, a private renowned university based in Bogotá. Humboldt Institute[3] is a mixed organization, operating as an independent not-for-profit scientific organization but also linked to Colombia's Ministry of Environment. Its mission is to promote, coordinate, and conduct research that contributes to the knowledge, conservation, and sustainable use of biodiversity, and it is a well-known authoritative institution in the fields of biodiversity, ecology and environment conservation. Amazonian Scientific Research Institute Sinchi[4] is a public organization, also under the Colombian Ministry of Environment, dedicated to scientific research on environmental issues with jurisdiction over the territory of the Colombian Amazon. Planet Labs[5] is another publicly listed company, also based in the United States, dedicated to providing high frequency satellite data to public and private sector clients, as well as research institutions.

1.2 Contribution to literature

This section outlines the relevant academic discourse that informs this case study, particularly at the intersection of AI, sustainability, and biodiversity monitoring. The literature on the intersection of AI and sustainability is recent and has constantly grown in the past 10-15 years as scientists in both fields are increasingly working on theoretical and empirical research and development. Two main avenues can be identified along two overarching lines of inquiry: how can AI be sustainable? And how can AI contribute to sustainability efforts? The research addressing the former question belongs to the stream that has been called 'Sustainable AI' or 'Green AI', while the latter has been named by academics as 'AI for sustainability' (Alzoubi and Mishra 2024; Bolón-Canedo et al. 2024; Dhiman et al. 2024; Natarajan et al. 2022; Ofek and Maimon 2023; Raman et al. 2024; Tabbakh et al. 2024; Verdecchia et al. 2023; van Wynsberghe et al. 2022). Nevertheless, both questions are deeply intertwined, and experts have claimed they are two sides of the same coin.

Until mid-2022 the most popular topics regarding Green AI (or Sustainable AI) research were monitoring, hyperparameter tuning, deployment and model benchmarking (Verdecchia et al. 2023). In other words, the focus of the scholarship around Green AI has been mostly on energy consumption and efficiency at the training stage of AI models. Additionally, the systematic literature review conducted by Verdecchia et al. (2023) shows that most studies are from laboratory experiments, and only 23% of them involve

[2] https://cinfonia.uniandes.edu.co/
[3] https://www.humboldt.org.co/sobre-el-instituto
[4] https://en.sinchi.org.co/acerca-del-instituto
[5] https://www.planet.com/company/

industry stakeholders or AI companies. They encourage the scientific community to collaborate more closely with private sector actors to increase their involvement, so that the potential of Green AI to reduce negative environmental impacts can be fully harnessed.

Dhiman et al. (2024) conducted an even broader study on Sustainability of AI as well as AI for Sustainability. Besides a confirmation of most trends identified in the previous state-of-the-art articles, they explicitly explore how Sustainability can be analyzed under one or more of these dimensions: economic, social and environmental. Their motivation lies in the potential of AI not only to diminish energy, water and land usage, but rather to enhance and nurture environmental governance at a higher level (Nishant et al. 2020); an approach that matches closely the holistic critical view of Crawford (2021), Suleyman and Bhaskar (2023), and Acemoglu and Johnson (2024). To understand the design characteristics and potential contributions of Project Guacamaya, a multidimensional perspective may offer a more comprehensive understanding than approaches focused solely on net ecological impact.

In 2024, Rohde et al. took a step towards substantiating the call for an integral perspective of sustainable AI by presenting the Sustainability Criteria and Indicators for Artificial Intelligence Systems (SCAIS) Framework, meant to assess AI-based systems across the dimensions of organizational embeddedness, society, ecology and economy. The authors propose a set of criteria and indicators for each dimension designed to evaluate the sustainability impacts of an AI system at concrete specific levels. Their contribution aims to provide researchers, developers, companies and policymakers concrete measures to improve AI development and deployment.

On the specific applications of AI for biodiversity and deforestation monitoring, several authors have laid important foundations for the discussion and identified open challenges to be further researched. On a general note, Xu et al. (2023) and the Global Partnership on AI (2022) pointed out challenges regarding policy, resource allocation, planning, stakeholder coordination as well as promising trends regarding the use of machine learning for biodiversity and conservation. Pollock et al. (2025) exhaustively discuss how artificial intelligence can be used to address seven clearly defined shortfalls in biodiversity knowledge because of its capacity to integrate disparate and inherently complex data types, such as images, video, text, audio and DNA, to subsequently help to answer important ecological questions. Reynolds et al. (2025) identified 21 promising ways in which AI could support biodiversity conservation, from species recognition and improved biodiversity loss predictions to monitoring wildlife trade and mitigating human-wildlife conflict. However, the study also warns of possible downsides, such as AI colonialism and skill loss, and calls for thoughtful adaptation within the conservation field. Sandbrook (2025) adds to the warnings by pointing out the risks of Conservation AI, which may enhance conservation efficiency but also introduce challenges such as biased data, environmental costs, and disruptive shifts in labor and decision-making. The author argues that optimism has outpaced caution and calls for a more responsible approach grounded in transparency, risk awareness, and attention to the broader societal impacts of AI on biodiversity.

Regarding the specific context of the Amazon forest, research about the use of AI for biodiversity and deforestation monitoring has been published, especially focusing on the monitoring of deforestation and illegal mining using satellite data aimed towards law enforcement in Brazil (Alshehri et al. 2024; Assuncao et al. 2023; Ferreira 2024; Fonseca et al. 2024; Moffette et al. 2021; Saavedra 2024; Torres et al. 2021). On the side of biodiversity monitoring, more gaps have been found by researchers, as they seem to agree on a gap between the data and models available for ecosystems in the global north and those in the global south, where large neotropical forests like the Amazon basin and the Congo basin are receiving insufficient camera trap research attention (Mugerwa et al. 2024). In the case of Colombia, a group of scientists from Humboldt Institute have documented and synthesized the main experiences and challenges for machine learning-aided biodiversity monitoring in Colombian ecosystems (Cañas et al. 2025). Some of the open issues identified are related with data sovereignty and governance, transparency, organizational capacities and international cooperation, bridging the gap between local communities and monitoring tools. Bearing all this in mind, the case study of Guacamaya brings findings relevant to the literature on AI for sustainability, particularly in relation to its use for biodiversity and monitoring in neotropical ecosystems, and in the socio-economical context of Latin America.

1.3 Research objectives and questions

Building on the contextual background and literature outlined above, this research aims to examine Project Guacamaya through a case study lens. The focus is not only on the technical performance of the system, but also on how it engages with broader goals of environmental governance and sustainable development. The research is guided by the following objective and questions:

Main objective: Assess Project Guacamaya as a case of AI for Sustainability and understand its potential to contribute to forest monitoring and conservation.

Research questions:

- How does Project Guacamaya perform across the 19 criteria of the SCAIS framework?
- What does the SCAIS framework reveal about Guacamaya's ability to contribute to the greater efforts of environmental sustainability that drive it (Sustainable Development Goals and scientific mandates of its partners)?
- How can the case of Guacamaya contribute to policymaking for biodiversity monitoring and conservation in the Amazon Forest Region?

As the scholarly work on sustainability and AI increasingly calls for deeper exploration of the interaction between social, economic and ecological dimensions, these questions aim to contribute to the discourse with the analysis of a real-life case, through an operationalizable multidimensional lens. Additionally, they will also contribute to the current discussion on the potential of AI to solve conservation challenges in the Amazon Forest. Reflections on applying the SCAIS framework to the case of Guacamaya might also be relevant for its methodological discussion as it has been published only months ago. This research builds directly on the work of Rohde et al. (2024) and aims to respond to their call for further research and reflection on the interdependencies between sustainability-related impacts.

1.4 Structure of the paper

This thesis is structured in six chapters. Following this introduction, Chapter 2 presents a literature review that covers the intersection between artificial intelligence and sustainability, the Amazon rainforest, biodiversity and deforestation dynamics, and the role of environmental monitoring technologies. Chapter 3 explains the methodological approach, including the rationale for choosing Project Guacamaya as a paradigmatic case, the structure and relevance of the SCAIS framework, and the procedures for data collection and analysis. Chapter 4 presents the empirical findings, beginning with a description of the data gathered and an in-depth account of the project's objectives, technical activities, organizational dynamics, and early results. It then evaluates Guacamaya's performance against the 19 sustainability criteria defined by the SCAIS framework. Chapter 5 discusses the broader relevance of these findings by comparing Guacamaya with similar initiatives, exploring its policy implications, reflecting on future development paths, and assessing the value and limitations of the framework used. Finally, Chapter 6 concludes by summarizing key insights, addressing the research questions, acknowledging limitations, and suggesting directions for future research.

2 Literature review

This chapter outlines the key theoretical and empirical literature that informs this research. It is divided into three parts: (2.1) the evolving relationship between AI and sustainability, (2.2) the ecological and political complexity of the Amazon as a case context, and (2.3) the role of environmental monitoring, with focus on biodiversity and deforestation, as the focal applications of AI examined in this study. Together, these sections establish the conceptual foundation for the case study of Project Guacamaya and the application of a multidimensional framework. Despite growing academic interest in the intersection of AI, biodiversity, and sustainability, there remains a notable lack of in-depth case studies documenting the design and implementation of AI systems in biodiversity-rich but governance-fragmented regions such as the Amazon. This thesis contributes to filling that gap by analyzing Project Guacamaya using the SCAIS framework to assess both its technical and socio-ecological dimensions.

2.1 Intersection between AI and sustainability

Russell and Norvig (1995)—two of the most influential and pioneering figures in the field of artificial intelligence—define it as the attempt to understand and build intelligent agents, and adopt a definition of intelligence closely linked with rational action. That is, an intelligent (rational) agent takes the best possible action in a situation. Nevertheless, Russell and Norvig acknowledge other valid understandings of intelligence, as it can be defined in terms of human-likeness in contrast to rationality. Suleyman and Bhaskar define AI as “the science of teaching humanlike capabilities” (2023, p. vii). Regardless, the field has developed to a point where listing all activities involving AI is virtually impossible. Such list includes, at a minimum, robotics, speech recognition, autonomous planning and scheduling, language translation, computer vision, prediction and forecasting, etc. In other words, it is nowadays a general-purpose technology, and like any other general-purpose technology it deserves research and discussion about its impact on all spheres of society: economy, politics, environment or arts.

Concerns over the ecological, economic, and social consequences of AI have increasingly fuelled research into both sustainable AI and AI for sustainability. On the ecological side, the development of state-of-the-art models, particularly in natural language processing, demands massive computational power, translating into high energy consumption and a sizable environmental footprint (Strubell et al. 2019). Economically, the rapid adoption of AI technologies has raised alarms about stagnant real wages and the potential for labour market disruption, especially in sectors vulnerable to automation (Acemoglu and Johnson 2024; Santor 2020). Socially, issues such as algorithmic discrimination, the spread of misinformation, and the erosion of public trust have sparked ethical debates around fairness, accountability, and the unintended consequences of AI systems (Crawford 2021; Dastin 2022; Jin et al. 2017). These challenges have motivated scholars to critically examine how AI can support or undermine sustainability goals across all three dimensions: environmental, economic, and social.

The intersection between Artificial Intelligence and environmental sustainability covers a wide array of topics, and its discussion in academia—as well as in the industry—is very much alive. As mentioned in the previous section, two main currents can be identified in the literature under the following umbrella questions: how can AI be sustainable? And how can AI contribute to sustainability efforts? The research addressing the former question belongs to the stream that has been called 'Sustainable AI' or 'Green AI', while the latter has been named by scholars as 'AI for sustainability' (Alzoubi and Mishra 2024; Bolón-Canedo et al. 2024; Dhiman et al. 2024; Natarajan et al. 2022; Ofek and Maimon 2023; Raman et al. 2024; Tabbakh et al. 2024; Verdecchia et al. 2023; van Wynsberghe et al. 2022). According to Dhiman et al. (2024), most existing literature tends to focus narrowly on either AI for sustainability or the sustainability of AI, while a minority of scholarly works consider both aspects simultaneously.

2.1.1 Sustainable AI

The definition of 'Green AI' is still under debate, and although popularized a few years ago, scholars have transitioned to the term 'Sustainable AI'. Figure 1 shows there is a predominant understanding in terms of energy efficiency in the literature, plus a number of broader definitions with additional considerations such as carbon footprint or ecological footprint; the latter examining the holistic impact AI has on the natural environment beyond the greenhouse gas emissions or the energy consumption (Verdecchia et al. 2023). Based on these observations, the following definition statement is provided: "Green AI regards practices aimed at utilizing AI to mitigate the impact that humans have on the natural environment in terms of natural resources utilized, and/or mitigating the impact that AI itself can have on the natural environment." (Verdecchia et al. 2023, p.17).

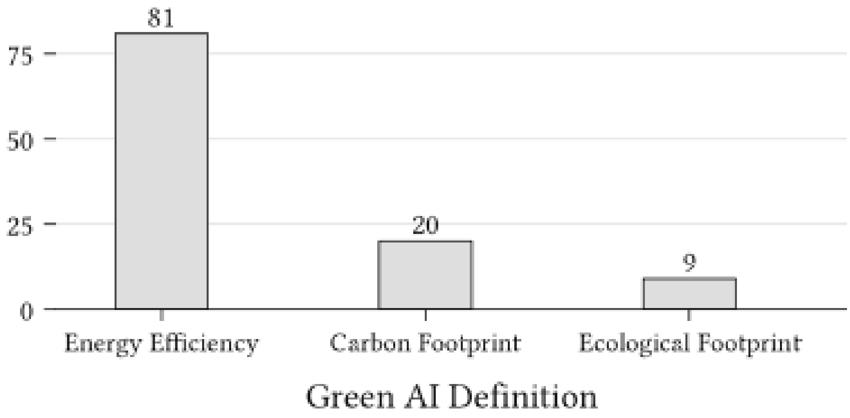

Figure 1. Number of publications per type of Green AI definition. Taken from Verdecchia et al., 2023, p. 6

Alzoubi and Mishra (2024) propose a useful classification of green AI initiatives that illustrates the range of emerging tools designed to reduce the environmental footprint of artificial intelligence. Based on a review of 55 initiatives, they identify six categories: (1) cloud optimization tools like Google AI Platform and Microsoft Azure ML that reduce infrastructure energy use; (2) model efficiency tools such as Apple Core ML and Hugging Face Transformers that aim to lower computational demand; (3) carbon foot-printing tools like the Google Cloud Sustainability Calculator that help track and mitigate emissions; (4) sustainability-focused AI development efforts like EarthAI and Microsoft AI for Good, which apply AI to tackle environmental issues; (5) open-source initiatives that promote collaborative development of greener technologies, including the Green Software Foundation; and (6) green AI research and community initiatives such as EcoAI and the Green AI Foundation that foster knowledge sharing and interdisciplinary dialogue. Their framework helps distinguish 'Green AI'—focused on the sustainability of AI systems themselves—from 'AI for sustainability', which uses AI as a tool to support environmental objectives, although it can be argued that 'AI for sustainability' belongs to the 4th category. This analysis shows how the field is evolving, with ongoing debates about how best to assess and improve the sustainability of AI systems.

In complement to the literature reviews published by the end of 2023 (Natarajan et al. 2022; Verdecchia et al. 2023), Dhiman et al. (2024) conducted an even broader study on Sustainability of AI as well as AI for Sustainability, using a Systematic Mapping Study approach. In addition to a confirmation of most trends identified in the previous state-of-the-art articles, Dhiman et al. (2024) explicitly explore how Sustainability can be analysed under one or more of these dimensions: economic, social and environmental. Their motivation lies in the potential of AI not only to diminish energy, water and land usage, but rather to enhance and nurture environmental governance at a higher level; an approach that matches closely the holistic critical view of Crawford (2021) and seems more relevant to understand the design characteristics and potential contributions of Project Guacamaya. They find that, since 2019, research of Sustainability and AI increasingly covers more than one dimension of sustainability, as shown in Figure 2[6].

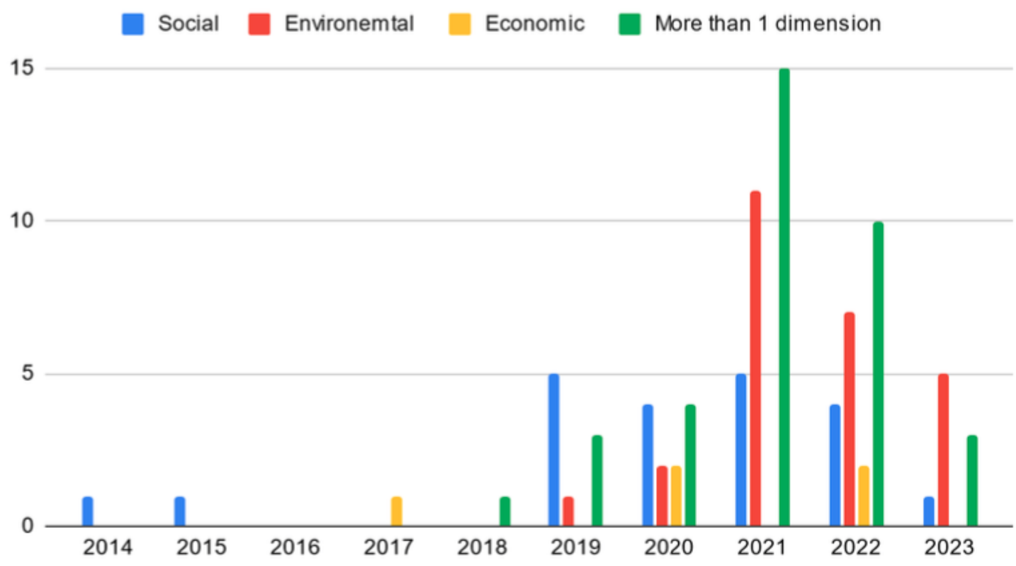

Figure 2. Number of papers by year by dimension of sustainability. Taken from Dhiman et al., 2024, p.157

Following the trend of assessing the Sustainability of AI through a multidimensional understanding, Rohde et al. (2024) presented the Sustainability Criteria and Indicators for Artificial Intelligence Systems (SCAIS) Framework. By addressing 19 different sustainability criteria embedded in four dimensions of sustainability—organizational governance, social, ecological and economic—the framework compresses a set of 67 indicators designed and operationalized based on the existing literature that has been extensively reviewed as shown above. The rationale behind this holistic Framework is that AI Systems are Socio-Technical-Ecological Systems (STES), and as such, there are impacts that need to be addressed on a different level, as seen in Figure 3. Additionally, the SCAIS Framework is meant to assess sustainability following 6 life-cycle phases of AI artifacts: 1) organizational embeddedness; 2) conceptualization; 3) data management; 4) model development; 5) model implementation; 6) model use and decision-making (Rohde et al. 2024). On a more abstract level, this STES approach is an effort to understand interactions between society, environment, and technology, as they are never isolated. Technology nowadays mediates human-environment relationships, bringing ambivalence while enhancing and transforming human agency (Ahlborg et al. 2019).

[6] The cutoff of their review was in mid-2023, which explains the low number of papers found for that year.

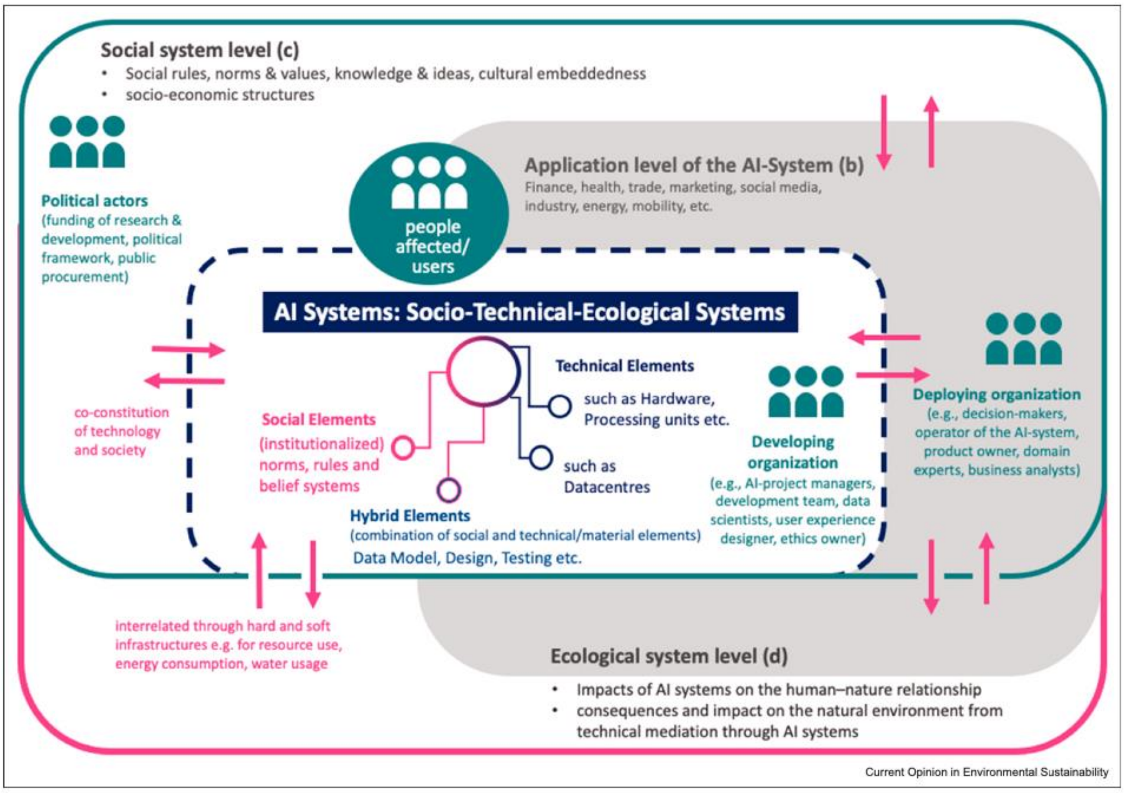

Figure 3. AI systems as socio-technical–ecological systems, with impact levels and relevant actors for sustainable AI. Taken from Rohde et al., 2024, p.3

2.1.2 AI for sustainability

Policy strategies like the Sustainable Development Goals (SDG), on top of a generalized awareness of climate change and sustainability challenges faced by society, have led to multiple attempts of enhancing all kinds of sustainability efforts with AI technologies. Table 1 shows a comprehensive list of applications of Machine Learning (ML) to address climate change, by domain and type of activity, compiled by Rolnick et al (2023). Some of the examples of ML applications observed in these activities include causal inference, computer vision, interpretable models, natural language processing, reinforcement learning, time-series analysis, uncertainty qualification, unsupervised learning, among others.

Sustainability purpose	Domain	Activities
Mitigation	Electricity systems	Enabling low-carbon electricity Reducing current-system impacts ensuring global impact
	Transportation	Reducing transport activity Improving vehicle efficiency Alternative fuels & electrification Modal shift
	Buildings and cities	Optimizing buildings Urban planning The future of cities
	Industry	Optimizing supply chains Improving materials Production & energy
	Farms & forests	Remote sensing of emissions Precision agriculture Monitoring peatlands Managing forests
	Carbon dioxide removal	Direct air capture Sequestering CO_2
Adaptation	Climate prediction	Uniting data, ML & climate science Forecasting extreme events
	Societal impacts	Ecology Infrastructure Social systems Crisis
	Solar geoengineering	Understanding & improving aerosols Engineering a control system Modelling impacts
Tools for action	Individual action	Understanding personal footprint Facilitating behaviour change
	Collective decisions	Modelling social interactions Informing policy Designing markets
	Education	
	Finance	

Adapted from Rolnick et al. (2023), p. 42:5

Table 1. Applications of ML for climate change solutions

Natarajan et al (2022) explore AI for sustainability in the context of commerce and markets. They distinguish four not mutually exclusive application categories: sustainable conception, sustainable production, sustainable consumption and sustainable business processes. They also identify seven positive affordances: material and product design optimization, process monitoring and optimization, predictive and proactive maintenance, anomaly detection, demand-responsive products and services, sustainability monitoring, sustainability sensemaking. These set of affordances allow organizations to achieve outcomes such as low carbon designs, energy conservation, resource efficiency, production efficiency and reduction of GHG and pollutant emissions.

These examples make clear that AI has the potential to reduce the natural resource and energy demands of human activities seems evident because of its capacity to efficiently process large amounts of information, automate tasks without supervision, or analyse highly heterogenous data. Its many possible applications can lead to the reduction of energy, water and land usage, or greenhouse gas (GHG) emissions by individuals, organizations and society overall. Additionally, it has great potential to enhance environmental governance (Nishant et al. 2020). Through large-scale pattern-recognition with vast amounts of data, AI offers tools to overcome controversy and address information gaps and cognitive bias, potentially accelerating the development of data-driven approaches to environmental challenges. However, to grasp this potential, several gaps between policy and science must be closed (Nishant et al. 2020). Furthermore, AI has significant potential to accelerate other scientific fields, thus contributing indirectly to improving environmental sustainability. Chemistry, materials science, or biotechnology are fields benefited greatly by the computational power and capabilities provided by AI (Greif et al. 2024).

Conservation, the specific field that encompasses the topics of biodiversity and deforestation, has seen extensive use of AI, mostly of computer vision for biodiversity monitoring, as supervised learning can be very helpful to identify animals or classify land cover. Additionally, AI technologies can be potentially used in prioritization of resources within protected areas, and to improve conservation area management activities (Xu et al. 2023). More than 24 researchers and practitioners, who met in 2022 for a workshop on AI-assisted decision making for conservation at the Center for Research on Computation and Society at Harvard University, agree on 3 main conservation priorities (Xu et al. 2023):

1. Understand the world and develop an understanding of species populations, distributions, land cover, threats and human activity, in order to inform decision making.

2. Act in the world, through actions such as designating new conservation areas, allocating resources, intervening in illegal wildlife trade, supporting sustainable economies, among others

3. Evaluate impact to learn whether actions are meeting their goals and iteratively improve decision making based on results.

Risks such as undetected or underestimated biases in key datasets, insufficient explainability of systems, the eventual reliance on generative tools (highly intensive in water, energy and land use), or changes in the working practices, structure and function of organizations of the conservation sector are warned by Sandbrook (2025). As in other sectors, scalability is not trivial. For example, risks around endangered species, fragile socioeconomic conditions of communities, or government restrictions on data sharing because of sovereignty reasons (to protect local knowledge, indigenous heritage, etc.) add complexity to policy discussions. The hype of AI may distract conservation practitioners or policymakers from applying more appropriate techniques (Xu et al. 2023). Moreover, the broader adoption of AI, especially the generative technology, is likely to deepen the challenges in conservation, not only because of its material footprint, but because of its potential to significantly transform society. For example, agriculture techniques and scale, patterns of consumption of goods and services, or political discourse on environmental issues—all of them drivers of biodiversity loss—might be altered with unpredictable consequences (Sandbrook 2025).

Accordingly, most of these challenges and risks have been identified by practitioners in Colombia. Promoting collection and sovereign management of biodiversity data, ensuring transparency and human-in-the-loop mechanisms, or empowering communities via open data and open models are some of the generalized challenges observed both globally and locally in Colombia (Cañas et al. 2025). But as argued earlier, conservation and the technologies that leverage the efforts around it are not isolated from socio-economic phenomena. Practitioners also face context-specific challenges and risks. For example, existing biodiversity data is biased in favour of species and ecosystems from the Northern Hemisphere as more funding and infrastructure are available for such purposes (Daru and Rodriguez 2023; García-Roselló et al. 2023; Pollock et al. 2025). Another challenge (with more elaboration further on) is about the coordination of regional AI policies and biodiversity strategies. In contrast with the European Union, there is little policy coordination or common frameworks for practitioners to follow, even when ecosystems are shared across multiple countries like the Andes Mountains or the Amazon Forest. Additionally, there is significant dependence on foreign funding and technology providers (Cañas et al. 2025).

2.2 The Amazon Rainforest

While Section 2.1 discussed the conceptual and technological foundations of AI in the sustainability space, the next section shifts focus to the Amazon: a region with unique biodiversity, facing multiple challenges in regards to conservation, governance and technology deployment.

The Amazon Forest region, also called Amazonia or Amazon basin, stands out as the most biodiverse biome on the planet, home to an extraordinary variety of microorganisms, plants, birds, mammals, reptiles, fish, insects, and invertebrates (IPBES 2018). Endemism is notably high, particularly among mammals and freshwater fishes, while diversity varies geographically, with peak tree richness in the northwestern and central basin and distinct avian and mammalian diversity in the western Amazon and the Andean foothills. At the same time, amphibians and fishes exhibit the highest local diversity in the western Amazonian lowlands. Despite ongoing species discoveries—occurring at a rate of nearly one every two days—large portions of Amazonian biodiversity remain poorly documented, and scientific knowledge of their ecology and distributions is still limited (Science Panel for the Amazon 2021).

Its vast network of waterways connects the Andes to the Atlantic Ocean, playing a vital role in global climate regulation by shaping air and ocean currents as it connects the Andes mountains to the Atlantic Ocean. Its forests release immense amounts of moisture into the atmosphere via evapotranspiration, which contributes to cloud formation and rainfall, particularly in the Andes and surrounding areas. This recycling of water vapor—nearly a third of which is generated within the basin itself—sustains precipitation patterns and helps extend the rainy season (Science Panel for the Amazon 2021). Moisture generated in the Amazon also travels far beyond the basin through narrow atmospheric corridors known as aerial or flying rivers, feeding water into ecosystems and agricultural regions across central and southern South America. Alongside water vapor, these currents also carry smoke and aerosols from forest fires, intensifying pollution in downwind urban areas. The Amazon Basin also plays a major role in the global carbon cycle, storing between 150 and 200 billion tons of carbon and contributing around 16 percent of terrestrial productivity. That is the world's largest stock of forest carbon, due to its immense surface area and dense vegetation (Pan et al. 2011).

Figure 4. Main Neotropical biogeographical regions and the Amazon River. Taken from Guayasamin et al. 2024

The Amazon is not only the world's largest tropical forest but also home to over 30 million people, making it a region of immense socio-environmental complexity. It supports local and regional livelihoods through both market goods like timber and agricultural products, and non-market ecosystem services such as climate regulation and biodiversity conservation (FAO (ed.) 2011; Peres et al. 2010; Ponce de León et al. 2023). Although extensive research exists on the Amazon's ecological and social dynamics, scientific efforts are often criticized for falling short in supporting sustainability goals. Key limitations include fragmented, discipline-bound approaches, narrow scopes on specific ecological or social problems, and limited engagement with local actors and institutions ultimately responsible for shaping land-use decisions and policy implementation. (Gardner et al. 2013; Lahsen and Nobre 2007; Perz et al. 2010).

The Amazon biome spans nine countries: Brazil, Peru, Colombia, Venezuela, Ecuador, Bolivia, Guyana, Suriname, and French Guiana. Each with distinct political systems, environmental policies, and levels of institutional capacity. This fragmented jurisdictional landscape complicates efforts to coordinate monitoring, conservation, and sustainable development across the basin. Differences in land-use policy, enforcement mechanisms, and national priorities create barriers to the implementation of basin-wide strategies, while ecological processes happen across borders, such as water and wildlife flows, or fire and pollution transport. Efforts like the Amazon Cooperation Treaty Organization (OTCA) and the Leticia Pact represent important regional commitments to environmental protection, knowledge exchange, and sustainable development in the Amazon Basin. These agreements aim to coordinate policies that mitigate the impacts of extractive industries and promote science, innovation, and a forest-based bioeconomy (Science Panel for the Amazon 2021). In this context, the private sector, research institutes, and civil society organizations can play a key role by building partnerships at different scales to support investment, science, innovation, and research.

2.2.1 Biodiversity

Biodiversity in the Amazon supports not only ecological processes but also a wide range of benefits to human societies. It underpins the livelihoods of many who depend on forest products such as fish, fruits, and medicinal plants, while also serving as a frontier for biological research with global implications, including for medicine and sustainability science (Fearnside 1999, 2021; Ferreira 2024). Beyond its instrumental value, Amazonian biodiversity carries intrinsic worth due to the complex evolutionary and ecological relationships it represents. This depth of interconnection suggests that protecting biodiversity is not only about conserving species but about maintaining the ecological processes they enable.

The role of biodiversity in ecosystem functioning is increasingly recognized at a global scale. Loss of species richness has been shown to affect critical ecological processes such as primary productivity and decomposition, at magnitudes comparable to other global environmental changes like nutrient pollution, ozone acidification or climate warming (Hooper et al. 2012). These processes are essential to regulating carbon and nutrient cycles, which in turn support broader ecosystem services. In the Amazon, where ecological interactions are highly specialized, such losses could cascade in ways that affect regional and global environmental stability.

However, biodiversity conservation cannot be reduced to preserving forest cover alone. Evidence shows that human disturbances within remaining forest areas—such as logging, fires, and fragmentation—can result in biodiversity loss even more severe than that caused by deforestation itself. For example, in parts of the Brazilian Amazon, disturbance-related degradation led to greater losses in conservation value than permitted deforestation levels under existing laws (Barlow et al. 2016). These findings highlight the need for policies that go beyond surface-level protection and address the ecological integrity of forests more comprehensively.

At the governance level, biodiversity is increasingly being understood as a source of public goods at both local and global scales. While ecosystem services like flood control may generate mostly local benefits, others—such as carbon sequestration, species existence, and genetic diversity—are global in nature and provide non-market benefits that are underprovided by the private sector (Deke 2008). Because many of these services are non-rival and non-excludable, they fall into the category of public goods and require collective action to be sustained. This perspective underscores the need for policy action and private initiatives that capture the broader environmental benefits of biodiversity and secure the continued delivery of ecosystem services across different spatial and institutional contexts.

2.2.2 Deforestation

Deforestation refers to the destruction of forest biomass, typically to convert land for economic use. When only part of the forest is cleared or degraded, this process is referred to as forest degradation (Ferreira 2024). In the Amazon, the main agricultural products linked to deforestation are soy, corn, and cattle, with coca and palm oil contributing on a smaller scale. In Brazil, soy was the main driver of deforestation in the early 2000s, but by the late 2000s and into the 2010s, deforestation became more strongly linked to cattle ranching (Macedo et al. 2012). In Bolivia, Peru, and Colombia, cattle grazing also plays a significant role, though in these cases, deforestation is often intertwined with coca cultivation (Dávalos et al. 2016). Palm oil expansion, meanwhile, is rapidly replacing forest in parts of Ecuador and Peru (Vijay et al. 2016). Timber and mineral extraction, such as logging for mahogany and ipê or small-scale gold mining, are also contributors, but tend to affect smaller areas due to their dependency on specific local resources.

The process of deforestation often unfolds in three stages: selective logging of high-value species, mechanical clearing and burning of vegetation, and finally, burning of remaining biomass to fertilize the soil with ash (De Almeida et al. 2022; Nepstad et al. 1999). Fires are typically set at forest edges and allowed to spread inward, weakening vegetation to ease further clearing.

Regarding the specific cases of Colombia and Perú, Dávalos et al. (2016) critically examine long-standing assumptions about the relationship between coca cultivation and deforestation in the Amazon regions of these two countries. Contrary to the prevailing ‘immiserization’ model, which holds that poor farmers clear forests to grow lucrative coca crops in the absence of better economic options, their findings support a ‘frontier’ model. According to this model, state-led infrastructure and colonization projects in the 1960s and 1970s laid the groundwork for Amazonian deforestation by opening new settlement frontiers, with coca cultivation emerging later in already-disturbed landscapes. The authors demonstrate that coca does not significantly increase deforestation on its own, nor does it drive migration. Instead, it appears more as a symptom of broader land-use dynamics shaped by road building, expanding legal agriculture, and state presence (or absence) on the forest frontier.

Furthermore, mining—both legal and illegal—has become an increasingly significant driver of deforestation in Colombia. González-González et al. (2021) show that between 2001 and 2018, legal mining alone accounted for over 120,000 hectares of deforested land, with a steep increase after 2013. Gold and coal were the primary materials associated with this forest loss. Importantly, this deforestation is often concentrated in a small number of large-scale concessions, with over 90% of mining-related deforestation coming from just 3% of mining leases. Despite these impacts, there is limited compliance with environmental regulations: fewer than 2% of mines requested the required permits for forest exploitation during that period. The lack of enforcement and transparency reflects a broader pattern of weak environmental governance in mining regions, where law enforcement is often absent or ineffective.

Closely related to the mining and illegal crops issues is the role of armed conflict and its aftermath. As Liévano-Latorre et al. (2021) argue, the presence of armed groups such as the FARC guerilla had complex ambivalent effects on deforestation. On the one hand, their military presence often deterred logging and other forms of environmental exploitation. On the other hand, these groups financed their operations through illegal mining and coca cultivation, contributing to deforestation indirectly. After the 2016 peace agreement, areas previously controlled by guerrillas experienced a power vacuum that led to spikes in forest loss, particularly due to land grabbing and the expansion of extractive frontiers. The study shows that although FARC-occupied regions sometimes acted as de facto conservation areas, they also represented zones of latent socio-environmental conflict, and their post-conflict trajectories are closely tied to broader governance and development failures.

Across the broader Amazon region, beyond Colombia, the economic gains from deforestation come mainly from timber sales and agricultural production, though coca and gold are considered among the most profitable per hectare. However, these profit calculations often exclude externalities. That is: costs borne by society but not by the actors involved. These include greenhouse gas emissions, smoke and particulate matter from fires, disruptions to rainfall and water vapor transport, and pollution from mining.

According to Ferreira (2024), if such costs were factored in, many deforestation activities would likely show negative net economic value, indicating a market failure.

These externalities can be understood at multiple scales. Globally, deforestation contributes to climate change by releasing stored carbon into the atmosphere. Regionally, vegetation loss reduces evapotranspiration, leading to declines in rainfall and longer dry seasons, while fires contribute to transboundary air pollution (Araujo et al. 2023; Leite-Filho et al. 2019; Nepstad et al. 1999). Locally, deforestation disrupts ecosystem services and accelerates biodiversity loss by fragmenting habitats and making it harder for species to survive and reproduce (Barlow et al. 2016; Ochoa-Quintero et al. 2015). Other mid-scale impacts include increased malaria transmission (MacDonald and Mordecai 2019), the destruction of cultural and non-use values (Chan et al. 2011), violence linked to extractive industries (Pereira and Pucci 2024), and threats to Indigenous communities (Barsanetti and Ferreira 2022).

2.2.3 Social conflict and indigenous rights in the Colombian Amazon region

As it was mentioned briefly in section 2.2.2, the Colombian Amazon is not only a globally significant ecological biome but also a complex social and political landscape shaped by decades of armed conflict, extractive development, and Indigenous resistance. Despite the 2016 peace agreement between the Colombian government and the FARC-EP guerrilla group, violence in the region has not ceased. Instead, the vacuum left by demobilized combatants has been filled by new and existing criminal organizations competing for control over land, illicit economies, and resource extraction (Krause et al. 2025; Palau-Sampio 2025). These dynamics have turned Colombia into the world's most dangerous country for environmental and human rights defenders (EHRD), who continue to face threats, displacement, and assassination, particularly in Amazonian departments like Putumayo and Caquetá (Global Witness 2023; Le Billon and Lujala 2020; Palau-Sampio 2025).

EHRDs play a central role in environmental peacebuilding by linking ecological protection to broader struggles for social justice, especially for rural and Indigenous communities (Krause et al. 2025). Yet, their work is undermined by persistent inequalities in land tenure and access to decision-making. Even with increasing cultural and political recognition under recent administrations, economic abandonment and environmental degradation remain entrenched in the region. The expansion of cattle ranching, coca cultivation, and extractive industries has driven deforestation and human displacement, while environmental governance efforts often ignore or marginalize local knowledge and leadership (Krause et al. 2022; Palau-Sampio 2025). This disconnect between top-down conservation policy and ground realities raises concerns about equity, representation, and the long-term legitimacy of environmental interventions.

Indigenous Peoples of the Colombian Amazon, such as the Uitoto and Andoque communities of the Middle Caquetá, have repeatedly denounced initiatives like the 'Visión Amazonía REDD Early Movers programme' for violating their rights to self-determination, collective property, and customary law (Andoke Andoke et al. 2023). Although these programmes often claim to include Indigenous beneficiaries, they are typically designed without meaningful consultation and implemented through external intermediaries, perpetuating patterns of dependency and internal division. These shortcomings not only undermine procedural and distributional justice but also dismiss the depth and validity of Indigenous science and territorial care practices. For millennia, Indigenous communities have sustained Amazonian ecosystems through holistic governance systems that recognize the interconnectedness of human and non-human societies. Ignoring these frameworks limits the transformative potential of conservation and risks reinforcing colonial power dynamics in new forms.

The legacy of violence, combined with extractive economic pressures and poorly implemented peacebuilding efforts, has left Amazonian communities in a precarious position. While courts have recognized the Amazon as a subject of rights and Indigenous Peoples as legitimate stewards of their territories, institutional protections remain weak or unfulfilled (Krause et al. 2022). Furthermore, the militarization of environmental policy, as seen in operations like Artemisa, often criminalizes small-scale farmers and Indigenous groups instead of addressing the structural forces behind deforestation and land grabs (Krause et al. 2022). Understanding these sociopolitical realities is essential for any initiative that aims to monitor and protect biodiversity in the region. Without direct engagement with the communities most affected by environmental degradation, technological tools risk becoming detached from the justice and sustainability goals they claim to serve.

2.3 Environment monitoring

Given the Amazon's global ecological significance and its socio-environmental vulnerability, understanding how environmental change is monitored in this region is crucial. The following section reviews the literature on environmental monitoring, with particular attention to biodiversity and deforestation.

Environmental monitoring has become a central tool for understanding and responding to the growing interdependence between ecological systems and human activity. In the context of the Anthropocene—an era in which human influence is embedded in virtually all natural processes—scholars argue that the long-standing conceptual divide between nature and society is no longer valid (Keskitalo et al. 2023; Palsson et al. 2013). Contemporary environmental challenges such as biodiversity loss, deforestation, climate variability, and pollution cannot be interpreted in isolation from the social and economic systems that drive them (Bartlein and Matthews 2012; Cline 2014; Stenlid and Oliva 2016). This shift in understanding requires a parallel transformation in the way ecosystems are observed and governed. Monitoring is no longer simply a matter of recording environmental variables, but of capturing the evolving relationships between human activity, ecological dynamics, and socio-political decision-making.

According to the European Environment Agency (1999), environmental monitoring encompasses both observation and measurement to assess the implementation and impact of policies, plans, or programs. It not only informs compliance with environmental objectives but also provides feedback that allows institutions to adapt their strategies and interventions in real time. This dual function as both a technical and governance tool makes monitoring especially relevant for ecologically complex and politically fragmented regions like the Amazon. As pressures mount from infrastructure expansion, land-use change, and climate impacts, monitoring serves as a critical interface between scientific knowledge and environmental management.

2.3.1 Monitoring biodiversity

Monitoring biodiversity is a vital tool for understanding the status and trends of species and ecosystems, particularly in regions like the Amazon, where ecological complexity and human pressures converge. As Allard et al. (2023) explain, biodiversity monitoring can take different forms depending on the questions asked, the resources available, and the institutions involved. They outline five primary types of monitoring: curiosity-driven, mandated, question-driven, citizen science–driven, and community-driven. Each plays a role in documenting biodiversity change and informing conservation action.

Curiosity-driven monitoring emerges from individual or institutional interest without formal statistical design or policy mandates. While typically informal, it can generate long-term datasets if structured around clear parameters for what, where, and when observations occur (Allard et al. 2023; Likens and Lindenmayer 2018). Mandated monitoring, by contrast, is policy-driven and often tied to legal or regulatory frameworks, such as national biodiversity inventories or environmental impact reporting under international conventions. These programs typically monitor broad ecological indicators across long timeframes, though they may suffer from overly generic targets.

Question-driven monitoring is designed to test hypotheses or detect ecologically significant change using rigorous statistical methods. It often underpins adaptive management by explicitly defining thresholds, effect sizes, and acceptable levels of uncertainty (Allard et al. 2023). Citizen science-driven monitoring shares some of this rigor but involves volunteers in data collection. Programs like the UK Butterfly Monitoring Scheme and the Swedish Nesting Bird Inventory have shown how citizen science can sustain large-scale, long-term datasets (Brlík et al. 2021; Macgregor et al. 2019). Another well-known example is Audubon's Christmas Bird Count, which has been performed annually since year 1900 and nowadays happens in over 7 countries, including Colombia since 1989 (Audubon 2025; Ferner 1977). Finally, community-driven monitoring is embedded in specific social contexts, with local actors either collecting data or setting monitoring priorities. These approaches are particularly valuable in Indigenous and rural settings, where local knowledge and environmental stewardship intersect (Allard et al. 2023).

New technologies have reshaped biodiversity monitoring by increasing both the scale and resolution of data collection. Nilsson et al. (2023) describe how remote sensing tools, such as satellite and airborne imagery, are used to monitor species distributions, vegetation cover, and habitat conditions. When paired with field data, these tools support multi-scale assessments of biodiversity, though challenges remain in detecting fine-scale biological change. Earth observation systems like Landsat and MODIS (powered by satellite technology) are widely used, and new constellations of high-resolution sensors—along with lidar and radar technologies—are increasingly accessible for biodiversity applications.

Allard et al. (2023 b) discuss how camera traps, drones, and AI-driven classification systems have also expanded monitoring possibilities. Camera traps enable non-invasive detection of elusive or nocturnal species, while drones provide a flexible platform for collecting data in remote or otherwise inaccessible areas. Deep learning techniques, especially convolutional neural networks (CNNs), are increasingly used to automate the classification of species in images and sounds, reducing the labour intensity of data processing and opening space for real-time analysis.

Despite growing technological capacities, critical gaps persist in our understanding of biodiversity. Pollock et al. (2025) outline seven well-established shortfalls that limit the global ability to monitor, manage, and conserve species and ecosystems. For each challenge, the authors comment on promising AI developments with potential to address them. They are as follows:

1. The Linnaean shortfall, which refers to the vast number of species that remain undescribed. Taxonomic work is slow, and many species—especially in highly diverse regions like the Amazon—go extinct before being scientifically recorded. AI tools such as image and audio classification algorithms can accelerate species identification by helping researchers flag unknown or rare species based on morphological or acoustic features.

2. The Wallacean shortfall involves limited knowledge of species' geographical distributions. Many species are known from only a handful of localities. AI-enabled species distribution models (SDMs), particularly those using machine learning, can integrate scattered occurrence data with environmental variables to predict likely species ranges more accurately and at higher resolution.

3. The Raunkiæran shortfall concerns the lack of data on species traits, such as reproductive strategies, growth forms, or dispersal capacity, that are essential to understanding ecological roles. AI can assist in automating trait extraction from digital records, images, and herbarium sheets, and can be used to infer traits from closely related species or ecological analogues using pattern recognition and data fusion.

4. The Eltonian shortfall refers to limited understanding of species' ecological interactions. This includes predation, pollination, and competition, complex relationships that structure ecosystems. Although harder to observe directly, AI can help identify potential interactions by analysing co-occurrence patterns, network structures in ecological communities, or synchronized behaviours from acoustic and visual data.

5. The Prestonian shortfall reflects the poor coverage of data on species' population abundances and trends. Traditional monitoring of abundance is labour-intensive, but AI can be applied to process large volumes of camera trap or acoustic data to estimate relative abundance over time and across sites, enabling better detection of population declines or surges.

6. The Hutchinsonian shortfall relates to the lack of detailed knowledge about species' environmental tolerances or niche dimensions, key for predicting how they may respond to climate or land-use change. Machine learning models trained on known occurrences and environmental layers can help define and simulate species' niches, including responses to novel conditions.

7. The Darwinian shortfall deals with incomplete information about species' genetic diversity and evolutionary potential, which is crucial for resilience under environmental stress. While AI is less central in producing genetic data, it is increasingly used to process genomic sequences, identify patterns of variation, and flag populations at genetic risk, especially in combination with spatial and ecological data.

Pollock et al. (2025) emphasize that these shortfalls are interconnected and cumulative, meaning one gap often reinforces another. While AI cannot substitute for fieldwork or taxonomic expertise, it provides an unprecedented capacity to synthesize unstructured datasets, identify hidden patterns, and scale biodiversity assessments across time and space. Its effectiveness, however, depends on robust, high-quality input data and sustained collaboration across disciplines and institutions.

In sum, biodiversity monitoring today spans a range of practices—from locally driven initiatives to high-tech, large-scale systems—and reflects growing recognition of the need to bridge ecological knowledge with policy and management. In the Amazon, where biological richness is extreme and threats are intensifying, monitoring frameworks that integrate local participation, advanced technology, and analytical flexibility are particularly needed. The challenge lies not only in capturing data, but in translating it into actionable knowledge that can support conservation at multiple levels: from site-specific interventions to regional strategies.

2.3.2 Monitoring deforestation

Monitoring deforestation has gained significant institutional support and technological advancement, particularly in comparison to biodiversity monitoring. In countries like Brazil, deforestation monitoring systems are well established, comprehensive, and tightly linked to environmental policy enforcement. Assunção et al. (2023) describe how Brazil's DETER system, based on satellite imagery, provides near-real-time alerts that have been used to guide environmental law enforcement since the early 2000s. This system has proven to be one of the most influential tools in the reduction of deforestation in the Amazon. However, satellite-based monitoring also presents challenges, such as persistent cloud coverage, which can obscure deforestation activity and affect the frequency and accuracy of image capture.

In Colombia, as Ferreira (2024 b) points out, satellite monitoring also plays a central role, but its effectiveness depends on a chain of conditions: that alerts are informative, that environmental authorities make active use of them, and that citizens and actors in the territory respond accordingly. Without these conditions, the mere availability of satellite-based information does not necessarily lead to a decrease in deforestation. This limitation is particularly relevant given that enforcement in Colombia has historically struggled due to lack of capacity and institutional coordination.

Another key point is the involvement of citizens in deforestation monitoring, as it also happens in biodiversity monitoring. McCallum et al. (2023) and Saavedra (2024) highlight how citizen engagement, including crowd validation of satellite image-based alerts and the training of AI models through manual labelling, contributes to more accurate systems and greater public awareness. These participatory approaches increase the legitimacy and transparency of environmental monitoring and have the potential to complement top-down enforcement mechanisms.

In addition to technical and participatory dimensions, deforestation monitoring in Colombia is shaped by complex political and institutional dynamics, on top of the armed conflict and illicit economies issues mentioned before. According to González-Balaguera et al. (2024), the country has developed a legal and institutional framework that includes monitoring systems like IDEAM's Forest and Carbon Monitoring System, as well as national commitments linked to international agreements such as the REDD+ program (Reducing Emissions from Deforestation and Forest Degradation, funded by the Food and Agriculture Organization of the United Nations, FAO). Nonetheless, the effectiveness of these mechanisms is often limited by fragmented implementation, weak coordination among institutions, and incentives that are not always aligned with environmental goals. For example, while deforestation is formally penalized, extractive activities such as mining often receive economic incentives or are tolerated despite their environmental impact. As mentioned in section 2.2.3, 'Visión Amazonía', the initiative denounced by the indigenous Communities in the Colombian Amazon is part of the REDD+ program (Andoke Andoke et al. 2023).

Understanding these sociopolitical dynamics is essential for effective deforestation monitoring and conservation. As the Colombian case shows, forest loss cannot be decoupled from broader issues such as land tenure insecurity, illicit economies, political instability, and weak law enforcement. Monitoring systems may provide timely and accurate alerts, but their impact ultimately depends on political will, institutional coordination, and the ability to align incentives for conservation at multiple scales.

Finally, it is important to remember that deforestation is a major driver of biodiversity loss. Clearing forests not only destroys habitats but also fragments ecosystems, reduces species mobility, and increases vulnerability to other pressures such as hunting or climate change. As noted earlier in this chapter, maintaining forest cover is crucial to safeguard the Amazon's exceptional biodiversity. Thus, monitoring deforestation is also indirectly an essential tool for biodiversity conservation, reinforcing the need for integrated approaches across both fields.

In summary, this literature review has outlined the theoretical foundations and current trends in sustainable AI, detailed the ecological and political complexities of the Amazon region, and highlighted how biodiversity and deforestation monitoring are evolving through technological and institutional innovation. Despite the rapid advancement of AI tools, there remains a lack of critical case studies documenting their real-world application in biodiversity-rich, institutionally complex environments. The following chapters address this gap by analysing Project Guacamaya as a case study of AI for sustainability.

3 Methodology

This research adopts a qualitative case study design to explore how a multi-actor AI-based environmental monitoring initiative emerges and operates in the Amazon region. The selected case, Project Guacamaya, is a rich example useful for examining the interactions between technological innovation, institutional collaboration, and sustainability goals. The case study method is especially suited to understanding contemporary, complex phenomena within their real-life settings, where boundaries between the phenomenon and its context are blurred. As Flyvbjerg (2006) argues, case studies are not limited to exploratory or illustrative functions; rather, they are instrumental for generating nuanced knowledge and deepening understanding of practice, particularly when conventional rules and generalizations fall short.

To guide the analysis, this study draws on the Sustainability Criteria and Indicators for Artificial Intelligence Systems (SCAIS) framework (Rohde et al. 2024). SCAIS was developed to assess AI projects through a multidimensional sustainability lens, considering ecological, social, and technical dimensions in an integrated manner. Its emphasis on both process and outcome, as well as its attention to unintended consequences and power asymmetries, makes it a suitable tool for examining socio-technical systems like Guacamaya. Together, the case study approach and the SCAIS framework offer complementary pathways to investigate how technological initiatives aimed at environmental governance are conceptualized, negotiated, and implemented in practice. Building on the literature reviewed in Chapter 2, and the research questions framed in Chapter 1, this chapter details the methodology used to examine Project Guacamaya.

3.1 Case study

This research adopts a case study approach based on the premise that AI systems—particularly those deployed for sustainability purposes—are inherently socio-technical-ecological in nature. As Rohde et al. (2024) argue, such systems are deeply embedded in their contexts and shaped by the interplay of institutions, actors, technologies, and ecosystems. In this view, context is not a backdrop but a constitutive part of the system itself, which makes generalization across cases both analytically risky and methodologically premature. Thus, a case study approach is the most appropriate methodology for exploring phenomena whose meanings, mechanisms, and implications are inseparable from their settings.

Beyond this conceptual alignment, the case study method also supports the production of expert knowledge in emerging research domains. As Flyvbjerg (2006) emphasizes, case studies contribute to the accumulation of context-rich insights that are essential for advancing knowledge in fields that are still taking shape. This applies to the intersection of AI and sustainability, where the scientific community recognizes the novelty and urgency of both Sustainable AI and AI-for-Sustainability as research agendas. Project Guacamaya is proposed here as a paradigmatic case: an example that stands out for its potential to inform broader theoretical and practical debates. At least three features support this claim of Guacamaya being a paradigmatic case. First, it is one of very few AI-for-Sustainability initiatives in Latin America with a clear co-creation backbone, as only eight comparable cases have been identified by Gutiérrez et al. (2025), alongside two additional examples found independently. Second, its design choices (such as the open-source publication of models, the use of public datasets, and a transdisciplinary, co-creative development model) aim explicitly at replication and adaptation. Finally, its real-world implementation aligns with proposals by Ahlborg et al. (2019) to focus sustainability research on the tensions between different knowledge systems and on collaborative innovation processes grounded in specific places and change dynamics.

3.2 SCAIS Framework

To guide the sustainability assessment of Project Guacamaya, this study applies the Sustainability Criteria and Indicators for Artificial Intelligence Systems (SCAIS) framework developed by Rohde et al. (2024). The framework provides a structured approach to understanding the impacts of AI systems not only from a technical perspective but also in relation to broader ecological and social contexts. Its core assumption is that AI systems should be analyzed as socio-technical–ecological systems (STES), where outcomes are shaped by the interaction between algorithms, institutions, human decisions, and environmental constraints. This framing acknowledges that AI development and deployment cannot be attributed solely to technical design, nor only to human intention, but must be situated in the hybrid space where infrastructure, governance, and ecosystems co-evolve (as shown in Figure 3, Chapter 2).

Rohde et al. organize the analysis of AI systems along six lifecycle phases: 1) organizational embeddedness, 2) conceptualization, 3) data management, 4) model development, 5) implementation, 6) use in decision-making. Together, these phases capture the dynamic process through which AI systems are imagined, built, and operated. The sustainability perspective adopted in the framework builds on the triad of social, ecological, and economic dimensions, not as isolated categories but as interrelated lenses through which tensions and trade-offs can be explored. While this division is presented as ideal-typical, the authors recognize the complex entanglements across domains and the need to assess how sustainability impacts unfold and interact across scales and systems.

To operationalize the assessment, the authors define four levels of impact: the AI system itself, the application level, the macro-social level, and the ecological system level. These levels reflect the multiple sites where sustainability outcomes may emerge: from the material and energy inputs of machine learning infrastructure to the long-term societal effects of decision-making processes influenced by AI. Table 2 presents the full set of sustainability criteria, and 67 indicators derived from literature reviews and expert workshops, covering both cross-cutting concerns and those specific to each dimension. These indicators provide an entry point for assessing whether and how AI systems like Guacamaya align with sustainability goals, though the authors caution that this list is not exhaustive and should evolve alongside new insights.

Crucially, the framework emphasizes the need to account for interdependencies and potential trade-offs between sustainability impacts. For instance, shifting data processing to more energy-efficient cloud infrastructures might reduce environmental strain, but also reinforce concentration in the tech industry. As Rohde et al. argue, sustainability assessments of AI must be paired with broader societal reflection and negotiation. Questions about which sustainability impacts deserve priority, and how to address tensions between them, cannot be resolved by technical metrics alone. The SCAIS framework offers a foundation for this kind of dialogue, combining analytical structure with openness to political and ethical dimensions.

	Criteria	Indicators (operationalization)	Life-cycle phase
(Organizational) governance dimension (cross-cutting criteria)	(1) Defined responsibilities	(1) There are contact persons for ethical and social matters (2) The allocation of responsibility is clearly and transparently regulated and documented (3) There are regulations on liability aspects	1
	(2) Code of conduct	(4) Norms and values for the implantation and use of AI systems defined in a code of conduct	1
	(3) Stakeholder participation	(5) Identification and classification of stakeholders (6) Integration of stakeholders into design, test, and release processes	1,2,4,5,6
	(4) Documentation	(7) Documentation of information regarding objectives, domain, users, data, model, feature selection, inputs, tests, metrics, and so on (model card)	1,2,3,4,5,6
	(5) Risk management	(8) Implementation of risk assessment (9) Implementation of risk monitoring (10) Implementation of risk management	1,2,4,6
	(6) Complaint mechanism	(11) Option to report errors, unfair and discriminatory decisions, privacy intrusions, and so on to AI-operating company	
Social dimension	(7) Transparency and accountability	(12) Parameter count (13) AI type (deep learning vs. statistical learning) (14) Use of methods for increasing transparency and explainability (15) Information about AI usage available (16) Access to information about functionality	1,3,5,6
	(8) Nondiscrimination and fairness	(17) Assessment of the potential for discrimination (18) Usage of methods for measuring fairness and bias (19) Definition of vulnerable groups and protected attributes (20) Measures to eliminate discrimination	1,3,4,5,6
	(9) Technical reliability and human supervision	(21) Mechanisms for performance control (22) Ensuring appropriate data quality (23) Opportunity for human control	3,5,6
	(10) Self-determination and data protection	(24) Privacy-by-design (25) Users have control over their data (26) Earmarked data use (27) Notifications regarding data use (28) Self-motivated use of AI systems (29) Abandonment of addiction-enhancing mechanisms (nudging, dark patterns)	2,3,6
	(11) Inclusive and participatory design	(30) Applying codesign principles (31) Ensuring accessibility	2
	(12) Cultural sensitivity	(32) Team diversity (33) Integration of local experts and natives	1,2,5

	Criteria	Indicators (operationalization)	Life-cycle phase
		(34) Transferability of the AI system to adapt to local and new application contexts, norms, and values	
Ecological dimension	(13) Energy consumption	(35) Energy consumption is considered during the system development (36) Models with lower complexity are favored during model selection (37) Pretrained models and transfer learning are used (38) Parameters that capture the model efficiency are measured (39) Methods for model compression are used (40) Methods for efficient training of the models are applied (41) Measures are used to reduce the amount of data	1,4,6
	(14) CO_2 and GHG emissions	(42) CO_2 footprint (43) CO_2 efficiency (44) Emission compensation	1,3,4,5,6
	(15) Sustainability potential in application	(45) Sustainable target function (46) Consideration of sustainability criteria in decision systems (47) Promotion of sustainable products (48) Promotion of sustainable consumption or sustainable consumption patterns (49) Reduction of resource consumption of processes or products (50) Impact of the AI system on the product quality and service life	1,2,3,6
	(16) Embodied and shared resource consumption of hardware infrastructure	(51) Certified hardware (energy and resource efficiency) (52) Certified data center (transparency, energy, and resource efficiency) (53) Efficiency metrics for data centers (e.g. power-/water-/carbon usage effectiveness) (54) Hardware recycling rate (55) Hardware reuse rate (56) Use of waste disposal scenarios for hardware	1,2
Economic dimension	(17) Market diversity and exploitation of innovation potential	(57) Accessibility of code (58) Accessibility of data (data pools) (59) Accessibility of AI tools (60) Interfaces (APIs) (61) Multihoming and compatibility	1,3,4,5,6
	(18) Distribution effect in target markets	(62) Adaptability to data volumes and action requirements (63) No differences in accuracy between major and marginalized market players (64) Diversity of employing customers (65) Support for SMEs and NGOs	1,2,5,6

	Criteria	Indicators (operationalization)	Life-cycle phase
	(19) Working conditions and jobs	(66) Evaluation of effects on working conditions (67) Fair wages along the AI lifecycle	1,6

Adapted from Rohde et al. 2024, p.4

Table 2. SCAIS Assessment Framework

3.3 Data collection

The primary data for this study was collected through semi-structured interviews with individuals directly involved in the design and implementation of Project Guacamaya in Colombia. The sampling strategy aimed to include at least one representative from each of the core partner institutions operating in Colombia: Microsoft, CinfonIA (Universidad de los Andes), Humboldt Institute, and Sinchi Institute. Although the Peruvian Ministry of Environment is a Guacamaya partner, it was excluded from the interview pool because its involvement began after data collection had already started. Planet Labs was not contacted either, as its participation in the project remains indirect.

To gain an initial understanding of the project's goals, partner roles, and public framing, the research began with a review of publicly available sources such as press releases, media coverage, technical documentation, and scientific publications. These materials served as a foundation for the development of an initial set of questions and themes, which were refined iteratively as interviews progressed. The first iteration of the questionnaire was built based on the 67 SCAIS indicators, so answers could be operationalized accordingly. In complement, an expert in the use of AI in the public sector in Colombia was also interviewed. The first set of interviews focused on exploratory themes (background, partnerships, objectives and progress so far) while a second round aimed to delve deeper into the project's institutional dynamics and sustainability-related design choices, guided by the 19 criteria of the SCAIS framework. Both groups of interviews were semi-structured, following the recommendation of Rohde et al. (2024) to allow flexibility in the assessment of a case. Interviews were conducted in Spanish, via videocall through Taltech's institutional Teams account, transcribed and translated using Microsoft Teams' transcription features alongside ChatGPT 4o, and manually revised to ensure fidelity and clarity. Transcriptions are available upon request.

3.4 Data analysis and limitations

The analysis followed a thematic approach informed by the Sustainability Criteria and Indicators for Artificial Intelligence Systems framework. Rather than evaluating impact or results—none of which are officially documented for Guacamaya yet—the focus was on examining how sustainability considerations were reflected in the project's design and in the early stages of execution. The SCAIS framework provided a structured lens through which to organize and interpret the interview material across technical, social, and ecological dimensions, while remaining flexible to emergent themes. Coding was guided by the framework's life-cycle phases and operationalizable criteria, with the goal of identifying how sustainability was interpreted, enacted, or negotiated across organizational and technical decisions.

Several limitations must be acknowledged. This study does not include perspectives from actors beyond Guacamaya's core implementation team, such as high-level institutional decision-makers. Therefore, it does not examine how Guacamaya fits into each organization's broader institutional strategy, as access and time constraints limited the scope of the interviews. Given the field-based nature of many participants' work, scheduling was difficult, and this delayed the research process. Additionally, since the project has yet to produce formal outputs or measurable conservation results, this study does not assess Guacamaya's effectiveness in achieving its environmental objectives. Instead, it offers an early account of the project's conceptual and organizational development.

While this limits external validity in the conventional sense, the case holds broader relevance as an example of AI-for-sustainability in the Global South, still rare and evolving field as it was described earlier. Guacamaya's emphasis on open-source tools, public data, and co-creation makes it a potentially replicable model. As such, the case contributes to early theorization and benchmarking efforts in the design of AI-based environmental governance systems, especially relevant in the context of the Amazonian Region, or neotropical ecosystems in general.

4 Results

This chapter presents the findings of the study, based on a thematic analysis of interviews with core actors involved in Project Guacamaya. The analysis is structured around the Sustainability Criteria and Indicators for Artificial Intelligence Systems framework, allowing for a multidimensional examination of how sustainability considerations shaped the project's design and early implementation. Direct quotes from interviewees are included throughout the text to illustrate key themes and provide insight into the institutional and technical dynamics at play. The first section describes information sources. The second section provides an overview of the project's goals, structure, partners and core activities, organized along the SCAIS lifecycle phases. The third section delves into the project's sustainability-related practices, tensions, and challenges across the four SCAIS dimensions, based on the 19 criteria.

4.1 Data collected

To grasp empirical data and answer the research questions several semi-structured interviews with members of the core team of Project Guacamaya were conducted via videocall. Although the four organizations comprising the initial partnership were contacted with interview requests, responses were obtained from two of them: CinfonIA, and Microsoft. A researcher from Instituto Sinchi was effectively contacted with a positive reply, but it was not possible to meet their agenda as it was full of fieldwork during the time of this research. To help balance the absence of an active Humboldt Institute representative, a former researcher from Humboldt Institute was contacted and successfully interviewed. In addition, a professor specialized in AI for the public sector and public policy in Colombia was interviewed to reflect upon the context of the case and scope of the study.

To preserve the privacy of participants, only initials are used in this document. Institutional affiliations are reported as they are necessary for analytical purposes and were disclosed with participant awareness. The interviewees are:

- JC: mathematician, former researcher at Humboldt Institute, and currently affiliated with two labs specialized on biodiversity and nature conservation in London. Main research tracks: artificial intelligence, biodiversity monitoring with focus in bioacoustics. Interview length: 72 minutes.

- DC: engineer, researcher at both CinfonIA Lab and Microsoft AI for good, specialized on Artificial Intelligence. Interview Length: 28 minutes.

- AH: engineer, researcher at both CinfonIA Lab and Microsoft AI for good, specialized on Artificial Intelligence. Interview Length: 60 minutes.
- GO: business administrator, Regional Digital Transformation Officer at Microsoft, Spanish-speaking Latin America. Interview Length: 75 minutes
- JG: Lawyer, researcher at Universidad de Los Andes, Escuela de Gobierno. Research fields are AI for the public sector, algorithmic transparency, regulation, public policy evaluation. Interview Length: 32 minutes.

Other primary sources consulted are the paper on Pytorch-Wildlife (Hernandez et al. 2024)—one of the models developed by Project Guacamaya and published in 2024 as open source; as well as press releases by the partner organizations (Instituto Sinchi 2023; Lavista Ferrés 2024; Ministerio de Ambiente, Perú 2025; News Center Microsoft Latinoamérica 2023; Smith 2024).

4.2 Project Guacamaya according to empirical findings

As Guacamaya is still in an early stage of execution with no published results or evaluated impact so far, press releases and related publications are insufficient to analyze even preliminarily its performance across the SCAIS criteria, nor to understand how it functions in general. Interviewing members of the project allows a more complete understanding of its objectives, governance mechanisms, challenges and day-to-day work, as it is presented in this subsection.

4.2.1 Project origins and strategic framing

According to two of the Microsoft affiliated interviewees, the main goal is to preserve and protect the Amazon forest. JC explained from a more scientific-oriented perspective "it's mostly about sensing and monitoring, not about direct intervention or policy enforcement.", and invoked Xu et al's (2023) distinction of AI used to understand the world (instead of acting in the world to undertake conservation actions, or evaluating impact of performed actions). As JC stated:

> *It's hard to measure [the impact these projects have in the Amazon or in conservation more broadly]. Reforestation and deforestation operate on different timelines and involve complex social-ecological dynamics. Some projects aim to empower communities, but Guacamaya is more model- and data-oriented. Any societal or policy impact would be indirect and long-term — if at all.*

Microsoft's senior officer claimed the initiative comes from their company, as it is framed by broader strategic corporate objectives to be carbon neutral by 2030 and water positive by 2050. As they realized how important is the Amazon basin to regulate climate through carbon and water cycles, the company began its search for partners and a roadmap to implement impactful actions in that direction. They eventually partnered with the expert organizations, discussed and conceived Project Guacamaya as a long run effort to improve the knowledge of the Amazon forest that is necessary to inform climate action. The multimodality of Guacamaya (i.e. collecting data from cameras, microphones and satellites) is a key first step, as they are aware of how it enables an integral analysis of ecosystemic behaviour. According to AH, Guacamaya has internally established more specific objectives operationalizable in the short- and mid-term, but they are not officially shared to the public.

4.2.2 Multimodal approach: three data verticals

The core technical activities of Project Guacamaya are structured around three data verticals: camera traps, satellite imagery for deforestation monitoring, and bioacoustics. According to DC, each vertical has its own objectives, models, and associated institutional collaborators, but all share the broader goal of enabling improved sensing and monitoring of the Amazon ecosystem. In DC's words, "the idea is to understand the ecosystem using complementary, multimodal data sources."

In the camera trap vertical, AI models are trained to detect the presence of animals in images captured by motion-activated field cameras. The models allow for the automatic classification of species or, when classification granularity is limited, higher-order taxonomic groups. So far, these systems have significantly reduced the time and manual effort previously required from researchers, particularly those at Instituto Sinchi, who are currently the main operational partner for this branch. The framework upon which these models have been developed has also been published as open-source and hosted on GitHub under the name Pytorch-Wildlife. It is iteratively updated based on user feedback, aiming to increase their accuracy and usability in real-world research settings.

The second vertical focuses on deforestation monitoring through satellite imagery. AI models in this branch use semantic segmentation to classify every pixel in a satellite image as either "forest" or "non-forest." The data used comes from Planet Labs, though access and use of such imagery involve licensing and cost considerations. Guacamaya has access to them thanks to a global agreement between Planet and Microsoft. A particularly important technical innovation in this area was introduced to solve the challenge posed by persistent cloud cover in Amazonian regions. As GO explained, "you look up in Bogotá this time of year, and it's always cloudy… [the] satellite photos [are] full of clouds—those cloud shadows mess up the model completely.” To address this issue, the engineering team led by researchers at CinfonIA implemented spectral filtering and image compositing techniques, resulting in 30-day “mosaics” that stitch together clearer portions of images across time. This solution improves model reliability and enables clearer analysis of forest loss. The improved visibility not only enhanced classification performance but also laid the groundwork for a shift in modelling focus, from detecting deforestation that has already happened to predicting where it is most likely to occur in the near future. Models from this vertical have not been released to the public yet, as refinement is still ongoing.

In the bioacoustics vertical, the team developed a model and a graphical interface that allows users to search for specific sounds using natural language queries. Users can, for example, ask if the sound of a specific bird, or perhaps heavy machinery, were detected. The system highlights corresponding patterns in spectrograms, streamlining the process of annotating large audio datasets. Without a system like these, scientists would normally spend hundreds of hours listening to audio recordings where nothing of their interest happens. The tool was delivered to the Humboldt Institute and was integrated into ongoing biodiversity research workflows. According to DC, the bioacoustics line is currently paused, though it is expected to be reactivated soon with the help of a new technological component: a field-deployable device called Sparrow.

Sparrow is a new-generation edge device that integrates camera trap, acoustic, and satellite transmission functionalities into a single unit. Designed by Microsoft’s AI for Good alongside CinfonIA, and shared with Guacamaya partners for pilot deployment, Sparrow enables real-time data collection and model execution directly in the field, without relying on high-speed terrestrial internet. As explained by DC, “Sparrow combines cameras, microphones, and satellite connection (via Starlink) into one unit.” According to Microsoft’s researchers, openness is a key feature of this development, as its software and hardware plans to its 3D-printable designs are open source and accessible to all kinds of researchers (Lavista Ferrés 2024). The device aims to reduce friction between data collection and analysis while also enabling faster response times to ecological changes. AH explained:

> *“I was actually out in the field installing these devices, and all the different organizations that are part of the Guacamaya project are receiving them. For example, we installed one at the Universidad de los Andes' reserve, one at the Fundación Biodiversa reserve, which is another foundation, and we’re going to install one at Sinchi in another month. So there will also be announcements related to that. These monitoring stations run Python scripts in the background.*

> *They run the models we trained with each of the institutes… The devices at Sinchi run with the Guacamaya model, trained with Sinchi's data. The ones at Fundación Biodiversa—which is in the Magdalena Medio region—also run with Sinchi's models for now, because we don't yet have a model trained specifically with data from that ecosystem. The same goes for Universidad de los Andes. But the idea is that as these devices collect more data, we'll have the opportunity to refine the models. Through Sparrow and the data it collects, we hope to improve Sinchi's model even further so it serves them better."*

Although each vertical currently operates semi-independently with their respective partner institutions, interviewees indicated that the long-term vision is to develop fully integrated, multimodal models that analyse combined data from all three sources: image, sound, and satellite. According to DC, the team is working toward standardizing data collection protocols to allow interoperability and fusion between verticals. A more unified model would, in theory, be capable of correlating animal presence (camera traps), species activity (bioacoustics), and habitat change (deforestation models) to create more holistic insights into Amazonian ecological dynamics.

4.2.3 Institutional collaboration and co-creation philosophy

The coordination of these activities is guided by a co-creation philosophy, as repeatedly emphasized by multiple interviewees. Regular coordination occurs through multi-stakeholder meetings such as the Guacamaya Summit, where representatives from each partner institution share updates and collaboratively define yearly priorities. The decision-making model privileges consensus, and each institution contributes according to its expertise and needs: Microsoft provides the infrastructure (cloud computing, storage, AI engineering) while CinfonIA contributes academic and algorithmic knowledge. The scientific institutes, namely Sinchi and Humboldt, provide biological expertise, long-term ecological data, and logistical capacity for fieldwork and community engagement.

GO highlighted the trust-based nature of these relationships, especially with institutions that are protective of their data or have experienced extractive partnerships in the past. In their words: "This kind of arrangement—what we call co-creation—has been key. Not just in terms of operations, but also for building trust." The choice to distribute decision-making and embed partners' perspectives into the design and iteration of models appears to be one of Guacamaya's distinctive organizational features.

While Project Guacamaya operates through a collaborative framework, each participating organization brings distinct institutional goals, constraints, and forms of expertise to the alliance. As previously noted, for Microsoft, the initiative aligns with broader corporate commitments to become carbon neutral and water positive by 2030 and 2050, respectively. The project is framed within Microsoft's regional sustainability agenda, which recognizes the Amazon as a vital climate regulator and biodiversity hotspot. From this perspective, Guacamaya allows the company to operationalize its sustainability objectives through long-term investment in environmental data infrastructure and technological support.

From the academic side, the CinfonIA Lab at Universidad de los Andes and Microsoft's AI for Good Lab contribute the core machine learning expertise and coordinate most of the model development work. According to AH, the AI for Good Lab is "entirely dedicated to social good" and operates independently from Microsoft's commercial lines of business. While the two labs had previously worked together in open science projects, particularly during the COVID-19 pandemic as described by AH, Guacamaya marked a transition into long-term environmental monitoring. CinfonIA plays a key role by anchoring the technical development process in Colombia and ensuring continuity through a research group that bridges academia and industry. It is led by prof. Pablo Arbeláez, and covers global health, computer vision, sustainability and ethics in AI as its main research tracks. CinfonIA has other partnerships in the sector, both Colombian and international. For example, Google-DeepMind offers scholarships for admitted graduate students aiming to partake in research projects at CinfonIA (Universidad de Los Andes 2025).

From the perspective of environmental science and biodiversity conservation, the Humboldt Institute plays a complementary but no less crucial role. GO pointed out the leadership of this organization in knowledge and research of biodiversity, as it is thanks to their work that Colombia is regarded as the second most biodiverse country in the world, holding the record for largest number of bird species found in a single country, for example. To JC, Humboldt "doesn't have the computational resources to develop models itself," but instead focuses on identifying scientifically relevant problems and building structured datasets. In this sense, the institute acts as a problem-framing hub, working to articulate research questions that can be addressed using advanced analytical tools and their robust datasets. JC described this strategy as one of targeted alliances: "Humboldt seeks alliances with Microsoft, CinfonIA, universities, to make these problems actionable through technical development." This model has been applied in other projects beyond Guacamaya, such as amphibian detection and camera trap research, where Humboldt led the design and curation of datasets while leaving the development of detection algorithms to collaborating institutions (for instance, the Camera Trap Days (CTD) project, launched in 2021 in collaboration with the google-powered platform Wildlife-Insights (Interlace

Hub 2023)). In terms of values, JC emphasized the Institute's commitment to social relevance and local benefit, noting that many of its biodiversity monitoring initiatives aim to be community-centred. Nonetheless, this varies by project, and some technically oriented lines of work—like Guacamaya—tend to have less direct community engagement.

4.2.4 Governance structure

Guacamaya's governance structure is formally anchored in a Memorandum of Understanding (MoU) signed by the participating institutions. According to AH, the MoU serves to establish co-creation as the foundational principle of the partnership. It allows partners to share information securely, coordinate development efforts, and maintain parity in decision-making. Each organization retains control over its own data and models, and responsibilities are distributed to reflect their respective areas of expertise. The MoU also outlines that no single institution can unilaterally admit new members into the project; any expansion of the partnership must be agreed upon by all current members. As explained by AH, this clause ensures that each organization's voice is respected and that new alliances do not undermine existing arrangements.

While the MoU provides a formal basis for collaboration, interviewees repeatedly emphasized that governance in Guacamaya is not just a matter of institutional procedure: it is deeply shaped by the need to build trust among partners. GO offered a detailed account of the process that led to the incorporation of Instituto Sinchi into the project before it was formally conceived. At the beginning, there was visible scepticism. GO recalled that after numerous invitations, a first meeting was held between Microsoft and Sinchi's executive director, which started with cautious, even confrontational questions: "Why do you want to meet with me? What's the point?" and later, "You're a gringo multinational. Others like you have already come here and tried to take everything. They left nothing for the communities, nothing for the institutions, nothing for the scientists."

The tone shifted only after the Microsoft team presented the project's core premise: that all models developed through Guacamaya would be open source. This principle, according to GO, proved pivotal. It helped move the conversation away from suspicion and toward a possible collaboration. GO narrated how Sinchi's team emphasized three key conditions for their support: they would not accept payment, the data must remain open, and the project could not exploit communities or their information. These conditions were accepted and later formalized in the MoU. The director of Sinchi at the time, described by GO as a long-standing leader based in Leticia, played a central role in facilitating this agreement. According to GO, this episode exemplifies how co-creation, beyond being a design principle, became a tool for repairing or pre-empting trust deficits rooted in past experiences with extractive partnerships.

The operational side of governance is equally distributed. AH described Guacamaya as a "roundtable," where all institutions meet regularly to align technical decisions with organizational needs. Model development is coordinated collectively, with each vertical having shared objectives but partner-specific requirements. Microsoft contributes cloud resources to ease budgetary pressure on public institutions and ensures that model deployment is accessible. CinfonIA leads algorithmic development and iterates on model architecture based on partner feedback. Scientific institutes contribute the field data and domain-specific knowledge essential for training and validating the models. In practice, this means that if different institutions have preferences regarding model outputs (for instance, formatting standards or integration into existing systems) these are discussed and resolved collaboratively.

AH noted that even though models are built on data from specific institutions, the training data itself is not necessarily published. Data publication remains at the discretion of the institution that owns it. However, the trained models are meant to be released as open source, fulfilling a baseline commitment of the partnership. This allows others, inside and outside the project, to benefit from the technical outputs while respecting data governance boundaries.

The process for integrating new partners further illustrates how governance decisions operate in practice. When the Ministry of Environment of Peru joined Guacamaya, it brought its own acoustic datasets and specific goals, such as detecting the presence of the "Gallito," Peru's national bird. According to DC, Peru was treated as "another ally in a new territory." While the project was originally developed in Colombia, its design is intentionally regional, and scaling across the Amazon basin is considered both a technical aspiration and a political commitment. Still, the inclusion of a new partner, even one as prominent as a national ministry, was contingent upon agreement from all active members.

In sum, governance in Guacamaya combines formal mechanisms with deliberate practices of transparency, negotiation, and reciprocity. While the MoU provides a legal and procedural backbone, the legitimacy of the partnership appears to derive equally from how well it embodies the co-creation ethos in day-to-day interaction. Interviewees consistently emphasized that Guacamaya is not led by one actor, but jointly held, developed, and maintained by a distributed network of institutions, each with agency and accountability.

4.2.5 Community engagement and indirect participation

Guacamaya's relationship with local communities is largely indirect and mediated through the partner institutions. Interviewees acknowledged that neither Microsoft nor CinfonIA have established direct contact with communities in the Amazon region. This decision, while sometimes misunderstood in international contexts, is the result of both legal constraints and a strategic division of labour within the co-creation model.

According to GO, Colombian legislation requires that any formal interaction with local or Indigenous communities be preceded by a legal mechanism known as consulta previa (prior consultation). In practice, GO noted, this often translates into complex negotiations involving compensation or financial incentives. For technology-driven environmental projects such as Guacamaya, which do not involve infrastructure or direct exploitation of natural resources, navigating this legal framework can still prove cumbersome. "It's not pretty to say," GO remarked, "but when you're dealing with oil drilling, fiber optic cables, or anything involving infrastructure, you end up facing the same thing. The lawyers handle it." In this context, Microsoft and CinfonIA have opted to rely on the scientific institutes—particularly Sinchi—as intermediaries that already have established relationships and ongoing engagement with the communities.

This arrangement does not mean communities are excluded from the project. Rather, their involvement takes place through existing collaboration channels managed by Guacamaya's institutional partners. For instance, in the deployment of camera traps and Sparrow devices, members of local communities often play a key role in the field logistics. They assist with placement, movement, and maintenance of the equipment. As described by GO, "Sinchi puts cameras out in the field. The local communities set up and move them around." AH provided a similar account from firsthand experience with the Sparrow pilots, explaining that local collaborators provided practical advice based on lived experience in the territory, such as which trees receive sufficient sunlight, where animal corridors are likely to pass, and how to protect antennas from lightning. In many cases, their knowledge shaped design adaptations. "They told us, for example, 'The battery is too heavy to carry through the jungle,'" AH recalled, or "'You're hanging the antenna too high, it could get hit by lightning.'" Feedback like this was frequently offered and integrated into the ongoing development of the devices.

Despite this indirect model, interviewees emphasized that community participation is not peripheral. According to AH, "even if we don't interact with communities directly, each of the partner institutes does," and in the field, it is community knowledge that often determines the success of deployments. From selecting camera trap locations to maintaining solar-powered hardware, the technical operation of Guacamaya depends on a tacit knowledge base that resides in the territories themselves. While the community members involved may not be formally documented as participants or beneficiaries of the project, they contribute insight that shapes both data quality and device functionality.

In some cases, participation also generates excitement and curiosity. AH described how people in the field reacted with interest to the Sparrow units, often asking about durability and technical function: “Will it hold up in the humidity? What about the monkeys? What if it gets struck by lightning?” Such reactions suggest that even if community engagement is not formalized through direct governance or participation mechanisms, it still plays a role in shaping the practical implementation of the project and may grow into more defined collaboration lines over time. Future ambitions, according to GO, include enabling community-led data uploads through improved internet access and further training in device use, although legal hurdles around formal engagement remain.

Overall, Guacamaya’s interaction with local communities is not structured as a component of its core governance but unfolds in practice through co-creation. The institutes serve as intermediaries, absorbing the complexity of working in socially and legally sensitive territories while also ensuring that local knowledge feeds into the technological design and deployment processes. From the project’s perspective, this model of indirect engagement is both a practical necessity and a reflection of its broader commitment to collaborative, non-extractive research.

4.2.6 Early outcomes and gains

While Project Guacamaya is still in an early stage and has not yet published peer-reviewed results or conducted external impact evaluations, several of the models developed and shared among partners are already being used to support ongoing scientific work. Interviewees from both Microsoft and CinfonIA offered concrete examples of how the tools are currently saving time, improving analytical workflows, and increasing the scale and speed of biodiversity and deforestation monitoring.

The most consistently cited outcome was the reduction in manual labour previously required for image and audio analysis. According to DC, the camera trap model has reduced Sinchi’s image review time by approximately 90 percent, while the bioacoustics tool has helped researchers skip over 80 percent of audio segments, accelerating the review of more than 600 hours of field recordings. In practical terms, this means researchers no longer have to sift manually through long stretches of uninformative material. GO provided a similar account, recalling that one researcher told the team: “We went from having to listen to 600 hours of audio manually to focusing only on the 20 percent that actually contained bird calls or relevant sounds.” These time savings are not only operationally significant, they also open analytical possibilities. As GO described it, the freed-up time allows biologists to ask more complex questions: Why is a species vocalizing more in one location than another? Are there signs of distress? Is illegal activity like logging detectable in the background soundscape?

The deforestation monitoring model has also begun to show practical utility, particularly in reducing the time required to generate land cover classifications. According to DC, the production of national deforestation maps, which previously took days or even weeks, can now be completed in a matter of hours. GO illustrated this with the case of the Meta department in Colombia, an area spanning 83,000 square kilometres. With Guacamaya's current tools, a deforestation map for Meta can be generated in around 30 minutes. A map for all of Colombia takes approximately one hour, and a map of the entire Amazon basin (covering over 14 million square kilometres) can be processed in about six hours. These gains in processing speed do not only streamline internal workflows; they potentially allow for more regular and responsive monitoring, a capacity that is critical in regions experiencing rapid land use change.

Beyond operational improvements, interviewees highlighted that the tools have been designed to be open and accessible. The camera trap model, published as open-source code, has been downloaded more than 35,000 times. However, GO pointed out a geographical asymmetry in this uptake: "Most of those downloads are not from Latin America. They're from Europe and the United States." While the statistic is seen as a marker of technical interest and tool quality, it also underscores the challenge of ensuring that innovation developed in and for the Amazon reaches and benefits researchers and institutions in the region.

The interviewees also discussed a more experimental functionality that is beginning to mature: a generative AI interface for querying audio recordings. The system allows researchers to upload an audio file and ask, in natural language, whether a certain event occurred, such as the presence of a bird. The model then returns a timestamped response and classifies the species, offering a starting point for deeper behavioural analysis. According to GO, this type of tool functions not just as a productivity enhancer, but as what they described as "the jungle's early warning system." Beyond saving time, it allows researchers to detect patterns that may signal larger environmental changes: species stress, mating behaviour, or background noise indicating habitat disturbance.

Taken together, these early results point to a set of concrete gains in efficiency, usability, and access. While it is still too soon to assess Guacamaya's broader impact in terms of conservation outcomes, the internal feedback from partner institutions suggests that the project is achieving meaningful progress toward its short-term operational goals. As more models reach maturity and are deployed at scale, further evaluation will be necessary to assess how these tools are shaping ecological research, institutional workflows, and potentially, policy-relevant environmental monitoring in the Amazon basin.

4.2.7 Challenges to policy uptake and future aspirations

While Guacamaya has delivered early technical outputs with measurable internal benefits for its partner institutions, translating those gains into formal adoption or integration within public sector decision-making remains a significant challenge. Interviewees identified several factors that complicate the pathway from model development to policy impact, ranging from institutional distrust in artificial intelligence to administrative instability and political fragmentation.

One example shared by GO involved a recent meeting with Colombia's newly appointed Minister of Environment, a figure described as deeply familiar with the Amazon region and its violent history of extractive practices. According to GO, the minister responded enthusiastically to the project's goals and requested direct access to Guacamaya's deforestation monitoring data. However, the request could not be fulfilled through official channels, as Guacamaya's outputs are not formally recognized by IDEAM, the national agency in charge of climate and environmental information systems. GO noted that while IDEAM scientists are highly respected, they have shown resistance toward the project's tools, in part due to a general scepticism about AI and cloud-based solutions. Preference remains for on-premises data processing infrastructure, which slows down operations considerably. As GO put it, "they still want a physical server of their own to process thousands of images, and that's just not going to cut it."

This institutional reluctance exists alongside broader political instability. In GO's account, Colombia has changed 53 ministers in just over two years (under a single government), a level of turnover that makes follow-through difficult even when interest is expressed. In contrast, Peru's Ministry of Environment, which more recently joined Guacamaya, was described as more agile and receptive. Peruvian authorities brought their own datasets and clearly defined goals, such as detecting the presence of the Gallito bird. The difference in pace between countries was attributed not only to political openness but also to technical culture and willingness to adopt cloud-based, open-source technologies.

Guacamaya's open-source model is intended to facilitate broader international uptake, and this is beginning to happen, albeit unevenly. For instance, Norway currently pays Planet Labs to provide open access to satellite imagery for environmental monitoring in several countries, including Colombia. Despite having access to the same datasets used in Guacamaya, GO noted that IDEAM still takes up to 18 months to process and publish results, whereas Guacamaya's models can deliver comparable outputs in a matter of hours. The availability of faster, open tools does not guarantee their adoption when institutional preferences and frameworks remain unchanged.

To address this, the team is developing a variety of strategies for broader participation and validation. GO recalled an example they are finding inspiration from: another Microsoft-led initiative in Chile involves user participation through a feature embedded in Microsoft Flight Simulator, a game that integrates Planet's satellite imagery. As players fly over the Andes Mountain range, they can visually identify signs of deforestation and tag coordinates. Similar reporting mechanisms are intended to be integrated into Guacamaya's datasets as a form of crowdsourced validation. While not real-time, this form of human feedback could improve the model's accuracy and increase public awareness of deforestation events.

Another element of the expansion strategy is Project Sparrow. These units have been deployed in a range of research reserves including those of Universidad de los Andes, Fundación Biodiversa, and Sinchi. While the devices currently run models trained on Sinchi data, the long-term goal is for them to support model refinement through continuous, location-specific data collection. In AH's words, "as these devices collect more data, we'll have the opportunity to refine the models… to serve them better."

Despite these advances, interviewees were careful to note that Guacamaya's predictive models still require validation before being used to inform public action at scale. The team's aspiration is to reach a level of technical robustness and institutional credibility that would allow models to inform policy across borders. As GO remarked, one possible route forward involves leveraging the role of Sinchi's director, who also leads an Amazon research network that includes Colombia, Peru, Bolivia, Ecuador, and Brazil. If models can demonstrate sufficient accuracy and relevance, there is hope they could be taken to regional authorities in Brazil, despite that country's existing satellite monitoring infrastructure. While Brazil's public systems are considered more advanced than those in neighbouring countries, they still rely on lower-resolution imagery and slower analysis workflows. By contrast, Guacamaya offers high-resolution, cloud-processed tools that could support integrated monitoring of deforestation and biodiversity.

Yet, as GO put it, these ambitions are still "a dream", especially the broader aspiration of monitoring "ríos voladores," or flying rivers, which refers to the Amazon's role in generating rainfall patterns that sustain ecosystems and urban water supplies throughout the continent. For now, the challenge remains twofold: to refine the existing models and to foster the institutional relationships needed for their formal adoption. According to interviewees, that process will require not only technical validation but also shifts in political will, epistemic trust, and inter-agency cooperation.

4.3 SCAIS criteria performance of Guacamaya

This subsection presents a structured analysis of Project Guacamaya based on the SCAIS framework (Rohde et al. 2024). It is designed to assess the sustainability of AI systems by considering their full lifecycle across six phases: organizational embeddedness, conceptualization, data management, model development, implementation, and use in decision-making. It organizes 19 sustainability criteria into four main dimensions: governance (as cross-cutting), social, ecological, and economic. These criteria are operationalized through a set of 67 indicators, which served as a reference for the coding and interpretation of empirical material gathered in this study.

As it has been mentioned, Guacamaya is still in the early stages of implementation. As such, this assessment does not cover all six lifecycle phases in full. Certain aspects—particularly those related to the system's deployment and use in formal decision-making—remain under development. Nevertheless, the analysis presented here reflects the current state of the project according to the data collection methods explained previously. Findings are reported criterion by criterion, grouped by dimension, and illustrated with excerpts from the interviews when relevant.

4.3.1 (Organizational) governance dimension (cross-cutting criteria)

<u>(1) Defined responsibilities</u>

Project Guacamaya's responsibilities are outlined and operationalized through a MoU signed by all core partner institutions. As explained by one of the interviewees, the agreement serves as the primary governance mechanism, defining the co-creation model and enabling data and knowledge sharing while preserving institutional autonomy. Although the MoU itself was not shared in full due to confidentiality reasons, multiple interviewees confirmed that it clarifies who is responsible for what within the partnership. Rather than centralizing accountability in a single coordinating body, the document affirms that each institution retains ownership and control over its own data, infrastructure, and internal standards.

In this distributed model, responsibility is not externally imposed but arises from negotiation and coordination among partners. For example, the definition of priorities and outputs for each data vertical takes place through regular collaborative meetings. Each institution is responsible for ensuring that outputs from shared AI models meet their internal operational needs. As one interviewee explained:

> "If Sinchi wants the output format from the AI model to look a certain way, and Humboldt wants it in another format, we sit down together, evaluate everyone's needs, and come up with an action plan that benefits the majority as soon as possible."

This process reflects a shared, transparent allocation of responsibility, even if it does not follow a rigid hierarchical structure. The governance arrangement does not include formal contact persons or ombudspersons for ethical or social matters as defined by institutional ethics boards, but discussions of data use and institutional roles appear to be handled directly within the partner network.

(2) Code of conduct

While Project Guacamaya does not appear to maintain a centralized code of conduct of its own, several boundary conditions have been agreed upon and serve as informal ethical guidelines. These conditions were originally proposed by the scientific partners, particularly Sinchi, as prerequisites for collaboration. As summarized in one interview: "1. You don't pay me. 2. The data stays open. 3. You don't exploit the information or the communities." These principles, although not codified in a formal document, function as a shared normative framework for the project and were critical for building trust among institutions. They echo values frequently associated with ethical AI initiatives, such as openness, non-extractivism, and respect for local sovereignty.

Instead of a uniform ethical policy, each institution within Guacamaya appears to be adhering to its own internal codes and regulations. The project's governance structure thus reflects a federated approach to values and norms, where alignment is achieved through negotiation rather than a single binding directive. This may be seen as both a strength because it allows for flexibility and contextual sensitivity, and a potential limitation, especially if the project grows and new actors enter the partnership as intended.

(3) Stakeholder participation

Stakeholder participation in Project Guacamaya is deeply embedded in its co-creation model and is formalized through the project's Memorandum of Understanding. Core institutional stakeholders have all been integrated into the design and implementation of the project from the outset. Each organization contributes distinct expertise and maintains ownership over its contributions, including data, infrastructure, or scientific knowledge. According to interviewees, Guacamaya functions as a roundtable: all partners meet regularly to align objectives, define outputs, and adjust priorities. Coordination occurs through mechanisms such as the Guacamaya Summit and smaller roundtable working groups, which allow for shared planning and mutual adaptation. Each institution has an equal voice in determining priorities and use cases within their respective verticals, ensuring that model development aligns with real institutional needs.

Although stakeholders external to the partner institutions (such as local communities or government agencies) are not formally integrated into the design or testing processes, the project's core collaborators have been systematically identified, their roles classified, and their participation operationalized through ongoing collaboration. As such, stakeholder participation can be considered one of the better-articulated and actively maintained aspects of Guacamaya's governance model.

(4) Documentation

At the current stage of the project's development, comprehensive external documentation remains limited. Interviewees acknowledged that most of the project's models and outputs are still under refinement and have not yet been formally published. As such, public-facing documentation materials—such as model cards or detailed release notes describing objectives, domain relevance, datasets, feature selection, performance metrics, or limitations—are not yet available for most components of the project.

The only model fully released and documented to date is PyTorch-Wildlife, an open-source tool for processing camera trap images. According to interviewees, further releases for other verticals are planned and will include accompanying documentation, sample datasets (pending partner approval), and use-case examples intended to support replicability and transparency. The intention, as expressed by project members, is to make not only the code but also the methodology and context explicit, particularly to foster trust and accountability in regions like Latin America, where skepticism about extractive scientific collaborations remains justified. Although this criterion cannot yet be fully assessed based on outcomes, the project demonstrates awareness of the importance of documentation and has begun to lay the groundwork for more robust, outward-facing communication in the future.

(5) Risk management

Interviewees identified several risks that have already been considered in the project's design, along with initial strategies to mitigate them. These risks relate primarily to the potential unintended consequences of data disclosure, especially in sensitive ecological and security contexts.

One of the clearest examples involves the risk of publishing location data related to endangered species. As described by project members, early design discussions around a unified, multimodal monitoring platform raised concerns about how such information might be misused if released without filtering or delay. In response, the future platform is being planned with two access levels: a restricted layer for registered researchers affiliated with trusted institutions, and a public-facing version with blurred location data and delayed updates. This layered access model is intended to reduce the risk of contributing to wildlife exploitation, while still supporting transparency and open science in a controlled manner.

A second form of risk emerged in conversations with Colombian law enforcement. When presented with Guacamaya's deforestation alerts, police authorities expressed enthusiasm but also requested that data be published with a 30-day delay, or a similar mechanism. Their concern was that public disclosure of deforestation hotspots in real time could compromise ongoing investigations or prematurely reveal the locations of planned enforcement actions. As a result, the project team is exploring options to adjust the temporal release of certain outputs in coordination with state actors, while maintaining its commitment to openness and public accountability.

Although a formal risk management plan or framework has not been described, these examples demonstrate that risk identification and mitigation are already part of the project's internal discussions. Risk assessment is being carried out at the design stage, particularly in relation to data sensitivity and potential downstream consequences of information release. Monitoring and management mechanisms, such as differentiated access protocols and time-delayed outputs, are being developed to address those risks. Given the project's lifecycle stage, these strategies remain preliminary, but they suggest a proactive approach to anticipating and responding to ethical and operational concerns.

(6) Complaint mechanism

At the time of writing, Project Guacamaya does not have a dedicated, project-level complaint mechanism for reporting model errors, discriminatory outputs, or privacy-related concerns. This is not unexpected given that the project is still in development and not yet directly interfacing with public users or policy decision-makers in a formal way. From the perspective of practical implementation, user-facing mechanisms for complaint or correction may not be necessary within Guacamaya itself, so long as they are upheld by the institutions conducting fieldwork, engaging communities, or publishing outputs. These institutions—such as Sinchi and the Humboldt Institute—typically have their own protocols for managing ethical concerns and public communication, especially when research involves sensitive ecological or social dimensions.

Additionally, Guacamaya's emphasis on open-source publication of models and data offers a degree of public transparency and informal accountability. Users accessing and deploying these tools can inspect, adapt, or critique the models directly, which may serve as a de facto mechanism for feedback and iterative improvement. While this approach does not substitute for formal complaint channels, it reflects a broader commitment to openness and responsiveness. If Guacamaya's tools are eventually integrated into public-facing platforms or decision-making systems, more structured mechanisms for redress may become necessary.

4.3.2 Social dimension

<u>(7) Transparency and accountability</u>

Transparency is one of the pillars of Project Guacamaya's co-creation model. Although many outputs remain under development, the team has consistently emphasized its commitment to open-source publishing and reproducibility. This has been already pointed out in detail. While technical details such as parameter count or precise model architecture are not yet published for most models, the intention is to make this information available upon release. The use of deep learning is the predominant AI type, particularly for image and acoustic analysis. As models mature, their release is expected to include not only the code but also documentation, datasets (when permissible), and applied results, allowing external users to understand, replicate, and evaluate the tools.

At present, formal explainability mechanisms such as interpretable AI methods or user-facing diagnostics are not central to the models' design. However, the emphasis on transparency is evident in the open-source strategy and in the collaborative, feedback-driven development process. Information about AI usage is shared with partners during each stage of the lifecycle, and public-facing documentation is planned as models stabilize. In this sense, while some indicators are not fully addressed yet, transparency and accountability are active commitments within the project's technical and governance philosophy.

<u>(8) Non-discrimination and fairness</u>

At this stage of Project Guacamaya's lifecycle, non-discrimination and fairness are not addressed through formal frameworks or structured measurement processes. Interviewees did not mention any explicit assessment of protected attributes or the identification of vulnerable groups, which reflects the project's current orientation toward environmental monitoring rather than direct engagement with social decision-making systems.

Nevertheless, model developers are aware of the issue of bias and have articulated informal strategies to mitigate it.

As noted in interviews, all data-driven models inevitably reflect the biases inherent in their training datasets. Guacamaya's approach to this limitation focuses on expanding data diversity and geographic scope, particularly through the deployment of additional devices like Sparrow and the inclusion of new institutional partners. The strategy emphasizes improving model generalizability over time, especially through the integration of data from multiple regions across the Amazon basin. While these efforts represent a valuable starting point, the absence of systematic fairness auditing or methods for quantifying bias means this criterion remains only partially addressed.

Given that Guacamaya's outputs may eventually inform public decision-making or be used in regions with distinct ecological and social contexts, a reassessment of this criterion may be warranted in later stages of the lifecycle, particularly during broader deployment and use.

<u>(9) Technical reliability and human supervision</u>

Guacamaya's model development process includes multiple layers of human validation and quality control. Interviewees described a structured pipeline in which training, validation, and test datasets are carefully prepared and reviewed both by the model developers and by the researchers who originally collected the data. This process ensures that the data is of adequate quality, correctly distributed, and appropriate for the intended model outputs. Before any public release, data also undergoes an additional curation process to align with each institution's internal publication standards. As the project scales and enters broader implementation contexts, further mechanisms for ongoing performance monitoring and in-the-loop human decision-making may become necessary.

<u>(10) Self-determination and data protection</u>

Although Guacamaya does not directly engage with individual users or collect personal data, concerns about data ownership, sovereignty, and ethical use have been addressed extensively within the partnership. One of the foundational agreements put forward particularly by Sinchi included three non-negotiable conditions: the data must remain open, communities must not be exploited, and no financial compensation would be accepted in exchange for participation. Humboldt Institute, the other scientific partner also signalled the need of establishing principles alike upfront. These stipulations helped define the boundaries of acceptable data use and reflect a strong normative stance on institutional autonomy and privacy.

Data remains under the control of the institutions that collected it, and model outputs are only released following explicit approval from the relevant partners. While the project does not implement privacy-by-design in the sense of user-level data protections (given the nature of its environmental monitoring focus) it has developed clear conventions around data earmarking and non-exploitative practices. Notifications and consent mechanisms for third-party users may become more relevant in future phases, particularly if public-facing platforms or community data contributions are introduced.

(11) Inclusive and participatory design

Guacamaya exemplifies the use of co-design principles throughout its development. As described in earlier sections, the project operates through a roundtable governance structure in which all partners contribute to decision-making processes, from defining model outputs to coordinating technical improvements. Feedback loops are integral to this arrangement, ensuring that tools are adapted to meet institutional needs and reflect the working conditions of field researchers.

In terms of accessibility, there are two notable features aimed at reducing barriers to entry. First, models like PyTorch-Wildlife are made available via open repositories such as Hugging Face, and Microsoft has contributed free cloud resources to host and run them, removing the need for users to maintain local GPU infrastructure (Hernandez et al. 2024). Second, the Sparrow hardware is designed for open replication: its components are 3D printable, and its deployment does not involve proprietary restrictions. These design choices reflect an intentional effort to ensure that the tools developed can be adopted widely, especially by under-resourced institutions in the Global South (Lavista Ferrés 2024).

(12) Cultural sensitivity

Guacamaya's approach to cultural sensitivity is shaped by the institutional diversity of its partner network and the socio-legal constraints of operating in the Amazon region. While the project does not have a formal cultural sensitivity policy, its design reflects an awareness of ethical obligations in territories with complex histories of scientific extractivism and marginalization. Interviewees emphasized that institutions like the Humboldt Institute are especially mindful of the need to ensure that scientific work benefits local communities, even if the degree of community engagement varies from project to project. This ethical stance is supported by a broader concern with respecting local autonomy and avoiding practices that might replicate historical patterns of external imposition.

The project's current structure does not involve direct engagement between Microsoft or CinfonIA and local or Indigenous communities. Instead, community connections are mediated through Sinchi and Humboldt, who bring longstanding relationships and contextual expertise. Colombian legal frameworks around consulta previa (prior consultation) add a layer of complexity to direct engagement, particularly for technology-driven initiatives that do not involve direct extraction or infrastructure development but are still subject to similar regulatory scrutiny. As such, Guacamaya's operational model places cultural sensitivity within the responsibilities of its field-facing partners, who are better equipped to manage local dynamics.

From a technical perspective, the project is designed to be adaptable to different ecological and institutional contexts. Sparrow devices are being deployed with the help of local collaborators who provide input on where and how they should be installed. Interviewees noted that field teams often include people from the communities themselves, who contribute practical and ecological knowledge to improve deployment. Plans to expand data collection across various parts of the Amazon including Peru, and eventually Bolivia or Brazil, also reflect a commitment to making the models more generalizable and regionally grounded. While there is limited information on team diversity or formal recognition of culturally specific norms in model design, the overall structure of the project encourages local integration through co-creation and indirect field participation.

4.3.3 Ecological dimension

<u>(13) Energy consumption</u>

Energy efficiency has been considered during Guacamaya's model development, particularly in relation to the hardware constraints of field deployment. According to interviewees, a key design goal is to ensure that models can run on low-power machines, including edge devices like the Sparrow stations. To achieve this, models have been kept intentionally small, using lightweight architectures that can operate without the need for GPU-intensive infrastructure. Some models have even been tested on mobile devices. While the use of specific methods such as transfer learning, model compression, or energy-aware optimization techniques was not explicitly mentioned, the overall emphasis on small model size reflects a practical orientation toward minimizing energy demands.

At this stage, no detailed metrics are being tracked regarding energy use during training or deployment, and parameters for model efficiency have not been formally reported. However, the design logic of running models in the field on solar-powered, low-spec devices, suggests that the project is oriented toward energy-conscious implementation.

As Guacamaya scales and enters broader usage phases, there may be opportunities to document and optimize energy consumption more systematically.

(14) CO_2 and greenhouse gas emissions

Project Guacamaya does not currently measure or report on its carbon footprint, nor does it engage in formal CO_2 efficiency assessments or offsetting. However, interviews suggest that the project team is aware of the environmental implications of machine learning and has made early design choices to limit computational intensity. The models developed so far are lightweight and, in the words of one interviewee, "can even run on a mobile phone." Compared to the training and deployment of large language models, Guacamaya's environmental impact is described as minor, close to negligible.

At the same time, interviewees acknowledged that the project's energy use is not zero. One participant noted that while the carbon footprint exists, the potential positive impact on biodiversity conservation by accelerating monitoring, analysis, and policy-relevant insights, offers a form of indirect environmental benefit. The team's current strategy appears to rest on minimizing model size, enabling efficient edge deployment, and avoiding the need for large-scale cloud computing wherever possible. As the project matures, more formal tools for estimating emissions and assessing trade-offs may become useful, especially if broader deployment increases system use across different contexts.

(15) Sustainability potential in application

Guacamaya is explicitly oriented toward sustainability, although the realization of its potential is still unfolding and subject to institutional timelines. The project's target function could be declared as automated environmental monitoring of deforestation and biodiversity, and it clearly aligns with global sustainability objectives. However, as interviewees noted, the system's societal and policy impact is expected to be indirect and long-term. The models are not designed to directly enforce environmental policy or intervene in ecological systems; rather, they aim to generate more timely and accurate data to support conservation-oriented decision-making by scientific and government institutions.

So far, early indicators suggest that the models are having a measurable impact on process efficiency. At Humboldt, pilot use of the bioacoustics tool reduced the time needed to analyse bird call recordings by approximately 80 percent. At Sinchi, animal classification from camera trap imagery saw a reported 90 percent reduction in manual effort. While results from the forest cover model are not yet available in public form, the models are reportedly being integrated into institutional workflows as part of an iterative development process. In other words, interviewees claim that models are already contributing to resource savings in ongoing scientific projects and improving the speed and scale at which monitoring can take place.

Guacamaya's design also supports long-term sustainability by extending the service life and functional reach of conservation hardware. Devices such as the Sparrow wildlife monitoring stations are configured to run the project's lightweight models directly in the field, enabling real-time, low-resource analysis. This not only reduces dependence on remote cloud services but also allows for a flexible deployment of tools across different reserves and research contexts. As data from these deployments accumulate, model refinement will further improve performance across diverse ecological conditions, increasing their usefulness for adaptive conservation management. While Guacamaya does not directly promote sustainable products or consumption patterns in a conventional sense, its contribution to optimizing environmental monitoring processes may lead to more effective use of conservation resources, indirectly advancing sustainability outcomes.

(16) Embodied and shared resource consumption of hardware infrastructure

Project Guacamaya does not currently track or report on embodied resource consumption related to its hardware infrastructure. Indicators such as the use of certified hardware, data centre efficiency metrics, hardware recycling or reuse rates, and waste disposal strategies are not directly addressed in the project's current scope. This is not unexpected, given Guacamaya's relatively limited scale and focus on low-resource edge deployments rather than large-scale centralized computing. While the project benefits from Microsoft's cloud infrastructure and engineering support, interviewees made no mention of specific efficiency certifications or sustainability standards associated with the hardware or data centres used. Additionally, no systematic measures have been introduced for hardware lifecycle management, such as recycling or disposal protocols.

Although these indicators are not yet addressed, their relevance may increase if Guacamaya's models and devices are adopted more widely or integrated into national-level monitoring systems. At that stage, questions of embodied energy, component reuse, and hardware lifecycle management could become more salient, particularly if the scale of deployment grows beyond research pilots.

4.3.4 Economic dimension

(17) Market diversity and exploitation of innovation potential

Guacamaya’s model of co-creation and open-source development supports some aspects of market diversity, even though the project is not structured around commercialization. Several of the technical outputs such as PyTorch-Wildlife and future model iterations are shared openly through platforms like GitHub and Hugging Face. These tools are designed to be compatible with low-power devices, allowing broader accessibility, including for institutions in the Global South with limited infrastructure. While no dedicated APIs or multi-platform interfaces have been publicly released at this point, the design of models and hardware reflects a strong orientation toward technical openness and interoperability. Guacamaya’s use of Microsoft cloud services comes with donated resources, but hosting is decentralized, and no single partner holds exclusive access, supporting multihoming in practice. Overall, while this criterion was likely conceived with commercial ecosystems in mind, Guacamaya does promote inclusive access to innovation through open design choices and shared infrastructure.

(18) Distribution effect in target markets

Although Guacamaya does not operate within a conventional market, the project’s structure encourages equitable participation among scientific and public-sector partners. The models are being developed with adaptability in mind, both in terms of input data (e.g., diverse formats, volumes, and geographies) and intended use (e.g., reserve-level monitoring, national assessments). The emphasis on lightweight models further enhances accessibility across institutions with varying capacities. While there is no formal tracking of accuracy differentials between major and marginalized users, the open-source model and field validation approach reduce the risk of exclusionary design. In practice, Guacamaya’s outputs are explicitly intended for use by public institutions and NGOs, particularly those in Latin America, suggesting a prioritization of non-commercial actors in the project’s deployment. Support for under-resourced partners, including free access to infrastructure and training, aligns with the spirit of this criterion, even if many indicators are not directly measurable under current conditions.

(19) Working conditions and jobs

No information was collected during this study regarding the effects of Guacamaya on working conditions or wages. Given the project’s non-profit structure and research-oriented goals, no employment is generated directly by the project beyond what is sustained through the participating institutions. Likewise, no mechanisms are in place to evaluate impacts on labour standards or job quality along the AI lifecycle. Each partner retains responsibility for employment practices under its own jurisdiction and mandate. While the project may influence the skills and workflows of participating researchers (e.g. by reducing time spent on manual classification or enabling new types of analysis) these effects are currently anecdotal and not systematically tracked. This criterion may become more relevant if Guacamaya's tools are integrated into operational processes in the public sector or if new roles emerge around their use, maintenance, or adaptation.

5 Discussion

5.1 Guacamaya compared with the literature and other cases

Project Guacamaya stands on shared ground within the typologies of AI and sustainability found in the literature. From a design perspective, its emphasis on openness, accessibility, and low computational demand makes it a relevant case of sustainable AI. However, Guacamaya's primary goal is not to be green by itself but to deploy AI as a tool to address environmental challenges. Its core activities align it more clearly with the field of AI for sustainability, as its outputs are meant to support scientists, inform conservation policy, and eventually assist in environmental law enforcement. Moreover, it contributes to bridge the gap in conservation and monitoring between global north ecosystems and global south ecosystems, not only by developing tools to be implemented in the Neotropics, but also publishing the models trained on data captured in the Amazon Forest.

This position becomes clearer when Guacamaya is examined through the lens of Rolnick et al.'s (2023) classification of machine learning for climate action. According to their taxonomy, Guacamaya contributes to at least three categories: mitigation, by helping monitor forest loss and degradation; adaptation, by offering the possibility of forecasting ecosystem changes that result from climate stressors; and tools for action, through its capacity to provide timely, structured information to policymakers and scientific institutions. Although its most tangible use cases currently relate to deforestation and biodiversity monitoring, the multimodal capacity and planned scalability of the project position it to contribute across a wider spectrum of environmental challenges.

Guacamaya also reflects a plurality of motivations for environmental monitoring, if it were analysed under the typology described by Allard et al. (2023). For Microsoft and CinfonIA, the project was initially curiosity-driven, launched as part of a broader institutional interest in sustainability. However, from the perspective of Sinchi and Humboldt, Guacamaya is a means to strengthen ongoing question-driven monitoring, by automating and scaling their data analysis workflows. Microsoft interviewees have also expressed the intention to incorporate citizen science–driven mechanisms, for example through community validation of alerts or signals captured via the Flight Simulator platform. While still in early stages, this layered combination of motivations suggests a level of innovation in how monitoring technologies are imagined and deployed.

In the realm of biodiversity science, Pollock et al. (2025) identify knowledge shortfalls where AI can play a transformative role. Guacamaya is explicitly oriented toward addressing several of these, including the Wallacean shortfall (gaps in species distribution data), the Prestonian shortfall (uncertainty around population abundance), and potentially the Hutchinsonian shortfall (limited understanding of species' ecological niches). The models developed in the project are designed to enhance the generation and classification of spatiotemporal biodiversity data, which could help narrow these gaps over time.

One area where the empirical narratives from Guacamaya appear to diverge from established literature is in the assessment of Brazil's deforestation monitoring capacity. Interviewees from Microsoft described Brazil's systems as outdated and limited in resolution, implying that Guacamaya could outperform them. However, researchers such as Assunção et al. (2023) and Ferreira (2024) provide evidence of the effectiveness of Brazil's DETER system in supporting law enforcement and reducing deforestation through satellite-based alerts. While it is not within the scope of this research to evaluate the accuracy of these competing claims, the contrast suggests a possible opportunity: Guacamaya's open-source infrastructure and regional aspirations could serve as a platform to collaborate or cross-analyse data with established systems in Brazil, potentially enriching both efforts and opening the way for interoperability.

Finally, it should be noted that the Humboldt Institute has collaborated with other tech companies such as Google and Huawei on related projects. Because this study did not include a current Humboldt representative, it was not possible to determine how Guacamaya fits within Humboldt's broader institutional strategy for biodiversity science and technology transfer. As a result, this remains an open question for future research, particularly in understanding how different partnerships compare in terms of governance, openness, and long-term scientific value.

5.2 Policy relevant insights

Project Guacamaya offers several insights for environmental policy and digital governance, particularly in the context of AI-enabled conservation efforts in the Amazon region. While its primary outputs are technical, the project's evolution and institutional structure raise questions about how co-created, open-source AI systems can inform or be integrated into public decision-making, and what policy conditions are necessary to support this.

A first insight relates to scalability and regional coordination. As the project aspires to expand across the Amazon basin, the Memorandum of Understanding (MoU) that governs its operations will likely face pressure. Under the current framework, the inclusion of new partners requires unanimous approval from all existing members. This mechanism has been useful for building trust, but may become a constraint as the network grows. At some point, greater flexibility may be needed, even if it comes at the cost of slower consensus or more complex internal negotiations. This raises broader governance questions: Should Guacamaya adopt new legal structures or shared institutions to accommodate growth? Could regional mechanisms such as the Amazon Cooperation Treaty Organization (OTCA) or the Leticia Pact provide a platform for multilateral coordination? These options remain unexplored but are worth consideration as the project matures.

There is also significant potential to formalize citizen involvement in the project. Initiatives such as the Flight Simulator–based crowdsourcing and in-field validation by local communities demonstrate Microsoft's interest in hybrid forms of monitoring, where public participation complements AI predictions. Studies like McCallum et al. (2023) and Saavedra (2024) have shown that citizen-generated data not only improves system accuracy but also fosters public awareness and legitimacy. Guacamaya's next development cycle could benefit from formally incorporating these elements and encouraging institutional frameworks for citizen engagement.

Another policy lesson concerns the importance of co-creation for building institutional trust. Interviewees repeatedly emphasized that the open, iterative development model, where no single partner owns the system or the data, has allowed the project to overcome scepticism among scientific institutions, especially those wary of extractivist practices. While this lesson is not new, it reinforces findings from other fields of public-sector innovation and sustainability governance, where co-creation has been shown to foster ownership and innovation across organizational boundaries.

However, the project also reveals regulatory and institutional barriers to policy adoption. In Colombia, Guacamaya has struggled to find formal pathways to integrate its outputs into national monitoring and enforcement systems. Legal frameworks restrict government agencies from acting on non-official data, while bureaucratic inertia and mistrust toward private sector–led innovation have further slowed collaboration. As one interviewee noted, even the Ministry of Environment faces institutional resistance to incorporating predictive deforestation maps generated by Guacamaya's models. IDEAM, the agency in charge of official deforestation reporting, continues to rely on traditional processes that take up to 18 months to publish results, in contrast to Guacamaya's ability to produce near real-time data. While these dynamics are context-specific, they reflect broader tensions between open-source innovation and formal environmental governance, and highlight the need for legal frameworks that recognize and validate co-produced data systems.

In contrast, the Peruvian Ministry of Environment has joined the Guacamaya partnership with enthusiasm. Interviewees noted that the Peruvian authorities were more willing to adopt and experiment with open-source models, enabling faster coordination and implementation. This contrast suggests that political openness, ministerial continuity, and institutional culture play a significant role in determining whether co-created AI systems can be adopted by state actors. Guacamaya's experience thus offers an entry point to broader discussions about public sector digital maturity, data governance, and the role of open infrastructure in national and regional environmental policy.

Finally, Guacamaya's development highlights structural challenges in local AI capacity-building. As an interviewee noted, Colombia still lacks the institutional bridges to align ecological researchers with machine learning communities. This gap is not just technical: it reflects a disconnect between academic fields and between national development priorities and research infrastructure. AI for sustainability initiatives often rely on imported tools and generic models, while country-specific problems remain underexplored (Cañas et al. 2025). Guacamaya's co-creation approach is a promising step toward localization, but it remains an early-stage effort. Policy frameworks that support interdisciplinary collaboration, improve research pipelines, and promote context-sensitive AI development will be essential if such projects are to reach their full potential.

5.3 Towards the future of Guacamaya

Although Project Guacamaya has demonstrated promising early results, its long-term impact remains dependent on how it evolves technically, institutionally, and politically. As a monitoring tool, Guacamaya has so far been developed primarily to assist scientific institutions and, potentially, environmental law enforcement. However, monitoring has broader functions than merely describing environmental conditions. According to the European Environment Agency (1999) and elaborated by Keskitalo et al. (2023), environmental monitoring should also serve as a tool for continuous feedback, allowing institutions to adapt their interventions and strategies dynamically. Based on the findings of this case study, Guacamaya has not yet been configured with that feedback loop in mind. Its integration into public sector governance, particularly as a mechanism for adjusting or evaluating policy performance, seems to be a possibility rather than an established trajectory.

This uncertainty is reflected in the project's declared objectives. The goal of "preserving and protecting the Amazon Forest," as expressed by several interviewees, is clearly aligned with global sustainability aspirations, but remains broad and difficult to operationalize. For instance, Microsoft's corporate sustainability targets (carbon neutrality by 2030, water positivity by 2050) frame the rationale for Guacamaya, but the relationship between the project's outputs and those milestones is not explicitly defined. Interviewees mentioned that the project has internal objectives that are more concrete, yet these were not shared during the study. The lack of transparent, measurable goals makes it difficult for external observers to assess progress or to evaluate the project's alignment with broader climate and biodiversity commitments.

The assessment conducted through the SCAIS framework further highlights several areas that may require attention as Guacamaya scales and enters later lifecycle stages. Some criteria were only partially fulfilled, not due to neglect, but because they are more relevant once the project's tools are widely used by public authorities or exposed to broader user bases. For example, complaint mechanisms (criterion 6) may not be necessary in a research context, but will become important if Guacamaya's tools are embedded into decision-making systems or used by third parties beyond the initial partners. Likewise, non-discrimination and fairness (criterion 8) will require more systematic approaches if the models are deployed across regions with different social and ecological contexts. At present, bias mitigation is informal and focused on data expansion. More explicit definitions of protected groups and auditing processes may be needed in future stages.

The criterion of cultural sensitivity (12) also deserves attention. Although the project encourages local integration through partnerships with institutions like Sinchi and Humboldt, there is limited information on team diversity or formal incorporation of culturally specific norms into model design. As the project expands into other countries or engages more directly with communities, these questions will become more pressing, particularly if the project engages with Indigenous territories or transboundary governance frameworks.

In this regard, future developments of Guacamaya must go beyond indirect institutional channels and engage Indigenous communities through direct, respectful, and sustained dialogue. As highlighted in recent research (Andoke Andoke et al. 2023; Krause et al. 2025; Palau-Sampio 2025), merely informing Indigenous peoples about technological deployments does not suffice, especially when such deployments might produce outputs that inform state policies with tangible effects on their territories and ways of life. Responsible engagement should include free, prior, and informed consent as established in international human rights instruments, and should avoid reproducing extractivist patterns seen in previous conservation initiatives such as the aforementioned 'Visión Amazonía REDD Early Movers programme'. Indigenous peoples' holistic knowledge of forest ecosystems, rooted in long-standing territorial care practices and reciprocal relations with non-human life, offers not only ethical guidance but practical insights for long-term environmental stewardship. By involving Indigenous representatives early and meaningfully in the design, deployment, and interpretation of monitoring efforts, Guacamaya can help prevent harm, promote intercultural legitimacy, and strengthen the quality and relevance of its scientific contributions. Failure to do so could undermine trust and reinforce harmful dynamics of exclusion and marginalization already present in many parts of the Amazon.

From a technical and environmental perspective, energy consumption (13) and CO_2/GHG emissions (14) have been intentionally minimized through the development of lightweight models suitable for low-power devices. Still, as Guacamaya grows and its models are deployed more widely, there may be opportunities to track and optimize these impacts more systematically. While the models are far from the scale of large commercial AI systems, formal assessment of energy and resource use will help position the project more clearly within the sustainable AI conversation.

Finally, the project's impact on working conditions and jobs (criterion 19) remains anecdotal at this stage. Interviews suggest that researchers at partner institutions are experiencing time savings and workflow improvements, but no systematic evaluation of labour effects has been conducted. Acemoglu and Johnson (2024) categorically warn their readers to stay vigilant towards uses of AI where intensive automation happens. In contrast to narratives of displacement, Guacamaya appears to offer a case where AI augments rather than replaces human expertise. Also, if Guacamaya's tools become embedded in public sector operations or conservation strategies, they may give rise to new roles in model maintenance, field deployment, or data interpretation. These transformations could be beneficial but are worth of careful tracking to ensure they improve—instead of undermining—working conditions in the sector.

In summary, Guacamaya's future will depend not only on technical refinement but also on its ability to navigate complex institutional ecosystems, scale responsibly, and maintain the trust-based governance model that has been one of its most distinctive features.

5.4 Lessons and limitations of using the SCAIS framework

The application of the Sustainability Criteria and Indicators for Artificial Intelligence Systems framework proved useful for structuring a multidimensional assessment of a complex socio-technical-ecological initiative. However, the experience also surfaced several limitations that are worth reflecting on. First, Guacamaya has not yet progressed through the full lifecycle envisioned in the SCAIS framework. While model development is ongoing, and some verticals have entered early implementation stages within partner institutions, the later phases remain aspirational. As a result, several criteria and their indicators could not be meaningfully assessed at this time. This limitation is not specific to Guacamaya; it is common to early-stage AI-for-sustainability projects. Yet it raises an important methodological consideration: the framework may benefit from a more explicit acknowledgement of maturity stages. Although the framework suggests in which stages of the lifecycle the indicators are observable, it does not consider its application before the lifecycle is completed. In larger projects, an iterative approach to the SCAIS framework might come as beneficial because it would help raise early alerts of lacking elements or unsustainable practices.

Second, the framework's economic dimension appears to be less applicable to non-commercial, co-creation-based projects like Guacamaya. Indicators focused on market dynamics, APIs, and customer diversity may be meaningful in private-sector settings, but they offer limited traction in cases where no monetization is involved. A more suitable set of indicators for such contexts might instead address issues like funding sustainability, donor transparency, infrastructure dependence, and the long-term integration of AI tools into public institutions or non-governmental partners. These would allow for a richer understanding of economic sustainability that goes beyond commercial viability.

A third insight concerns the broader use and uptake of comprehensive frameworks like SCAIS within the research community. As JC observed during one of the interviews, few researchers currently apply socio-technical-ecological frameworks rigorously. The challenge lies partly in measurement methodologies and partly in incentives. Most projects aim to demonstrate functionality, publish results, or release open datasets and tools. Critical self-assessment, particularly along sustainability metrics, is rarely a formal requirement and often falls outside the scope of funded work. This suggests that while frameworks like SCAIS offer valuable structure, institutional support and policy incentives may be needed to encourage their widespread use, particularly in Global South contexts where resource constraints are more pressing.

That said, the framework helped identify not only where Guacamaya performs strongly—such as in governance, openness, and co-design—but also where future work will be required to fulfil its long-term ambitions. It allowed for a granular assessment of project choices, and surfaced considerations that might otherwise have remained implicit. In this way, applying SCAIS contributed not only to the evaluation of Guacamaya, but also to a broader reflection on what sustainability means in the context of early-stage, interdisciplinary, collaborative AI initiatives. Moreover, this research contributes not only to Guacamaya's evaluation, but to the broader discussion on how frameworks like SCAIS can evolve to better accommodate hybrid, transdisciplinary projects emerging in the Global South.

6 Conclusion

Project Guacamaya offers a paradigmatic case through which to examine the emerging field of AI for sustainability, particularly in the context of environmental monitoring in the Amazon rainforest. As a collaborative initiative that brings together research institutes, technology providers, and conservation stakeholders, Guacamaya sheds light on how artificial intelligence can support biodiversity monitoring and deforestation tracking efforts in one of the world's most ecologically significant regions. It is not only an example of how AI technologies can be adapted for sustainability goals, but also a valuable lens through which to explore broader governance, technical, and political dynamics that shape the development and deployment of such systems.

The central aim of this thesis was to analyze how Project Guacamaya performs in relation to the 19 criteria of the SCAIS (Sustainable and Critical AI Systems) framework, and what insights can be drawn from it to inform sustainability-oriented AI policies in the Amazon region and beyond. The case study method allowed for an in-depth exploration of Guacamaya's governance structure, technical design, field-level implementation, and institutional relationships, based primarily on semi-structured interviews with members of the project's core team, complemented by document analysis and relevant literature.

Overall, the findings confirm that Guacamaya is a rich example of AI for sustainability, with clear potential to support scientific research, conservation strategy, and potentially even policy enforcement. However, as the project is still in relatively early phases of development, some aspects of its impact and sustainability performance remain incipient. While model development is underway and implementation has begun at a pilot scale, the use of AI-generated outputs in formal decision-making remains largely aspirational. These findings illustrate both the promise and the limitations of current AI-for-environmental-monitoring projects, especially in complex sociopolitical contexts like the Amazon basin.

6.1 Answering the research questions

<u>RQ1: How does Project Guacamaya perform across the 19 criteria of the SCAIS framework?</u>

Across the governance dimension (criteria 1–6), Guacamaya demonstrates strong performance. The Memorandum of Understanding signed by partners lays out shared responsibilities, provides channels for coordination, and ensures that no single organization has unilateral control over data or models. Each partner contributes according to their own institutional strengths while respecting each other's autonomy.

Although the project does not yet have formalized complaint mechanisms or a unified code of conduct, these aspects are partially covered by each partner’s internal policies and the open-source nature of the tools.

In the social dimension (criteria 7–12), Guacamaya scores well due to its emphasis on co-creation, data ownership respect, and transparency. The decision to release models and tools as open source not only increases their accessibility but also allows for community-driven feedback and adaptation. However, direct engagement with local communities is still mediated through institutional partners such as Sinchi, which may limit the extent to which local knowledge, cultural norms, and social inclusion are fully integrated into the project. As the project matures, criteria such as cultural sensitivity and participatory design should be revisited and more systematically incorporated. As the project matures, criteria such as cultural sensitivity and participatory design should be revisited and more systematically incorporated. As shown in recent critiques of top-down conservation efforts in the Amazon, projects that fail to secure free, prior, and informed consent or disregard Indigenous law and knowledge cannot be considered socially sustainable in a meaningful sense. This has significant implications for the long-term legitimacy and effectiveness of Guacamaya if it expands into territories governed by Indigenous peoples, or if its outputs are used formally to inform conservation policy in their territories.

The ecological dimension (criteria 13–16) highlights Guacamaya’s potential as a sustainable AI system. Developers are actively minimizing energy consumption through model compression and design choices that allow AI to run on low-power hardware such as edge devices. While no precise metrics are currently collected on carbon emissions or energy use, the project's design philosophy aligns with the broader goals of Green AI. As usage increases, however, more robust monitoring and reporting may be needed to ensure continued ecological responsibility.

Guacamaya’s performance in the economic dimension (criteria 17–19) is harder to evaluate. Because the project is explicitly non-commercial, many of the indicators (e.g. market exploitation, wage structures, business impact) do not apply directly. Nonetheless, the project promotes inclusive access to innovation and is adaptable across institutional contexts, including NGOs and public agencies. Future applications may create new jobs or transform research workflows, but such effects are currently anecdotal and not systematically measured.

<u>RQ2: What does the SCAIS framework reveal about Guacamaya’s ability to contribute to the broader efforts of environmental sustainability that drive it?</u>

Guacamaya's primary contribution to sustainability lies in its ability to support and enhance scientific research, particularly by reducing the manual workload associated with biodiversity and deforestation monitoring. Its technical outputs streamline the processing of large ecological datasets and allow researchers to focus on more analytical and interpretive tasks.

At the same time, Guacamaya holds indirect but important potential to support policy enforcement and real-time decision-making. While this is not yet a formalized component of the project, interviewees expressed a strong interest in collaborating with law enforcement and government agencies. Realizing this potential will require legal and institutional changes, particularly to recognize and validate co-produced data within national monitoring systems.

In scientific terms, Guacamaya contributes to addressing several foundational knowledge gaps identified by Pollock et al. (2025), such as the Wallacean shortfall (species distribution data), the Prestonian shortfall (species abundance), and the Hutchinsonian shortfall (ecological niche understanding). It also aligns with Rolnick et al.'s (2023) classification of AI for climate action, functioning across multiple categories including mitigation, adaptation, and decision-support tools.

<u>RQ3: How can the case of Guacamaya contribute to policymaking for biodiversity monitoring and conservation in the Amazon Forest Region?</u>

Guacamaya demonstrates how a regional, non-governmental initiative can develop and deploy technological infrastructure for conservation across borders. Because it is not tied to any single government or funding cycle, it enjoys a degree of flexibility in its operations, including partner selection and deployment strategy. The open-source nature of its models ensures that even institutions not formally part of the MoU can potentially benefit from its tools and findings.

However, this flexibility comes with trade-offs. As the project expands, the consensus-based governance structure may become a bottleneck. Future governance models might require more layered or federated structures to maintain trust while enabling agility. Institutions such as the Amazon Cooperation Treaty Organization (OTCA) or multilateral frameworks like the Leticia Pact may provide platforms for such regional collaboration.

Another area of potential growth lies in public engagement. Initiatives like the Flight Simulator–based citizen monitoring and in-field validation of AI predictions show that hybrid monitoring approaches (combining automated systems with human input) are not only feasible but potentially powerful. Formalizing these efforts into policy frameworks could help improve data accuracy, public trust, and democratic legitimacy.

Finally, Guacamaya shows how co-creation models can foster institutional trust and overcome initial scepticism, particularly among organizations that have experienced extractive partnerships in the past. This is a policy-relevant lesson for other initiatives seeking to operationalize AI in sensitive or contested regions.

6.2 Limitations

The main limitation of this study is that Project Guacamaya has not yet undergone all phases of the SCAIS lifecycle. Model development is still ongoing for some verticals, and implementation is taking place only in limited capacity. Full-scale use in decision-making has not yet occurred. Therefore, the findings represent a preliminary assessment that may need to be revisited once the project matures and moves into new phases. Interviews with project members representing Humboldt Institute and Sinchi institute are also lacking in this study, as it they were not available because of their fieldwork agendas. Including their vision and concerns would lead to a more complete picture of the Project, as well as a better understanding of the place Guacamaya takes in their own institutional strategy as scientific organizations.

Additionally, while this case study approach allowed for a detailed understanding of Guacamaya, it does not offer a comparative perspective. Other AI-for-sustainability projects in Latin America, such as those identified by Gutiérrez et al. (2025), may present different governance models, technical approaches, or political dynamics. Finally, public authorities were not interviewed as part of this study. This limits the analysis of institutional barriers to adoption, particularly within the Colombian regulatory and bureaucratic context.

6.3 Directions for Future Research

Future research should revisit the case of Guacamaya once it enters broader implementation and begins to influence decision-making processes more directly. At that point, it would be valuable to assess how public sector agencies use its outputs, whether its models remain transparent and inclusive at scale, and what new organizational challenges emerge as more partners join the initiative.

In parallel, more empirical research is needed on how AI is used by actors whose activities contribute to deforestation and biodiversity loss. While AI-for-good narratives dominate the current literature, less attention has been paid to how similar technologies may be used to maximize extraction, evade detection, or consolidate control over land and resources. Understanding the ambivalent nature of AI in forested regions is essential to designing countermeasures and anticipating future threats.

Lastly, there is an urgent need to evaluate and possibly revise sustainability assessment frameworks like SCAIS to better accommodate non-commercial, collaborative AI initiatives. Many of the current indicators, particularly within the economic dimension, assume a for-profit logic that may not be applicable to multi-stakeholder research collaborations. Developing complementary tools or adapting existing frameworks to account for such cases would enhance the relevance and usability of sustainability assessments in this rapidly evolving field.

References

Acemoglu, D., and Johnson, S. 2024. *Power and progress: our thousand-year struggle over technology and prosperity*, London: Basic Books.

Ahlborg, H., Ruiz-Mercado, I., Molander, S., and Masera, O. 2019. "Bringing Technology into Social-Ecological Systems Research—Motivations for a Socio-Technical-Ecological Systems Approach," *Sustainability* (11:7).

Allard, A., Webber, L., Sundberg, J. H., Brown, A., and Allard, A. 2023. "New and changing use of technologies in monitoring: drones, artificial intelligence, and environmental DNA," in *Monitoring Biodiversity*, United Kingdom: Routledge, pp. 148–173.

Allard, A., Wood, C., Norton, L., Christensen, A. A., Van Eetvelde, V., Brown, A., et al. 2023. "Monitoring as a field," in *Monitoring Biodiversity*, United Kingdom: Routledge, pp. 9–33.

Alshehri, M., Ouadou, A., and Scott, G. J. 2024. "Deep Transformer-Based Network Deforestation Detection in the Brazilian Amazon Using Sentinel-2 Imagery," *IEEE Geoscience and Remote Sensing Letters* (21), pp. 1–5.

Alzoubi, Y. I., and Mishra, A. 2024. "Green artificial intelligence initiatives: Potentials and challenges," *JOURNAL OF CLEANER PRODUCTION* (468).

Andoke Andoke, L., Arazi, E., Castro Suárez, H., Griffiths, T. F., and Gutiérrez Sánchez, E. 2023. "Amazonian visions of Visión Amazonía: Indigenous Peoples' perspectives on a forest conservation and climate programme in the Colombian Amazon," *Oryx* (57:3), pp. 335–349.

Araujo, R., Assuncao, J., Hirota, M., and Scheinkman, J. A. 2023. "Estimating the spatial amplification of damage caused by degradation in the Amazon," *Proceedings of the National Academy of Sciences - PNAS* (120:46), pp. e2312451120–e2312451120.

Assuncao, J., Gandour, C., and Rocha, R. 2023. "DETER-ing Deforestation in the Amazon: Environmental Monitoring and Law Enforcement," *American economic journal. Applied economics* (15:2), pp. 125–156.

Audubon 2025. "Audubon Christmas Bird Count," in *Audubon Christmas Bird Count*.

Barlow, J., Lennox, G. D., Ferreira, J., Berenguer, E., Lees, A. C., Nally, R. M., et al. 2016. "Anthropogenic disturbance in tropical forests can double biodiversity loss from deforestation," *Nature (London)* (535:7610), pp. 144–147.

Barocas, S., Hardt, M., and Narayanan, A. 2023. *Fairness and machine learning: limitations and opportunities*, Cambridge, Massachusetts: The MIT Press.

Barsanetti, B., and Ferreira, A. 2022. "Early Indigenous Extinctions and Modern Deforestation in the Amazon," *SSRN Electronic Journal*.

Bartlein, P. J., and Matthews, J. A. 2012. *The SAGE handbook of environmental change*, Los Angeles: SAGE.

Bolón-Canedo, V., Morán-Fernández, L., Cancela, B., and Alonso-Betanzos, A. 2024. "A review of green artificial intelligence: Towards a more sustainable future," *Neurocomputing* (599), p. 128096.

Brlík, V., Šilarová, E., Škorpilová, J., Alonso, H., Anton, M., Aunins, A., et al. 2021. "Long-term and large-scale multispecies dataset tracking population changes of common European breeding birds," *Scientific Data* (8:1), p. 21.

Cañas, J. S., Parra-Guevara, C., Montoya-Castrillón, M., Ramírez-Mejía, J. M., Perilla, G.-A., Marentes, E., et al. 2025. "Inteligencia Artificial para la conservación y uso sostenible de la biodiversidad, una visión desde Colombia (Artificial Intelligence for conservation and sustainable use of biodiversity, a view from Colombia)."

Chan, K. M. A., Goldstein, J., Satterfield, T., Hannahs, N., Kikiloi, K., Naidoo, R., et al. 2011. "Cultural services and non-use values," in *Natural Capital*, Oxford: Oxford University Press.

Cline, E. H. 2014. *1177 B.C: the year civilization collapsed*, Princeton: Princeton University Press.

Crawford, K. 2021. *Atlas of AI: power, politics, and the planetary costs of artificial intelligence*, New Haven: Yale University Press.

Daru, B. H., and Rodriguez, J. 2023. "Mass production of unvouchered records fails to represent global biodiversity patterns," *Nature ecology & evolution* (7:6), pp. 816–831.

Dastin, J. 2022. "Amazon Scraps Secret AI Recruiting Tool that Showed Bias against Women," in *Ethics of Data and Analytics*, CRC Press, pp. 296–299.

Dávalos, L. M., Sanchez, K. M., and Armenteras, D. 2016. "Deforestation and Coca Cultivation Rooted in Twentieth-Century Development Projects," *BioScience* (66:11), pp. 974–982.

De Almeida, C. A., Maurano, L., Valeriano, D. M., Câmara, G., Lúbia Vinhas, Da Motta, M., et al. 2022. "METODOLOGIA UTILIZADA NOS SISTEMAS PRODES E DETER -2 a EDIÇÃO (ATUALIZADA) INPE São José dos Campos 2022."

Deke, O. 2008. "Preserving Biodiversity as a Global Public Good: Protected Areas and International Transfers," in *Environmental Policy Instruments for Conserving Global Biodiversity*, Berlin, Heidelberg: Springer Berlin Heidelberg, pp. 185–342.

Dhiman, R., Miteff, S., Wang, Y., Ma, S.-C., Amirikas, R., and Fabian, B. 2024. "Artificial Intelligence and Sustainability—A Review," *Analytics* (3:1), pp. 140–164.

European Environment Agency 1999. "Monitoring definition," in *Monitoring definition*.

2011. *The state of forests in the Amazon Basin, Congo Basin and Southeast Asia: a report prepared for the Summit of the Three Rainforest Basins; Brazzaville, Republic of Congo; 31 May - June, 2011*, FAO (ed.), Rome: Food and Agriculture Organization.

Fearnside, P. M. 1999. "Biodiversity as an environmental service in Brazil's Amazonian forests: risks, value and conservation," *Environmental Conservation* (26:4), pp. 305–321.

Fearnside, P. M. 2021. "The intrinsic value of Amazon biodiversity," *Biodiversity and conservation* (30:4), pp. 1199–1202.

Ferner, J. W. 1977. "The Audubon Christmas Bird Count: A Valuable Teaching Resource," *The American Biology Teacher* (39:9), pp. 533–544.

Ferreira, A. 2024. *Amazon Deforestation: Drivers, damages, and policies.*, CAF.

Ferreira, A. 2024. "Satellites and Fines: Using Monitoring to Target Inspections of Deforestation."

Flyvbjerg, B. 2006. "Five Misunderstandings About Case-Study Research," *Qualitative Inquiry* (12:2), pp. 219–245.

Fonseca, A., Marshall, M. T., and Salama, S. 2024. "Enhanced Detection of Artisanal Small-Scale Mining with Spectral and Textural Segmentation of Landsat Time Series," *Remote Sensing* (16:10), p. 1749.

García-Roselló, E., González-Dacosta, J., and Lobo, J. M. 2023. "The biased distribution of existing information on biodiversity hinders its use in conservation, and we need an integrative approach to act urgently," *Biological conservation* (283), pp. 110118-.

Gardner, T. A., Ferreira, J., Barlow, J., Lees, A. C., Parry, L., Vieira, I. C. G., et al. 2013. "A social and ecological assessment of tropical land uses at multiple scales: the Sustainable Amazon Network," *Philosophical Transactions of the Royal Society B: Biological Sciences* (368:1619), p. 20120166.

Global Witness 2023. *Standing firm: The Land and Environmental Defenders on the frontlines of the climate crisis*, London.

González-Balaguera, J. E., Mendoza-Piñeros, V., and Sierra-Daza, C. A. 2024. "An approach to the analysis of deforestation in Colombia, applications of physical tools," *Journal of Physics: Conference Series* (2726:1), p. 012005.

González-González, A., Clerici, N., and Quesada, B. 2021. "Growing mining contribution to Colombian deforestation," *Environmental Research Letters* (16:6), p. 064046.

Greif, L., Kimmig, A., El Bobbou, S., Jurisch, P., and Ovtcharova, J. 2024. "Strategic view on the current role of AI in advancing environmental sustainability: a SWOT analysis," *Discover Artificial Intelligence* (4:1), pp. 45–19.

Guayasamin, J. M., Ribas, C. C., Carnaval, A. C., Carrillo, J. D., Hoorn, C., Lohmann, L. G., et al. 2024. "Evolution of Amazonian biodiversity: A review," *Acta Amazonica* (54:spe1).

Gutiérrez, J. D., Muñoz-Cadena, S., Castellanos-Sánchez, M., and David Stiven Peralta 2025. "Sistemas de IA en el sector público de América Latina y el Caribe."

Hernandez, A., Miao, Z., Vargas, L., Beery, S., Dodhia, R., Arbelaez, P., et al. 2024. "Pytorch-Wildlife: A Collaborative Deep Learning Framework for Conservation."

Hooper, D. U., Adair, E. C., Cardinale, B. J., Byrnes, J. E. K., Hungate, B. A., Matulich, K. L., et al. 2012. "A global synthesis reveals biodiversity loss as a major driver of ecosystem change," *Nature* (486:7401), pp. 105–108.

Instituto Sinchi 2023. "Proyecto Guacamaya: inteligencia artificial para preservar la Amazonía," in *Instituto Sinchi*.

Interlace Hub 2023. "Participatory Science in Colombia: Trap Camera Days," in *Interlace Hub*.

IPBES 2018. "The IPBES regional assessment report on biodiversity and ecosystem services for the Americas."

Jin, Z., Cao, J., Guo, H., Zhang, Y., Wang, Y., and Luo, J. 2017. "Detection and Analysis of 2016 US Presidential Election Related Rumors on Twitter," in *Social, Cultural, and Behavioral Modeling*, D. Lee, Y.-R. Lin, N. Osgood and R. Thomson (eds.), Cham: Springer International Publishing, pp. 14–24.

Keskitalo, E. C. H., Allard, A., Brown, A., and Allard, A. 2023. "Monitoring biodiversity: combining environmental and social data," in *Monitoring Biodiversity*, United Kingdom: Routledge, pp. 1–8.

Krause, T., Clerici, N., López, J. M., Sánchez, P. A., Valencia, S., Esguerra-Rezk, J., et al. 2022. "A new war on nature and people: taking stock of the Colombian peace agreement," *Global Sustainability* (5), p. e16.

Krause, T., Zelli, F., Vargas Falla, A. M., Samper, J., and Sjöstedt, B. 2025. "Colombia's long road toward peace: implications for environmental human rights defenders," *Ecology and Society* (30:1), p. art21.

Lahsen, M., and Nobre, C. A. 2007. "Challenges of connecting international science and local level sustainability efforts: the case of the Large-Scale Biosphere–Atmosphere Experiment in Amazonia," *Environmental Science & Policy* (10:1), pp. 62–74.

Lavista Ferrés, J. 2024. "Announcing SPARROW: A Breakthrough AI Tool to Measure and Protect Earth's Biodiversity in the Most Remote Places," in *Microsoft On the Issues*.

Le Billon, P., and Lujala, P. 2020. "Environmental and land defenders: Global patterns and determinants of repression," *Global Environmental Change* (65), p. 102163.

Leite-Filho, A. T., Sousa Pontes, V. Y., and Costa, M. H. 2019. "Effects of Deforestation on the Onset of the Rainy Season and the Duration of Dry Spells in Southern Amazonia," *Journal of geophysical research. Atmospheres* (124:10), pp. 5268–5281.

Liévano-Latorre, L. F., Brum, F. T., and Loyola, R. 2021. "How effective have been guerrilla occupation and protected areas in avoiding deforestation in Colombia?," *Biological Conservation* (253), p. 108916.

Likens, G. E., and Lindenmayer, D. 2018. *Effective Ecological Monitoring*, Collingwood: CSIRO Publishing.

MacDonald, A. J., and Mordecai, E. A. 2019. "Amazon deforestation drives malaria transmission, and malaria burden reduces forest clearing," *Proceedings of the National Academy of Sciences - PNAS* (116:44), pp. 22212–22218.

Macedo, M. N., DeFries, R. S., Morton, D. C., Stickler, C. M., Galford, G. L., and Shimabukuro, Y. E. 2012. "Decoupling of deforestation and soy production in the southern Amazon during the late 2000s," *Proceedings of the National Academy of Sciences* (109:4), pp. 1341–1346.

Macgregor, C. J., Thomas, C. D., Roy, D. B., Beaumont, M. A., Bell, J. R., Brereton, T., et al. 2019. "Climate-induced phenology shifts linked to range expansions in species with multiple reproductive cycles per year," *Nature Communications* (10:1), p. 4455.

McCallum, I., Walker, J., Fritz, S., Grau, M., Hannan, C., Hsieh, I.-S., et al. 2023. "Crowd-Driven Deep Learning Tracks Amazon Deforestation," *Remote Sensing* (15:21), p. 5204.

Mezzadra, S., and Neilson, B. 2017. "On the multiple frontiers of extraction: excavating contemporary capitalism," *Cultural studies (London, England)* (31:2–3), pp. 185–204.

Ministerio de Ambiente, Perú 2025. "Minam y Microsoft lanzan proyecto para monitorear ecosistemas usando inteligencia artificial."

Moffette, F., Alix-Garcia, J., Shea, K., and Pickens, A. H. 2021. "The impact of near-real-time deforestation alerts across the tropics," *Nature climate change* (11:2), pp. 172–178.

Mugerwa, B., Niedballa, J., Planillo, A., Sheil, D., Kramer-Schadt, S., and Wilting, A. 2024. "Global disparity of camera trap research allocation and defaunation risk of terrestrial mammals," *Remote Sensing in Ecology and Conservation* (10:1), pp. 121–136.

Natarajan, H. K., de Paula, D., Dremel, C., and Uebernickel, F. 2022. "A Theoretical Review on AI Affordances for Sustainability," in *28th Americas Conference on Information Systems, AMCIS 2022*.

Nepstad, D., Moreira, A., and Alencar, A. 1999. *Flames in the rain forest: origins, impacts and alternatives to Amazonian fires*, Washington, DC: World Bank.

News Center Microsoft Latinoamérica 2023. "Proyecto Guacamaya: inteligencia artificial para preservar la Amazonía," in *News Center Latinoamérica*.

Nilsson, M., Ardö, J., Söderström, M., Allard, A., Brown, A., Webber, L., et al. 2023. "Remote sensing and Earth observation systems," in *Monitoring Biodiversity*, United Kingdom: Routledge, pp. 122–147.

Nishant, R., Kennedy, M., and Corbett, J. 2020. "Artificial intelligence for sustainability: Challenges, opportunities, and a research agenda," *International journal of information management* (53), pp. 102104–13.

Ochoa-Quintero, J. M., Gardner, T. A., Rosa, I., Barros Ferraz, S. F., and Sutherland, W. J. 2015. "Thresholds of species loss in Amazonian deforestation frontier landscapes," *Conservation biology* (29:2), pp. 440–451.

Ofek, N., and Maimon, O. 2023. "Beyond Metrics: Navigating AI through Sustainable Paradigms," *Sustainability* (15:24), p. 16789.

Palau-Sampio, D. 2025. "Environmental Activism and Resistance in Latin America: Literary Journalism's Portrayal of the Struggle of Environmental Leaders," in *The Literary Journalist as a Naturalist*, P. Calvi (ed.), Cham: Springer Nature Switzerland, pp. 175–193.

Palsson, G., Szerszynski, B., Sörlin, S., Marks, J., Avril, B., Crumley, C., et al. 2013. "Reconceptualizing the 'Anthropos' in the Anthropocene: Integrating the social sciences and humanities in global environmental change research," *Environmental Science & Policy* (28), pp. 3–13.

Pan, Y., Birdsey, R. A., Fang, J., Houghton, R., Kauppi, P. E., Kurz, W. A., et al. 2011. "A Large and Persistent Carbon Sink in the World's Forests," *Science (American Association for the Advancement of Science)* (333:6045), pp. 988–993.

Pereira, L., and Pucci, R. 2024. "A Tale of Gold and Blood: The Consequences of Market Deregulation on Local Violence."

Peres, C. A., Gardner, T. A., Barlow, J., Zuanon, J., Michalski, F., Lees, A. C., et al. 2010. "Biodiversity conservation in human-modified Amazonian forest landscapes," *Biological Conservation* (143:10), pp. 2314–2327.

Perz, S. G., Brilhante, S., Brown, I. F., Michaelsen, A. C., Mendoza, E., Passos, V., et al. 2010. "Crossing boundaries for environmental science and management: combining interdisciplinary, interorganizational and international collaboration," *Environmental Conservation* (37:4), pp. 419–431.

Pollock, L. J., Kitzes, J., Beery, S., Gaynor, K. M., Jarzyna, M. A., Mac Aodha, O., et al. 2025. "Harnessing artificial intelligence to fill global shortfalls in biodiversity knowledge," *Nature Reviews Biodiversity* (1:3), pp. 166–182.

Ponce de León, C. G., Acebey, S., Gómez, R., Polanco, R., Aliaga-Rossel, E., Gamba Trimiño, C., et al. 2023. "Evaluación Rápida de la Diversidad Biológica y Servicios Ecosistémicos de la Cuenca/ Región Amazónica. Resumen para tomadores de decisiones," in *Evaluación Rápida de la Diversidad Biológica y Servicios Ecosistémicos en la Región Amazónica.*, Brasilia, Brasil.: Organización del Tratado de Cooperación Amazónica (OTCA), WAKAYA. Programa de Diversidad Biológica para la Cuenca/Región Amazónica, BIOMAZ. Gestión Regional de la Biodiversidad Amazónica, Ministerio Federal Alemán de Cooperación Económica y Desarrollo (BMZ), Instituto de Investigación de Recursos Biológicos Alexander von Humboldt.

Raman, R., Pattnaik, D., Lathabai, H. H., Kumar, C., Govindan, K., and Nedungadi, P. 2024. “Green and sustainable AI research: an integrated thematic and topic modeling analysis,” *Journal of Big Data* (11:1), p. 55.

Reynolds, S. A., Beery, S., Burgess, N., Burgman, M., Butchart, S. H. M., Cooke, S. J., et al. 2025. “The potential for AI to revolutionize conservation: a horizon scan,” *Trends in Ecology & Evolution* (40:2), pp. 191–207.

Rohde, F., Wagner, J., Meyer, A., Reinhard, P., Voss, M., Petschow, U., et al. 2024. “Broadening the perspective for sustainable artificial intelligence: sustainability criteria and indicators for Artificial Intelligence systems,” *Current Opinion in Environmental Sustainability* (66), p. 101411.

Rolnick, D., Donti, P. L., Kaack, L. H., Kochanski, K., Lacoste, A., Sankaran, K., et al. 2023. “Tackling Climate Change with Machine Learning,” *ACM Computing Surveys* (55:2), pp. 1–96.

Russell, S. J. 1995. *Artificial intelligence: a modern approach*, Upper Saddle River (N.J.): Prentice Hall.

Saavedra, S. 2024. “The response of illegal mining to revealing its existence,” *SSRN Electronic Journal*.

Sandbrook, C. 2025. “Beyond the Hype: Navigating the Conservation Implications of Artificial Intelligence,” *Conservation Letters* (18:1), p. e13076.

Santor, E. 2020. “The Impact of Digitalization on the Economy: A Review Article on the NBER Volume ‘Economics of Artificial Intelligence: An Agenda,’” *International Productivity Monitor* (39), pp. 81–90.

Science Panel for the Amazon 2021. *Amazon Assessment Report 2021*, C. Nobre, A. Encalada, E. Anderson, F.H. Roca Alcazar, M. Bustamante, C. Mena, et al. (eds.), UN Sustainable Development Solutions Network (SDSN).

Smith, E. 2024. “Project Guacamaya uses satellites & AI to battle deforestation,” in *Microsoft | Source LATAM*.

Stenlid, J., and Oliva, J. 2016. “Phenotypic interactions between tree hosts and invasive forest pathogens in the light of globalization and climate change,” *Philosophical Transactions of the Royal Society B: Biological Sciences* (371:1709), p. 20150455.

Strubell, E., Ganesh, A., and McCallum, A. 2019. “Energy and Policy Considerations for Deep Learning in NLP,” in *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, A. Korhonen, D. Traum and L. Màrquez (eds.), Florence, Italy: Association for Computational Linguistics, pp. 3645–3650.

Suleyman, M., and Bhaskar, M. 2023. *The coming wave: AI, power and the twenty-first century’s greatest dilemma*, New York: Crown.

Tabbakh, A., Al Amin, L., Islam, M., Mahmud, G. M. I., Chowdhury, I. K., and Mukta, M. S. H. 2024. “Towards sustainable AI: a comprehensive framework for Green AI,” *Discover Sustainability* (5:1), p. 408.

Torres, D. L., Turnes, J. N., Soto Vega, P. J., Feitosa, R. Q., Silva, D. E., Marcato Junior, J., et al. 2021. “Deforestation Detection with Fully Convolutional Networks in the Amazon Forest from Landsat-8 and Sentinel-2 Images,” *Remote Sensing* (13:24), p. 5084.

Universidad de Los Andes 2025. “Google-DeepMind and CINFONIA 2025 Scholarships – Masters opportunities – CinfonIA.”

Verdecchia, R., Sallou, J., and Cruz, L. 2023. “A systematic review of Green AI,” *WIREs Data Mining and Knowledge Discovery* (13:4), p. e1507.

Vijay, V., Pimm, S. L., Jenkins, C. N., and Smith, S. J. 2016. “The Impacts of Oil Palm on Recent Deforestation and Biodiversity Loss,” *PLOS ONE* (11:7), M. Anand (ed.), p. e0159668.

van Wynsberghe, A., Vandemeulebroucke, T., Bolte, L., and Nachid, J. 2022. “Special Issue ‘Towards the Sustainability of AI; Multi-Disciplinary Approaches to Investigate the Hidden Costs of AI,’” *Sustainability* (14:24), p. 16352.

Xu, L., Rolf, E., Beery, S., Bennett, J. R., Berger-Wolf, T., Birch, T., et al. 2023. “Reflections from the Workshop on AI-Assisted Decision Making for Conservation.”