# Enhancing Environmental Impact Studies with Advanced Biodiversity Monitoring Techniques

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# Enhancing Environmental Impact Studies with Advanced Biodiversity Monitoring Techniques

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## Bullet points

- Large infrastructure projects accelerate the loss of natural capital and ecosystem functionality
- Environmental threats, including biodiversity loss and ecosystem collapse, rank among the top risks to the global economy
- Environmental impact assessments (EIAs) are increasingly mandated by legislation and international finance institutions to mitigate biodiversity impacts
- Despite their potential, EIAs and monitoring requirements are often seen as costly bureaucratic hurdles, with limited applicability to development planning
- Technological advances like eDNA, passive acoustic monitoring, camera traps, and sensor-equipped drones offer non-invasive, efficient, and cost-effective ways to enhance EIAs
- Incorporating modern biodiversity monitoring tools can also strengthen mechanisms like biodiversity and carbon credits, ESG frameworks, and biodiversity performance indicators

## Abstract

The current threats to the natural capital and essential ecosystem services highlight the urgent need for more effective biodiversity monitoring toward risk mitigation. Despite legislative frameworks and certification schemes, environmental impact assessments (EIAs) are often viewed as bureaucratic and costly by developers. However, advancements in technologies like environmental DNA (eDNA), passive acoustic monitoring (PAM), camera traps, and drones provide non-invasive, cost-effective methods that enhance the accuracy and potential effectiveness of EIAs. These tools offer real-time data collection and improved spatio-temporal analysis, transforming EIAs into powerful tools for ecosystem management and conservation. This paper explores the potential integration of these modern monitoring techniques into EIAs to better address environmental risks from human activities.

**Keywords:** Conservation Technologies, eDNA and iDNA, Passive Acoustic Monitoring, Drones and UAVs, Non-Invasive Monitoring, Big data in Conservation

## Introduction

The biodiversity crisis, fueled by habitat conversion, climate change, exotic species, hunting, and large infrastructure projects (Jaureguiberry et al., 2022; Laurance et al., 2015; Maxwell et al., 2016), threatens natural capital and the ecosystem services they provide (Costanza and Daly, 1992; Sala et al., 2000). These issues pose financial risks (Kedward et al., 2022) and elevate the importance of biodiversity monitoring for humanity's future (IPBES, 2019; White et al., 2021). According to the Global Risks Report (World Economic Forum, 2024), five of the top ten global economic risks are environmental, including biodiversity loss and ecosystem collapse.

These environmental threats have spurred global initiatives aimed at mitigating further environmental damage. Most nations have implemented legislation mandating environmental impact assessments (EIAs) for large-scale infrastructure projects (Hironaka, 2002; Morgan, 2012), often required by international financial institutions (Glasson et al., 1999). Furthermore, several economic sectors are under increasing pressure to meet environmental certifications, such as those established by the Forest Stewardship Council (FSC), which promotes responsible forest management (Romero and Putz, 2018). The demand for compensating environmental impacts has also led to the development of market-based instruments like carbon credits and, more recently, biodiversity credits (Robertson et al., 2014). These mechanisms are gaining traction within global governance, especially as efforts to mitigate climate change and ecosystem collapse intensify (Wunder et al., 2024).

However, the processes of environmental impact assessment and monitoring are often seen by developers as bureaucratic hurdles. Many view them as obligatory steps that offer limited value to the planning and implementation of projects (Loomis and Dziedzic, 2024; Turra et al., 2017). This perspective is rooted in several factors, including outdated views that the environment is seen as an obstacle to development, and the high costs associated with environmental licensing, which fall on the developers. These costs can be substantial, and the risks of significant financial losses loom if a project is denied based on environmental grounds (Hochstetler, 2018). Moreover, the perception that better data could reveal more significant environmental impacts—such as the discovery of rare or endangered species—can complicate project implementation further, deterring developers from embracing thorough environmental assessments.

Given the rising risks and persistent knowledge gaps regarding the effects of human activities on biodiversity and ecosystem services, it is increasingly urgent to modernize environmental impact assessment and monitoring methods (Bond et al., 2020). The advances in new data collection and analysis technologies play a crucial role in making environmental impact assessment and monitoring processes effective tools for planning and decision-making across different scales, from the local level (e.g., project implementation) to broader-scale public policy formulation (Wunder et al., 2024). The new techniques being developed are typically less invasive, less reliant on specialists, and offer a better cost-benefit ratio (Table 1). Benefits include continuous data recording, which enhances transparency, better spatiotemporal representation, improved accuracy in estimating evaluated parameters, and increased ability to incorporate multiple variables or taxa into the analyses (Stephenson, 2020).

This paper presents several modern biodiversity survey and monitoring tools currently used in academic research and their application in environmental impact assessments. We explore methods, costs, and application approaches, aiming to provide managers and government agencies with the tools needed to evaluate these methods in the context of environmental impact planning and monitoring.

## Modern Techniques for Biodiversity Survey and Monitoring

### *Environmental DNA (eDNA) and Invertebrate-Derived DNA (iDNA)*

Environmental DNA (eDNA) is an emerging technique that allows species detection through the analysis of environmental samples, such as water, soil, or air. Organisms shed DNA into the environment through feces, urine, skin, or dead cells, which can be collected and analyzed to identify the presence of different species (Bohmann et al., 2014; Thomsen and Willerslev, 2015). The application of metabarcoding to soil samples has been used to identify functional groups of microorganisms related to ecosystem functioning, with a direct impact on ecological restoration and nutrient cycling (Duley et al., 2023). The analysis of invertebrate-derived DNA (iDNA) follows a similar approach, focusing on DNA extracted from vectors such as leeches, flies, mosquitoes, and ticks that feed on vertebrates (Saranholi et al., 2022). These techniques are non-invasive and have been used to monitor a wide range of organisms (Thomsen and Willerslev, 2015). Currently, various sequencing services are available both in Brazil (https://ecomolconsultoria.com.br/) and abroad (https://dna.macrogen.com/), and prices have rapidly decreased. Today, sequencing costs for a single sample are less than USD100$.

### *Passive Acoustic Monitoring (PAM)*

Passive acoustic monitoring (PAM) uses autonomous recorders to capture sounds in terrestrial or aquatic environments, such as bird songs, amphibian calls, primate vocalizations, and bat echolocation. These data can be analyzed to identify species and monitor changes in biological communities over time (Sugai et al., 2019). The approach is non-invasive, low-cost, and allows for real-time or near-real-time data collection when direct communication with the autonomous recorder is possible (Hill et al., 2018). After an initial phase where pattern recognition models are used to generate datasets for training artificial intelligence models (e.g., Convolutional Neural Networks), it becomes possible to accurately identify species (LeBien et al., 2020). These automated methods minimize human biases and can process data across multiple locations simultaneously, providing valuable insights into species behavior and changes in biological communities over time (LeBien et al., 2020). Currently, terrestrial and aquatic low-cost recorders can be obtained for around USD100$.

### *Camera Traps*

Camera traps are motion-activated devices that take photos or videos mostly of medium and large mammals and bird species (Burton et al., 2015). It is a non-invasive technique that provides rich visual data on species presence, abundance, and behavior (Rovero and Zimmermann, 2006), often contributing to environmental education efforts. AI models are becoming increasingly integrated into camera trap studies, reducing the time and costs involved in manual species identification, and enabling the automatic identification of species from large datasets (Vélez et al., 2023). Many different types of devices with different features, such as color imaging, video/photo capture, durability, and other details, are available, with prices varying significantly depending on these specifications, ranging from USD100$ to USD600$.

### *Drones or Unmanned Aerial Vehicles (UAVs) with Thermal, Lidar, Hyperspectral, Multispectral, and RGB Sensors*

Drones or UAVs equipped with advanced sensors have revolutionized biodiversity monitoring by providing high-resolution, spatially explicit data on vegetation dynamics, land use, and fauna behavior (Anderson and Gaston, 2013). Drones with thermal sensors are increasingly used to monitor arboreal species, such as primates, enabling accurate population estimates (Spaan et al., 2019). LIDAR-equipped drones generate detailed 3D models of vegetation structure and biomass, aiding in carbon stock assessments and habitat analysis (Wulder et al., 2012; Zhao et al., 2018; Zhou and Li, 2023). Hyperspectral sensors, although still in the early stages of application in environmental issues, show great potential for identifying tree species (Shen and Cao, 2017) and, when combined with Lidar and RGB sensors, can provide precise estimates of carbon stocks and primary productivity in different ecosystems (Sothe et al., 2019). Drones with RGB sensors, coupled with artificial intelligence tools, have also been successfully used to identify trees and other plant species (Onishi and Ise, 2021). Currently, drones with RGB sensors can be obtained for less than USD2,000$, while those with thermal sensors cost approximately USD10,000$, Lidar around USD30,000$, multispectral and hyperspectral are still > USD70,000$, however, prices are dropping rapidly.

### *Genomic Techniques for Demography Assessment and Gene Flow*

Genomic approaches encompass a series of techniques such as Whole genome resequencing (WGR), Reduced representation DNA sequencing (RRS), Genome skimming, and Transcriptome sequencing that allow for analysis of genetic diversity, inbreeding, effective population size, population structure, and gene flow (Theissinger et al., 2023). No single genomic analysis can answer all the potential questions, and they all have peculiarities in terms of DNA integrity needs, therefore, what type of DNA samples are required, reference genome demands, standardizations, and costs (Theissinger et al., 2023). For instance, WGR is the current genomic technique that can provide most information out of DNA samples. However, it benefits from a reference genome collection and has high costs of shotgun sequencing and computational demands, which still have limited its applications in management and conservation studies (Fuentes-Pardo and Ruzzante, 2017). Though, it offers valuable insights into population dynamics, including estimates of population demography, local adaptation, gene flow, and connectivity (Ellegren, 2014; Wang et al., 2022). The costs involved in these analyses are highly variable and depend on the availability of reference sequences, which, however, are growing exponentially (Ellegren, 2014). For species with available reference sequences, costs range around USD10,000$ for 30 to 40 individuals, and these costs have been rapidly declining in recent years.

### *Automated Stations for Measuring Bioclimatic Variables*

Real-time monitoring stations that measure bioclimatic variables, such as temperature, humidity, solar radiation, and water flow, are essential tools for ecosystem management (Bramer et al., 2018), as they provide continuous data streams that inform biodiversity studies, enabling researchers to assess species' responses to climate change and land-use alterations, monitor plant phenology, invasive species impacts, and changes in habitat suitability over time. The integration of such stations into EIAs enhances the ability to track environmental changes in real-time, providing valuable information for adaptive management strategies. The availability of such data also supports broader environmental monitoring efforts, particularly in multiscale studies using coarse climatic data available, tackling areas especially vulnerable to climate-induced shifts in biodiversity.

### *Cartography and Experimental Design*

With these advancements in sampling strategies, the volume and scope of biological data are entering the "big data" phase (Farley et al., 2018; Hampton et al., 2013). This data availability allows us to address previously unanswerable questions and provides more precise solutions to complex issues like natural resource management or large-scale problems (Niu et al., 2020). It also increases the need for well-defined experimental design and sampling evaluations to scale fieldwork effectively. A wealth of global cartographic resources exists (Potapov et al., 2022), including several for Brazil (MapBiomas - https://brasil.mapbiomas.org/, FBDS - https://www.fbds.org.br/, among others), enabling preliminary experimental design based on landscape ecology analyses, even before refined data from drones or high-resolution satellites are available. The design must always align with the specific threat or management question, considering spatial and temporal scales (Ferraz et al., 2008).

### *Data Management*

Data should follow a "data cycle," starting with a robust Data Management Plan (DMP) that outlines how data will be collected, processed, curated, and made available throughout its lifecycle. This includes standardized metadata, automated storage, and curation, filtering, and processing systems with minimal human intervention, thereby reducing errors (Wilkinson et al., 2016). Whenever possible, data should be collected in "real-time" or "near-real-time" and made openly available to ensure transparency, reuse, and facilitate analysis at different stages (See FAIR Principles at https://www.go-fair.org/fair-principles/). Preliminary species lists with potential occurrences in the study areas should also be evaluated to select suitable sampling methods and ensure the availability of reference sequences or sound templates for automated identification. These lists, combined with existing cartographic resources, provide valuable data for robust experimental design and determining sampling efforts to answer complex environmental planning and impact assessment questions.

## Final Considerations

This work does not aim to exhaustively review modern biodiversity sampling techniques but rather it highlights the potential applications of modern biodiversity sampling techniques in conservation studies and Environmental Impact Assessments (EIAs). These methods are becoming increasingly affordable and accessible, offering viable alternatives for long-term monitoring for environmental consultancy. Integrating various techniques reveals additional important aspects. For example, acoustic monitoring enables highly accurate detection of multiple taxa, while incorporating predictive variables from weather stations or remote sensing data enhances the ability to extrapolate information across both time and space. Compared to traditional methods they improve efficiency, enhance data quality, and reduce biases or sampling errors. Importantly, the data generated—like species vocalizations, genetic sequences, and photographs—are often stored in standardized databases, promoting transparency and reproducibility.

Incorporating these innovative methods into EIAs is timely and necessary. They can significantly enhance the accuracy and robustness of these assessments, transforming them into more reliable tools for evaluating potential environmental impacts (Sutherland et al., 2013). Additionally, integrating these methods into frameworks like Environmental, Social, and Governance (ESG) criteria and biodiversity performance indicators (KPIs) is essential. Following the Taskforce on Nature-related Financial Disclosures (TNFD) recommendations, these techniques will enhance environmental management, supporting both sustainability and corporate accountability (TNFD, 2021). These new techniques allow us to shift our mindset, treating biodiversity conservation and monitoring as investments for a more secure and sustainable future.

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## Conflict of interest

All authors declare that they have no conflicts of interest.

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## Declaration of Generative AI and AI-assisted technologies in the writing process

Statement: During the preparation of this work the author(s) used chatGPT to translate from Portuguese, the original language that the manuscript was written, to English. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

## Author contributions

Both ACM and AU conceptualized, obtained funding, wrote the original draft, and reviewed and edited the final version of the manuscript.

Table 1: Current and future methodological characteristics

| Methodology | Main sampled groups | Biodiversity expert dependency (current status and trend) | | | | | Current Cost Composition (in descending order of values) | Trends | Applications | Main Advantages | Main disadvantages |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Experimental Design | Data Collection | Sample Analysis | Data Interpretation | | | | | |
| eDNA and iDNA | Birds, amphibians, mammals, reptiles, fish, invertebrates and microorganisms | Current | ★★★★★ | ★★★☆☆ | ★★★★★ | ★★★★★ | Sequencing, data analysis, field logistics, field equipment | Drones and other UAVs/robots will be more employed for collecting samples and deploying traps in complicated access regions; low-cost mobile real-time PCR and DNA/RNA sequencing devices will significantly reduce prices; eDNA methods for plants will evolve; optimized bioinformatics pathways with user-friendly interfaces; improvements in the eDNA collection and extraction methodologies; expansion of the availability and reduction in prices of sampling kits, enhancing involvement of citizens in the collection of eDNA; primer developments | Species richness and composition; species detection, particularly rare, threatened and invasive species; identification of species that should be target for population monitoring; evaluation of restoration and landscape management projects; biodiversity monitoring across different habitat types and for different taxonomic groups; ancient ecosystem reconstruction; plant-pollinator interactions; diet analysis; DNA-based ecological network; many others | Non-invasive, samples multiple taxa in several areas simultaneously, less affected by observer bias, high efficiency in areas of difficult access, lower sampling costs compared to other techniques, free from the observer effect, fast compared to other methods, particularly suitable to detect rare/cryptic species | Just presence/absence data (richness), no abundance/age/sex data, lack of reference sequences particularly for understudy species groups, sample contamination problems (both in the field and in the lab), fast DNA degradation |
| | | Future | ★★★★★ | ☆☆☆☆☆ | ★★☆☆☆ | ★★★★★ | | | | | |

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|---|---|---|---|---|---|---|---|---|---|---|
| Passive Acoustic Monitoring (PAM) | Birds, amphibians and mammals (bats and primates) | Current | ★★★★★ | ★☆☆☆☆ | ★★★★★ | ★★★★★ | Audio recorders, field logistics, sound processing for species identification, data analysis, and storage | Connectivity among audio-record devices resulting in real-time information availability; improvements in species identification; enhancing availability of AI species identification models; reduction in device prices; improvements in data collection and analysis workflow; | Species richness and composition; species detection, particularly rare and threatened species; identification of species that should be target for population monitoring; evaluation of restoration and landscape management projects; biodiversity monitoring across different habitat types and for different taxonomic groups; invasive species detection; | Non-invasive, samples multiple taxa in several areas simultaneously, less affected by observer bias, continuous long-term monitoring, cost-effective compared to other techniques, particularly useful for cryptic/nocturnal species under-represented in standard sampling methods, keeps permanent records | Just presence/absence data (richness) - distinguishing between individuals or estimating their proximity to the recorder can be challenging for most of the species, Environmental background noise (e.g., wind, rain, human activity, water flowing) can interfere with recordings and species identifications |
| | | Future | ★★★★★ | ☆☆☆☆☆ | ☆☆☆☆☆ | ★★★★★ | | | | | |
| Camera traps | Medium and large mammals and land birds | Current | ★★★★★ | ★★☆☆☆ | ★★★★★ | ★★★★★ | Camera traps, field logistics, image analysis and storage platforms, data analysis | Connectivity among camera traps resulting in real-time information availability; improves in image quality allowing smaller species identification; automates image classification; expansion in citizen science involvement; applications in species interactions and in ecological network studies | Data on the presence, abundance, and behavior of species, often contributing to environmental education and awareness efforts with the rich image databases produced | Non-invasive, samples multiple taxa in several areas simultaneously, continuous long-term monitoring, cost-effective, less affected by observer bias, keep permanent records that can be used in environmental awareness and education actions, capture rare and elusive species, it could bring behavior insights (e.g. feeding, mating, social interactions), it can be used for much precise population monitoring (e.g. mark-recapture studies) when species could be identified at the individual level | Species-specific bias for medium to large terrestrial mammals and birds, whereas other species groups, or smaller, arboreal mammals, may be underrepresented or missed entirely, High initial costs from purchasing and deploying camera traps, Limited environmental coverage, since camera traps cover a relatively narrow field of view, limiting the area sampled, bias by the animal movement patterns, potential for theft or damage of expensive equipment |
| | | Future | ★★★★★ | ☆☆☆☆☆ | ☆☆☆☆☆ | ★★★☆☆ | | | | | |

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| Drone with multispectral or RGB sensors | Vegetation and land use | Current | ★★★★★ | ★★★☆☆ | ★★★★★ | ★★★★★ | Drone and sensor, field logistics, image processing, data analysis | Early signs of plant stress, such as nutrient/water deficiencies or diseases; phenology studies; high-resolution of vegetation indices; automated vegetation classification, and the detection of land use changes; plant species identification | Tracking shifts in vegetation; land degradation; species tracking; long-term monitoring changes in biodiversity in high-resolution; rural property planning | Production of high-resolution land use/cover maps, precise DEM, and DSM | The imaging capacity is constrained by battery duration, which complicates the logistics of mapping very large areas |
| | | Future | ★★★★★ | ☆☆☆☆☆ | ★★★☆☆ | ★★★☆☆ | | | | | |
| Drones with thermal sensors | Canopy mammals or grassland/savanna species | Current | ★★★★☆ | ★★★☆☆ | ★★★★☆ | ★★★★★ | Drone and sensor, field logistics, image processing, data analysis | Wildlife counting, particularly nocturnal, canopy, and cryptic species; behavior studies (grouping, nesting, movement); invasive species detection (e.g. feral swine, *Callithrix jacchus*), further developments will allow sampling species below the forest canopy. | Drones with thermal sensors are increasingly used to monitor arboreal species, such as primates, enabling accurate population estimates, also used for gathering population information of grasslands and savanna species. | Sampling of canopy individuals, possibility of identifying groups, and records can be used in environmental awareness actions | The sensors do not capture information about species that are beneath the forest canopy, limiting their use to species in open areas or those located on the tree canopies. |
| | | Future | ★★★★☆ | ★☆☆☆☆ | ★☆☆☆☆ | ★★★★★ | | | | | |
| Drone with LiDAR sensors | Vegetation and relief | Current | ★★★★★ | ★★★☆☆ | ★★★★★ | ★★★★★ | Drone and sensor, field logistics, image processing, data analysis | Automation of the analysis of the point cloud, high-resolution Lidar data obtained from low-orbit satellites | Captures data from the terrain and across forest strata. This allows us to generate high-definition digital elevation models that can support actions for water and soil conservation. Additionally, the metrics generated by the point cloud have been used for estimating forest biomass and carbon | Allows inferences about the structure and forest profile, create digital terrain and surface models with high precision | Post-processing is still laborious and time-demanding; sensors are still expensive |
| | | Future | ★★★★★ | ☆☆☆☆☆ | ☆☆☆☆☆ | ★☆☆☆☆ | | | | | |

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| Drone with hyperspectral sensor | Vegetation | Current | ★★★★★ | ★★★☆☆ | ★★★★★ | ★★★★★ | Drone and sensor, field logistics, image processing, data analysis | Expansion of reference information for different species, also evaluation of phenology and stress-related issues, potential applications in evaluating climate change impacts and/or changes in water availability for plant species | Identification of species in a forest, allowing for a better understanding of its conservation status, ecosystem functioning, and the presence of species of economic and conservation value. Additionally, this information is essential for parameterizing biomass and carbon models, thereby increasing their accuracy | Sampling and identification of multiple plant species | It is a still-expensive methodology that is in its early stages of development, especially for tropical forests. |
| | | Future | ★★★★★ | ☆☆☆☆☆ | ☆☆☆☆☆ | ★★★★★ | | | | | |
| Whole genome resequencing (WGR) | Population genetics of birds, amphibians, mammals, reptiles and fish | Current | ★★★★★ | ★★★☆☆ | ★★★★★ | ★★★★★ | Sequencing, sample collection, data analysis, field logistic | Expansion of reference genome and reduction in sequencing prices; high-coverage sequencing is becoming increasingly affordable | Significant potential for understanding population connectivity and gene flow, long-term population viability analysis, tracking genetic diversity in response to habitat fragmentation, or other environmental impacts, essential demographic data for conservation planning and decision-making, including relatedness, mating systems, inbreeding levels and local adaptations to different environments. | High-resolution information on population parameters, possibility of multiple applications; can provide data on cryptic species | Still expensive; demands good quality DNA samples; difficulties of sampling a considerable number of individuals to provide population demographic data, particularly for rare and endangered species; massive volume of sequencing data (big data) and the need for computational power to process such data. |
| | | Future | ★★★★★ | ☆☆☆☆☆ | ☆☆☆☆☆ | ★★★☆☆ | | | | | |
| Stations for Measurement | Water (e.g. temperature, ph, sediment | Current | ★★★★★ | ★★★☆☆ | ★★★★★ | ★★★★★ | Automatic stations, field | New sensors are being developed and improved, | It involves collecting chemical and | Long-term continuous collection allowing | The equipment used in monitoring stations is |

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| of Bioclimatic Variables | content, speed, amount), climate (e.g. humidity, temperature, wind, light), soil (e.g. water content, temperature) | Future | ★★★★★ | ☆☆☆☆☆ | ★★★☆☆ | ★★★☆☆ | logistics, data analysis | allowing for the estimation of a broader range of parameters for soil, water, and the atmosphere. | physical data from the environment, allowing for the assessment of its fluctuations over time. This type of data is essential for evaluating ecosystem services of regulation, particularly in the context of climate change. | high accuracy of estimates | relatively expensive, making it difficult to collect data from various sampling points that can adequately represent the heterogeneity of landscapes in a given region |

* Main sampled species group

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