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# Innovate 4 Nature

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# Executive summary

## Background and aims

Biodiversity is declining at an unprecedented rate, with global wildlife populations having declined by an estimated 73% on average, and over one million species at risk of extinction. This loss is not only an environmental crisis, but a social and economic one. Biodiversity underpins natural capital and supports livelihoods, food security, clean water, climate regulation, disaster risk reduction, and disease control, functions that are especially critical in Low- and Middle-Income Countries (LMICs), where dependence on natural resources is high.

As pressures from land-use change, climate change, over-exploitation, pollution, and invasive species intensify, robust biodiversity monitoring is essential. Monitoring provides the evidence needed to understand how ecosystems and species are changing, to evaluate the effectiveness of conservation actions, and to inform policy, planning, and investment decisions. It is also central to recognising and managing the economic value of nature, including its role in national accounting, development planning, and emerging nature-based finance mechanisms. Without reliable, trusted data, biodiversity cannot be effectively governed, valued, or protected.

Global frameworks such as the Convention on Biological Diversity (CBD) and the Kunming–Montreal Global Biodiversity Framework (GBF) place biodiversity monitoring at the centre of international commitments, requiring countries to track progress against agreed targets through standardised indicators and National Biodiversity Strategies and Action Plans (NBSAPs). Similar data demands arise from other global agreements, including the International Convention on Wetlands (Ramsar Convention), the Convention on Migratory Species (CMS) and the Convention on International Trade in Endangered Species of Wild Fauna and Flora (CITES). Together, these frameworks make clear that biodiversity goals cannot be assessed or achieved without sustained, high-quality monitoring and data systems.

Despite this, biodiversity monitoring remains fragmented and uneven with significant taxonomic, geographic, and ecosystem-level gaps. Monitoring efforts are further constrained by limited standardisation, weak data governance, inadequate infrastructure, and insufficient capacity. As a result, much biodiversity data remains inaccessible, poorly integrated, or under-utilised in decision-making. A persistent disconnect between data producers and data users, exacerbated by weak science–policy interfaces, limited data literacy, and unclear governance, undermines the impact of monitoring investments.

Whilst emerging technologies offer substantial potential to address these challenges by improving the scale and coverage of data collection, they also introduce new challenges, such as the need for adequate infrastructure and capacity to store, process, and analyse large volumes of data, and the requirement that data outputs align with the needs of diverse end users. Moreover, technologies can exacerbate existing inequities in whose knowledge is valued and who participates in data-to-decision pathways, both locally, where communities and Indigenous Peoples may be excluded, and globally, where power imbalances between the Global North and South persist, highlighting the need to centre LMIC experiences in the application of biodiversity monitoring technologies.

**Innovate 4 Nature (I4N)** aims to gather evidence on the use of biodiversity monitoring technologies and data in low- and middle-income countries. The **I4N** project is led by the UK Centre for Ecology & Hydrology (UKCEH) and funded by Defra. Defra is the UK government's Department for Environment, Food and Rural Affairs. Defra is responsible for improving and protecting the environment and aims to grow a green economy and sustain thriving rural communities. Project partners for **I4N** are the Tropical Biology Association (TBA) (https://tropical-biology.org/).

The programme assesses current use of technology, identifies barriers to the effective use of biodiversity monitoring technologies and data across diverse actors and examines the needs required to overcome these constraints. It further explores the opportunities that emerging technologies could unlock and develops solutions to support scalable, context-appropriate, and inclusive uptake. Together, these efforts seek to ensure that biodiversity monitoring technologies translate into actionable insights, support sustainable livelihoods, reduce poverty, attract investment, and strengthen ecosystem protection and restoration. The technologies covered in the Innovate 4 Nature programme follow the WildLabs assessment of conservation technology (Speaker *et al.*, 2022), applied globally across all taxa and habitats, and utilised by a range of user groups.

## Methods

We approached evidence gathering through a combination of four different methods: A rapid evidence assessment (REA) and questionnaire, focused across all LMICs, and a series of interviews and workshop, focused on East Africa. Across all evidence streams we addressed the following questions: 1) How are technologies currently being used in biodiversity monitoring across LMICs?, 2) What are the barriers to effective use of technologies and resulting data?, 3) What is needed to overcome these challenges?, and 4) What are the future opportunities that biodiversity monitoring technologies could unlock?

We adopted a Gender Equality, Disability, and Social Inclusion (GEDSI) approach, recognising that different social groups and identities experience technology, and biodiversity monitoring more broadly, in distinct ways.

**Rapid evidence assessment**
A rapid evidence assessment was conducted to examine how biodiversity monitoring technologies are used across LMICs and to identify key barriers to their adoption and impact. Guided by two main research questions and supporting sub-questions, the review covered all taxonomic groups, habitats, and a wide range of field-based and data-processing technologies across all Official Development Assistance (ODA) eligible countries. Peer-reviewed and grey literature were systematically searched between September and October 2025 using academic databases, organisational websites, and Google Scholar, using tailored search strategies. A two-stage screening process (title and abstract) applied defined inclusion criteria, focusing on empirical studies from 2010 onwards. Relevant data were extracted from 371 articles into a shared database, capturing technology type, application, and barriers or opportunities. Analysis was primarily descriptive, summarising patterns in technology use and synthesising evidence on technical, financial, institutional, and socio-political challenges affecting deployment and uptake.

**Questionnaire**
A targeted sampling approach was used to recruit participants, drawing on a database of collaborators, researchers, and organisations, with invitations distributed via email and online platforms and expanded through snowball sampling. The questionnaire was open from 27 October to 8 December 2025 and collected anonymous responses following informed consent. The survey combined multiple-choice, Likert scale, and open-ended questions.

Respondents (n = 62) brought professional experience from across a wide range of LMICs, professional backgrounds, and technology applications, with expertise spanning 40 countries across eight geographical subregions. The greatest representation of respondents' expertise was in Sub-Saharan Africa (n = 32, 48%) and South-eastern Asia (n = 12, 19%), followed by Latin America and the Caribbean and Northern Africa (n = 9, 13% each). Most respondents were affiliated with universities or research institutes (n = 27, 44%), non-governmental organisations or charities (n = 15, 24%), and governmental or regulatory agencies (n = 11, 18%).

**Interviews**
Interviews were conducted in Kenya by trained researchers with 56 participants, comprising key informants from government (n = 4), research (n = 6), NGO (n = 5), and business/finance sectors (n = 4), alongside 37 community stakeholders. Interviews were recorded with informed consent, transcribed, reviewed, and summarised to ensure accuracy, with translation support provided where necessary. Data were analysed using an iterative coding process, with multiple researchers developing and applying a shared coding framework to identify themes and viewpoints. Findings reflect participants' perspectives, capturing both commonly shared and individual perspectives, however, they were not independently verified and should be interpreted with caution given the sample composition.

**Workshop**
A 2-day workshop in Nairobi, Kenya, was organised and led by project partners TBA. Participants attended from Kenya (n = 27), Tanzania (n = 4), Uganda (n = 4) and the Democratic Republic of Congo (n = 1). They represented a wide range of professional backgrounds, including technology experts, conservation scientists, practitioners, and policymakers, and diverse experiences of using biodiversity monitoring technologies. The workshop adopted a participatory format to explore technology and data use in biodiversity monitoring, combining plenary talks, group discussions and facilitated exercises (e.g. fishbone analysis and visual tools) supported active engagement and the generation of shared insights.

## Headline findings

Our research uncovered the current landscape of technologies for biodiversity monitoring in LMICs, highlighting where they are being applied and the benefits they are bringing. We identified a range of interrelated barriers and needs affecting the effective use of biodiversity monitoring technologies and resulting data across LMICs. These challenges cut across all user groups and span the full monitoring pathway, from technology development and deployment through to data use in decision-making. We also investigated perspectives on the future opportunities for technology in biodiversity monitoring.

### Current use of biodiversity monitoring technologies in LMICs

**Technology use in LMICs has been increasing, with some tools more widely used than others.**
Established tools remain essential, while computational and molecular approaches are expanding quickly, but require development for wider and more effective uptake.

**Key evidence:**

- GIS and remote sensing the most commonly used technologies (41% literature reviewed, 46% questionnaire respondents, 30% interview respondents).
- Camera traps had strong representation in both published studies (21%) and practitioner use (46% in the questionnaire, 54% in interviews).
- Mobile applications were heavily used by community-based data collectors (54% of interviewees, 32% questionnaire respondents).
- AI/machine learning and eDNA/genomics both show fast recent growth in published studies, though used by fewer practitioners and ranked as least developed by questionnaire respondents.

**Technologies are being applied across diverse taxa, habitats and monitoring purposes.**
Plants and land mammals consistently rank among the most monitored groups. Freshwater systems are also well represented, while grasslands, savannas, shrublands and deserts remain comparatively under-monitored with technology.

**Key evidence:**

- Forests are the most common habitat for technology-enabled monitoring (41% of studies; 70% of survey respondents).
- Species identification and population monitoring dominate in the literature (63% of articles).
- Habitat assessment and mapping are widely reported (49% of articles).
- Management and intervention decisions are a major focus for practitioners (66% of interviewees).

**Technology is seen as valuable for improving the quality, efficiency, and usability of biodiversity data.**
Emphasis on technologies ability to enhance data collection and integration but should complement rather than replace traditional methods.

**Key evidence:**

- 75% of interview participants referred to the ease and efficiency technology brings to data collection.
- Interview participants mentioned potential for a reduction in bias (27%, n=15), and the increased transparency and verification of measurements (32%, n=18).
- Technology as a tool to improve data integration and reporting was mentioned by almost half of interview participants (46%, n=26).

## Barriers and needs related to use of biodiversity monitoring hardware in LMICs

**Cost remains a major barrier to the adoption of biodiversity monitoring technologies in LMICs, with affordable technology and sustained funding as key enabling factors.**
High upfront costs, expensive repair and maintenance requirements, and a lack of sustained funding significantly restrict technology adoption and long-term use across all user groups. These financial constraints limit not only initial access to equipment but also the ability to maintain, repair, and scale monitoring systems over time.

Participants consistently emphasised the need for more affordable technologies and sustained funding models that support the full lifecycle of monitoring tools. Without long-term investment, even technically effective solutions fail to translate into durable monitoring programmes.

**Key evidence:**

- Costs related to equipment and supporting infrastructure were identified as a barrier in 16% of reviewed studies.
- Upfront costs constrained technology adoption for 60% (n = 14) of questionnaire respondents using technology for data collection, and 42% (n = 24) of interview participants.
- Repair and maintenance costs were a barrier for 35% (n = 8) of questionnaire respondents using monitoring technologies.
- Nearly half (48%, n = 11) of questionnaire respondents using technologies reported a need for cheaper technologies, while over two-thirds (68%, n = 38) stated that access to funding was required to enable adoption of biodiversity monitoring technologies.

**Technologies designed and produced for higher income contexts are often inaccessible and poorly suited to LMIC needs, improved access and local co-production are key enablers.**
Technologies are predominantly produced in High Income Countries (HIC), creating access barriers through high import costs, lengthy procurement delays, and limited local availability. Many tools are also poorly adapted to local ecological, cultural, infrastructural, and operational conditions, reducing their effectiveness and uptake in LMIC contexts.

Improved access to existing technologies, alongside local or regional production, adaptation, and repair, was consistently identified as critical. Participants emphasised the need for technologies to be designed *with* local users, and supported by locally available technical expertise, data analysis tools, and storage capacity.

**Key evidence:**

- 57% (n = 13) of questionnaire respondents reported lack of access to technology as a barrier, with widespread examples of high import fees and long delays.
- 22% (n = 5) of questionnaire respondents collecting data reported that available technologies were not well suited to local conditions.
- 20% (n = 12) of interview respondents stated that current technologies were ineffective for collecting the data they needed.

**Users prioritise robust, easy-to-use technologies over complex or rapidly evolving tools.**
Frequent technological change, redundancy, and increasing complexity make it difficult to select appropriate tools and sustain their use. These challenges are particularly exacerbated where monitoring is carried out by rangers and local communities, for whom repeated changes in hardware or platforms undermine training, trust, and participation.

Participants consistently called for “frugal” technologies, tools that are durable, reliable, locally repairable, and usable with minimal training, designed to support decision-making rather than technological novelty.

**Key evidence:**

- 35% (n = 8) of questionnaire participants found monitoring technologies difficult to use.
- 27% (n = 15) of interview participants reported poor reliability as a key barrier.
- 23% (n = 13) of interview participants identified technological complexity as a major constraint.

## Barriers and needs related to use of biodiversity data in LMICs

**Biodiversity data are costly, fragmented, and often do not meet user needs, improved access and the collection of locally relevant data are key enabling factors.**
Access to biodiversity data is limited by cost, fragmentation across multiple platforms, inaccessible formats, and gaps in availability. Even where data exists, it often lack the spatial, temporal, or taxonomic resolution required for decision-making, significantly limiting its usefulness.

Participants emphasised the need for improved access to existing data, collection of additional, locally relevant datasets, and better access to data management and analysis tools. The development of national data platforms with tiered access that maintain the ownership rights of data collectors was highlighted as a priority to improve integration and usability.

**Key evidence**:

- 40% (n = 21) of questionnaire respondents who use biodiversity data identified upfront data access costs as a barrier.
- Data were reported as unavailable by 31% (n = 15) and difficult to access by 29% (n = 15) of questionnaire respondents; 25% (n = 14) interview participants reported access challenges overall.
- 23% (n = 13) of interview participants stated that available data were in the wrong format or not fit for purpose.
- Data gaps were reported by questionnaire respondents for spatial coverage (27%), taxonomic coverage (25%), and temporal resolution (15%).
- 30% (n = 15) questionnaire respondents reported a need for improved data access, and 26% reported a need for data that does not currently exist.

**Analytical infrastructure and skills lag behind data collection capacity, local investment in infrastructure and skill development is critical.**
Although field-based data collection has grown, limited computing power, unreliable electricity and connectivity, and insufficient data storage continue to restrict local analysis. Data collection is already extractive, with information gathered in LMICs but analysed in high-income countries. Without investment in local infrastructure, new technologies risk deepening this pattern and undermining current efforts to amplify the voices of local communities, especially traditional and indigenous knowledge. Many analytical tools developed in HICs, including AI models, are poorly suited to local species and contexts, leading to constrained use, biased outputs, reinforced skill gaps, and weaker data-to-decision pathways.

Investment is required in local analytical infrastructure, including computing resources, power and connectivity, data storage, and locally relevant analytical tools (e.g. classifiers and reference libraries), to enable contextually appropriate data processing and interpretation within LMIC institutions.

**Key evidence:**

- 34% (n = 17) of questionnaire respondents reported a need for improved access to data management and processing tools, and 26% (n = 13) for better access to analytical tools.
- 22% of questionnaire respondents cited unreliable computing infrastructure and 12% reported data storage limitations.

## Barriers and needs related to capacity for biodiversity monitoring in LMICs

**Widespread skills shortages limit effective use of technology and data.**
Capacity gaps span the full technology and data lifecycle, including deployment, maintenance, repair, data management, and analysis. A lack of training in data processing and interpretation is particularly evident, limiting the translation of data into actionable insights.

Participants identified the need for expanded, end-to-end training, extending beyond data collection to include analysis, interpretation, and decision-making, with emphasis on developing “data translators” rather than only data collectors.

**Key evidence:**

- Capacity-related challenges were identified as a major barrier in 24% of reviewed studies.
- 62.5% (n = 35) of interview respondents reported shortages in local technical capacity.
- Insufficient analytical capacity was reported by 39% (n = 9) of questionnaire respondents and 18% (n = 10) interview respondents.
- Increased training was identified as a priority by 48% (n = 11) of questionnaire respondents and 66% (n = 37) of interview respondents.

**Capacity is externally dependent and weakly embedded within local institutions.**
Analytical expertise is often concentrated away from data collection locations, either in city-based central offices or out of country, usually in HICs, creating disconnects between data producers and data users. Training is heavily weighted towards data collection, with limited emphasis on synthesis or use, reducing local ownership, trust, and long-term sustainability. If technology becomes the default tool for monitoring, and access and capacity remain unequal, we risk deepening existing inequalities. This would narrow the range of actors and knowledge shaping conservation and further erode local ownership of data.

Embedding technical and analytical capacity within local and national institutions was identified as essential to ensure continuity of monitoring, reduce reliance on external actors, and strengthen data-to-decision pathways.

**Key evidence:**

- 36% (n = 16) of questionnaire respondents reported lack of capacity or expertise as a key barrier to using data in decisions.
- Respondents from or working with local communities reported reduced buy-in where data analysis occurs externally, and feedback is limited.

**Practical infrastructure and funding constraints undermine capacity development**, **investment in sustained infrastructure and personal is critical**.
Even where skills exist, limited staff time, computing resources, power supply, connectivity, and sustained funding prevent effective application of technology and data.

Participants stressed the need for investment in practical capacity, including staffing, computing services, data management systems, power, connectivity, and long-term funding models to support sustained monitoring.

**Key evidence:**

- 22% (n = 5) of questionnaire respondents reported inadequate computing infrastructure for technology use, and 15% (n = 8) for data use.
- 54% (n = 30) of interview participants identified power and network constraints as major barriers.
- 36% (n = 20) of interview participants cited lack of sustained funding as a key challenge.

**Individual characteristics such as gender and Indigenous identity shape people's ability to access, use, and benefit from biodiversity monitoring technologies and data.**
These characteristics influence confidence levels, training needs, perceived barriers, and the suitability of available tools. Limited sample size prevented detailed analysis on these aspects and indicate results should be interpreted with care, but these within LMIC individual differences warrant attention.

**Key evidence:**

- Women were nearly three times more likely to report that technology was not suitable for their needs (11% vs 4.35%).
- 0% of Indigenous questionnaire respondents rated themselves as "expert," and 50% identified as novice/beginner.
- Indigenous respondents were four times more likely to request more training or technical support (23.53% vs 6.67%).

## Barriers and needs related to governance of biodiversity monitoring in LMICs

**Current governance arrangements risk reinforcing inequities in biodiversity monitoring, clear data governance frameworks are critical and co-design with local communities.**
Technologies can exacerbate inequities through Western-centric design, weak integration of Traditional and Indigenous Knowledge (TIK), unclear data ownership, and increased separation between data collectors and decision-makers. Complex technologies further limit community participation and relevance.

Participants highlighted the need for clear data governance frameworks, community co-design, equitable data ownership arrangements and technologies that complement rather than marginalise TIK and local priorities.

**Key evidence:**

- 43% of interview participants expressed uncertainty over who owns or controls biodiversity data.
- 24% of questionnaire respondents reported that TIK was not integrated or only slightly integrated.
- 20% (n = 12) of interview respondents cited limited understanding of technology value or lack of meaningful community involvement (11%, n = 6) as key barriers.

**Lack of standardisation, frameworks and trust in data limit data use in decision-making, standardisation frameworks and transparency are critical across the collection and data lifecycle.**
Weak standards, unclear policy frameworks and low trust in data quality result in fragmented systems and under-use of data. Many actors operate in silos, with limited coordination between data producers and decision-makers.

Participants emphasised the need for clear standards, policy frameworks and improved data quality and transparency across sectors

**Key evidence:**

- 37% (n = 21) of interview participants identified lack of frameworks or policies to guide data use as a barrier.

- Lack of standardisation was cited by 51% (n = 22) of questionnaire respondents, and lack of integration frameworks by 44% (n = 19).
- Data quality concerns were reported by 20% of questionnaire respondents, with 40% interview respondents participants identifying poor quality data as a key limitation for decision-making.

**Weak communication and collaboration significantly limit effective use of biodiversity data**. Poor coordination, siloed working practices, and weak communication between organisations and sectors constrain the translation of biodiversity data into decisions and action. Data sharing is particularly limited, with datasets dispersed across unlinked or inaccessible systems, leading to duplication and missed opportunities for synthesis. A critical disconnect exists between those collecting data and those making decisions, characterised by differing expectations, limited trust, and lack of clarity over data needs. These challenges are compounded by insufficient collaboration and limited co-design with local communities.

Participants emphasised the need for stronger collaboration mechanisms and clearer data-to-decision pathways, including regular dialogue between data producers and users, shared platforms for coordination and co-design of monitoring approaches with local communities. Improved communication was seen as essential to build trust, align data outputs with decision-making needs and ensure monitoring efforts lead to action.

**Key evidence:**

- 36% (n = 20) of interview participants identified siloed working as a major barrier to effective data use.
- 21% (n = 9) of questionnaire respondents reported difficulties related to communication and collaboration, and 18% highlighted challenges in coordinating with other groups or stakeholders.
- 38% of interview respondents identified fragmented or siloed working arrangements as significant constraints.
- 36% (n = 20) of interview participants expressed a need for stronger partnerships to improve monitoring outcomes, while 20% (n = 11) highlighted co-development as key to improving effectiveness.

## Future opportunities for biodiversity monitoring technologies

Participants identified a wide range of future opportunities that emerging technologies could unlock:

- The greatest opportunity is not new technology but applying existing data and tools to real-world conservation decisions.
- Integrating multiple data types into unified, interoperable systems is seen as the most critical enabler of impact.
- Continuous and long-term monitoring can unlock early-warning systems, trend detection, and more adaptive management.
- Artificial intelligence offers major efficiency gains, but only where local reference data, infrastructure, and capacity exist.
- High-quality biodiversity data can support finance, investment, and livelihoods by linking conservation outcomes to economic incentives.
- Inclusive collaboration, by centring Traditional and Indigenous Knowledge and strengthening partnerships between different stakeholders, identified as essential to translate technology into lasting outcomes.

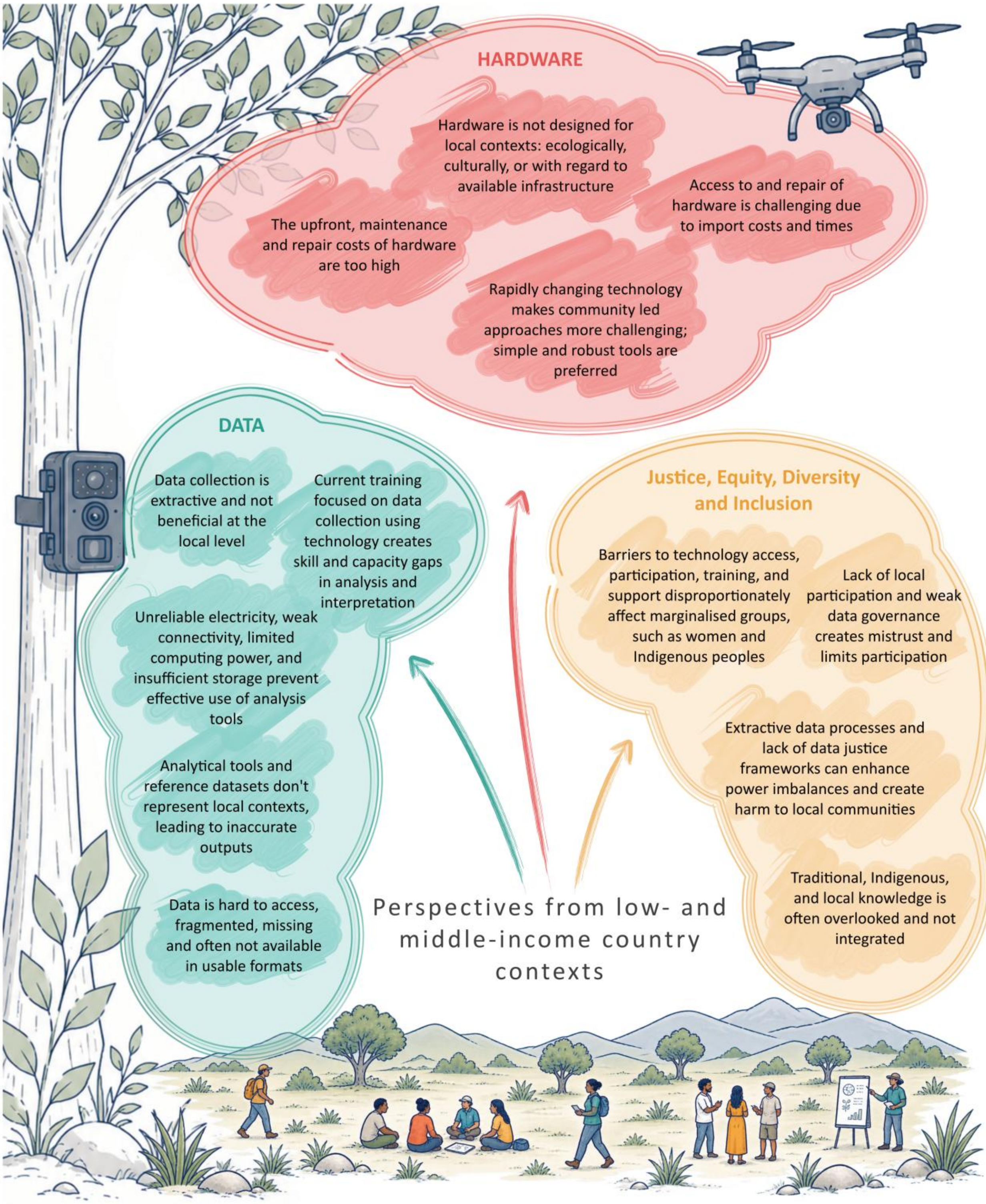


Figure 1 Headline findings from the Innovate 4 Nature project on experiences of accessing and using biodiversity monitoring technologies in low- and middle-income countries.

## Recommendations

### For technology developers:

1. **Design technologies for local realities:** Prioritise robust, affordable, and context-appropriate tools that operate under constrained conditions (e.g. limited power and connectivity). Technologies should be co-designed with local scientists, practitioners, and communities to ensure relevance, usability, and sustained adoption.

2. **Decentralise technology production, maintenance, and support:** Reduce reliance on external production and repair by supporting local or regional manufacturing, adaptation, and maintenance. Where this is not feasible, technologies should be designed to be repairable locally, with streamlined procurement, permitting, and access to spare parts and technical support. National or regional centres, such as the Subregional Technical and Scientific Cooperation (TSC) Support Centres (https://www.cbd.int/tsc/tscm/subregionalcentres) could be utilised for support.

3. **Develop locally relevant analytical tools and reference libraries:** Support the development of local taxonomic reference collections, species classifiers, and analytical tools required for emerging technologies such as AI and eDNA. Locally relevant tools will improve accuracy, usability, trust in data and use of data in decision making.

### For the research, NGO, and practitioner community

1. **Build local ownership and end-to-end capacity:** Expand capacity development beyond data collection to include data management, analysis, interpretation, and decision-making. Training should focus on developing "data translators" and embed technical and analytical expertise within local and national institutions to support long-term resilience. This could be supported through regional workshops and training events co-ordinated by local stakeholders, such as Subregional TSC Centres.

2. **Strengthen data systems through integration and standardisation:** Establish standardised national or regional biodiversity data platforms to consolidate datasets, improve access, and enable interoperability. Standardise data collection, formats, metadata, and analytical workflows to ensure comparability, integration, and trust in data outputs. Existing infrastructure, such as the Global Biodiversity Inventory Facility (GBIF; https://www.gbif.org/) and Group on Earth Observations' Biodiversity Observation Network in a BOX (BON in a BOX; https://boninabox.geobon.org/), can facilitate this process, but support and investment in local digital infrastructure is needed across many LMICs.

3. **Prioritise inclusive and participatory monitoring:** Ensure monitoring programmes are co-designed with communities and Indigenous Peoples from the outset, with clear benefit-sharing, feedback, and ownership mechanisms. To ensure equitable access to data, easy-to-use shared data platforms with informative and meaningful data visualisation is needed. Technologies should complement Traditional and Indigenous Knowledge and integrate biodiversity, socio-economic, and cultural values to support inclusive and equitable outcomes.

### For policy actors

1. **Improve data-to-decision pathways and policy integration:** Strengthen communication between data producers and decision makers through dedicated platforms, embedded scientific expertise in decision-making bodies, and clear requirements for how data informs policy. The Convention on Biological Diversity National Biodiversity Strategies and Action Plans (NBSAPs) should provide a good framework for this, but more support is needed on how to integrate these into national policies.

2. **Strengthen data governance, ownership, and trust**: Establish clear, transparent data governance frameworks that define data ownership, custodianship, sharing, and ethical use. Governance arrangements should safeguard community and Indigenous data sovereignty while enabling appropriate access and reuse.

3. **Enable decentralised technology ecosystems:** Policy actors can incentivise local manufacturing, reduce import barriers for components, streamline permitting for sensors and drones, and support regional repair hubs.

### For funders

1. **Invest in enabling infrastructure and long-term funding**: Move beyond short-term pilots by investing in power, connectivity, computing capacity, data storage, and long-term monitoring programmes. Sustained funding is essential to ensure technologies remain functional and data are usable over time.

2. **Ensure funding is diverse**: Funders should avoid concentrating resources solely on high-tech solutions and instead support a diversity of monitoring approaches, or risk excluding organisations without advanced infrastructure, narrowing who can participate in conservation, and weakening local ownership of data and decisions.

3. **Support local ownership and capacity building:** Funding should target local institutions, not only international partners. This includes training, institutional strengthening, and long-term support for local data collectors, technicians and analysts.

4. **Fund development of local analytical tools and reference libraries:** Funders can accelerate the creation of regional eDNA libraries, AI training datasets and taxonomic collections, which are essential for accurate biodiversity assessments.

5. **Incentivise inclusive and participatory monitoring**: Funders should require projects to demonstrate co-design with communities, benefit-sharing mechanisms, and integration of TIK as conditions for support.

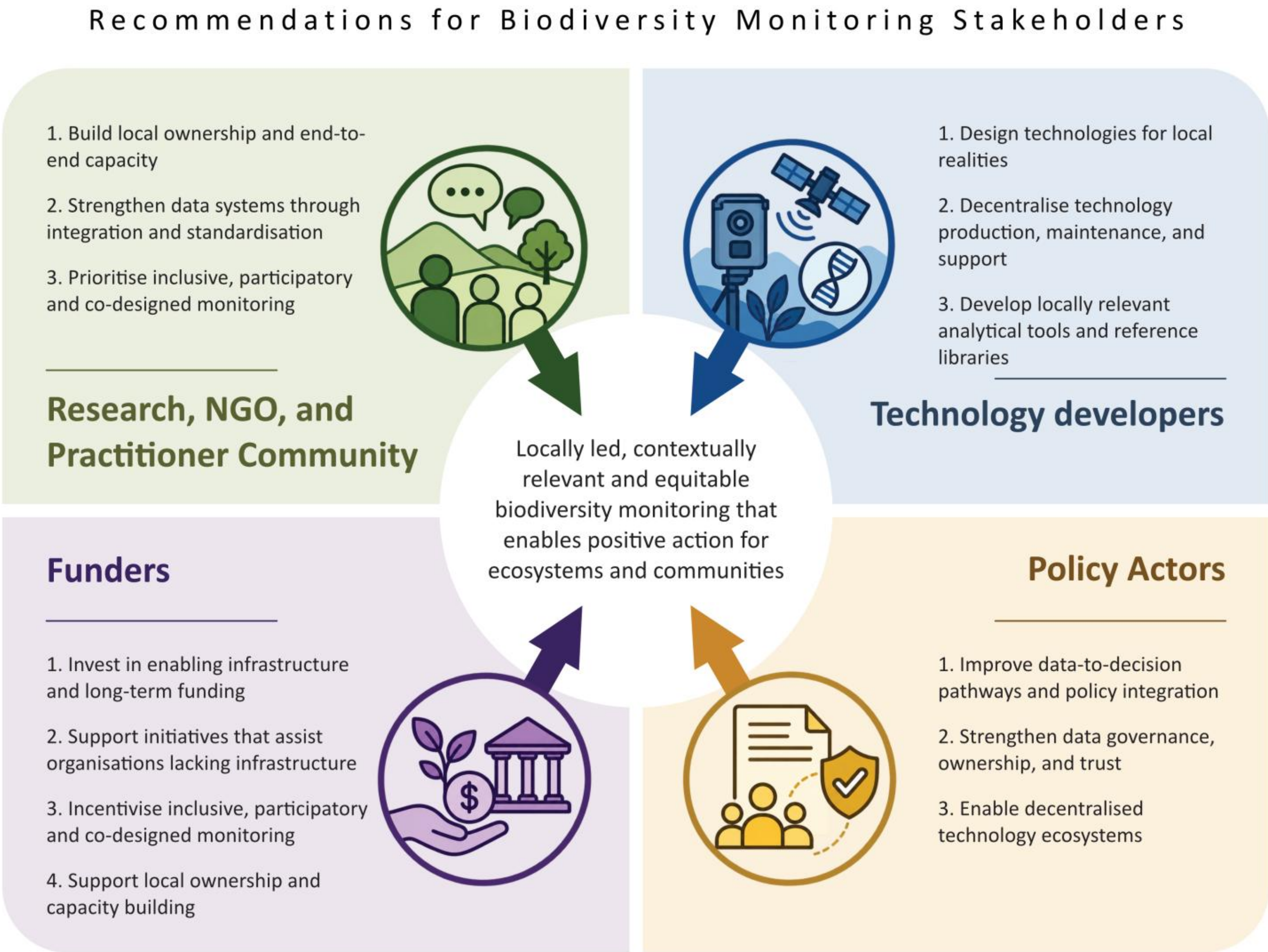


Figure 2 The key recommendations to increase effective and equitable technology use for biodiversity monitoring for each group of stakeholders considered in the Innovate 4 Nature programme

## Conclusion

There is great scope for technologies to enable the monitoring that is required to meet local, national, and global objectives. Participants highlighted the opportunities that technologies can bring to landscape-scale monitoring, to long-term continuous monitoring and early-warning systems for threat detection. Technologies are already being applied across multiple taxonomic groups and habitats, and being used to inform actions and decisions at scale. Participants widely reported that technology has enhanced their capacity to collect and use data, improved data quality, and delivered resource efficiencies in biodiversity monitoring. While a range of barriers and needs were identified, it is important to note that many of these, such as power imbalances between monitoring actors, siloed working practices, and weak links between data, practice, and policy, are systemic challenges that also occur in the absence of technology. At the same time, there is a risk that technology could exacerbate these existing challenges if it is poorly designed or implemented. It is therefore vital for targeted interventions that ensure biodiversity monitoring follows a more robust and equitable trajectory. As countries work towards their 2030 global biodiversity goals, there is a narrow window to ensure technologies are deployed in inclusive, integrated ways that respond to on-the-ground needs. Realising their full potential will depend not only on technological innovation, but on strong governance, collaboration across sectors, and a clear commitment to bridging the gap between data and action.

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# 1 Introduction

## 1.1 Biodiversity and the importance of monitoring

As the pressure of humanity on the environment increases, biodiversity is declining globally, with various sources suggesting a 73% average population decline  (WWF, 2024) and over a million species at risk of extinction (IPBES, 2019). This decline is causing significant concern as biodiversity underpins natural capital and is essential for poverty reduction, supporting ecosystems that provide food, clean water, raw materials and resources critical to the livelihoods of billions, particularly in Low- and Middle-Income Countries (LMICs) (UNEP-WCMC, 2007; Labrière *et al.*, 2015; Balasubramanian and Sangha, 2023). Healthy ecosystems also regulate climate, reduce the impacts of floods and natural disasters, and help control disease (OECD, 2021). However, ongoing ecosystem degradation is eroding the capacity of these systems to provide the essential services upon which societies depend, with far reaching consequences for human wellbeing and the long-term sustainability of the environment (Agarwala *et al.*, 2014).

In the face of these global challenges, monitoring biodiversity has never been so important. Monitoring provides the evidence needed to understand both the negative and positive impacts of human activity on the environment. Understanding how populations respond to harvesting and extraction (Fa and Luiselli, 2024), how species ranges are shifting with climate change (Bernatchez *et al.*, 2024), and how invasive species are spread (Maxwell, Lehnhoff and Rew, 2009) are key to managing environmental resources and are only possible through monitoring. Monitoring is also essential for evaluating the effectiveness of conservation actions, such as habitat restoration and the establishment of protected areas (Geldmann *et al.*, 2019; Ockendon *et al.*, 2026). Integrated monitoring systems can offer a comprehensive view of biodiversity change by linking ecosystem structure, function, and species diversity (Dalton *et al.*, 2024; Langlet-Uranüs, Wurm and Vadrot, 2026).

Beyond its ecological importance, monitoring also underpins the growing recognition of biodiversity as an economic asset. Biodiversity is increasingly being recognised for its economic value, including extractable resources such timber from forests, activities such as tourism or fisheries supported by coral reefs, and ecosystem services such as storm and flood protection. As with carbon finance, these benefits can only be incorporated in national accounting, accounted for in decision making and effectively managed, if they are quantified (Stephenson *et al.*, 2017). Without confidence in the underlying data, their credibility and usefulness for decision-making are compromised.

Together, these considerations highlight that robust biodiversity monitoring is not only necessary for research but also for conservation, policy and economics. However, the complexity of ecosystems, the diversity of indicators, and the need for comparability across regions present significant challenges for how monitoring is designed, implemented, and interpreted. In response, global frameworks have been created to guide biodiversity monitoring efforts.

## 1.2 Global frameworks supporting biodiversity monitoring

The Convention on Biological Diversity (CBD), a legally binding multilateral treaty, provides the overarching objectives for the conservation and sustainable use of biodiversity, alongside its supplementary agreements, including the Nagoya Protocol on access to genetic resources and benefit-sharing, and the Cartagena Protocol on Biosafety. Under the CBD, the Kunming–Montreal Global Biodiversity Framework (GBF), a non-legally binding agreement, was adopted in December 2022 by 196 countries (CBD, 2022). Its vision is to halt and reverse biodiversity loss by 2030 and put nature on a path to recovery by 2050, through four ambitious long-term goals for 2050, and 23 specific targets for 2030 (CBD, 2022, 2024b). Central to the GBF is a standardised monitoring framework, comprising headline, component, and complementary indicators to track progress across national, regional, and global scales (CBD, 2023). Unlike the previous framework, the Strategic Plan for Biodiversity 2011–2020, the GBF places stronger emphasis on measurable outcomes, transparency, and integration across sectors, providing a clearer pathway for national implementation (Hughes, 2023). This is key, as none of the previous Aichi Biodiversity Targets were met on a global scale, attributed to poor governance, their complexity, ambiguity and poor integration into national planning (Buchanan *et al.*, 2020; Perino *et al.*, 2022) The success of the GBF depends on decisive political commitment, adequate resourcing, and robust accountability mechanisms to ensure that global ambitions translate into effective action on the ground

Under the GBF, countries are responsible for creating National Biodiversity Strategies and Action Plans (NBSAPs), which outline approaches for conserving ecosystems and biodiversity and are the primary policy instruments used by countries to implement the GBF. NBSAPs are frameworks to integrate biodiversity conservation into national policy and to monitor and report progress on the headline indictors for each of the 23 targets (CBD, 2026). They are important tools to keep countries accountable to the GBF, and progress towards targets, actions taken, and lessons learned, are monitored through National Reports (CBD, 2006).

Aside from the GBF, countries must also report and deliver against conventions such as the International Convention on Wetlands (Ramsar Convention), the Convention on Migratory Species (CMS) and the Convention on International Trade in Endangered Species of Wild Fauna and Flora (CITES).

To meet their obligations under these global agreements, countries must regularly collect, assess and report high quality data related to biodiversity, requiring long-term, well-funded monitoring programmes and data standards (Lindenmayer *et al.*, 2012; Davidson *et al.*, 2019). If effectively implemented, these frameworks can help identify trends, pressures and priority areas for action, ensuring that conservation measures are evidence based and globally aligned. Ultimately, these global and national biodiversity agreements and targets cannot be assessed, implemented, or achieved without robust monitoring.

# 1.3 Challenges and biases in biodiversity monitoring

Biodiversity is complex because it cannot be captured by a single measure, existing across a hierarchical structure, with over 2 million species discovered and a few, to a few hundred million more in existence that are undiscovered and unidentified (May, 2010). It changes at different rates and responds differently to pressures that interact both together and with underlying social and economic pressures from humanity (Pereira, Navarro and Martins, 2012). This makes monitoring biodiversity change a complex and challenging task, requiring frameworks, standards and collaboration.

Global biodiversity datasets remain incomplete and biased, with substantial taxonomic, temporal and spatial gaps that leave many of the Earth's most diverse taxa and regions insufficiently documented (Geijzendorffer *et al.*, 2016; Lawson *et al.*, 2025). Invertebrates, for example, continue to receive far less attention than other taxa (Clark and May, 2002; Di Marco *et al.*, 2017; Lawson *et al.*, 2025), despite repeated calls to strengthen monitoring efforts (Thomas, Jones and Hartley, 2019) and evidence of rapid declines globally (Hallmann *et al.*, 2017; Lister and Garcia, 2018). Freshwater ecosystems similarly under represented, (Trimble and van Aarde, 2012; Di Marco *et al.*, 2017; Lawson *et al.*, 2025), despite being degraded at twice the rate of marine or terrestrial ecosystems (Linke *et al.*, 2018). Geographically, large areas of Africa remain poorly documented, despite being the world's second largest continent (Trimble and van Aarde, 2012; Di Marco *et* *al.*, 2017; Lawson *et al.*, 2025). A review of Africa's progress towards the Aichi Targets highlighted extensive gaps in biodiversity data for terrestrial mammals, birds and amphibians, with similar shortfalls expected for lesser studied taxa, primarily attributed to constrained national resources and limited local capacity (Farooq *et al.*, 2021). These taxonomic, geographic and ecosystem-level gaps severely compromise our ability to generate reliable assessments of species status, trends and threats, often resulting in misplaced conservation priorities (Di Marco *et al.*, 2017; Farooq *et al.*, 2021).

A further challenge is the limited standardisation in what and where to monitor, the tools employed, and the measurements reported. This inconsistency produces data that are difficult to compare, often fragmented and ultimately underutilised in biodiversity reporting (Pereira *et al.*, 2013; Geijzendorffer *et al.*, 2016). In an effort to make it easier to compare biodiversity data at national and global scales, the Group on Earth Observations Biodiversity Observation Network (GEOBON) defined the Essential Biodiversity Variables (EBVs) (Pereira *et al.*, 2013). EBVs are a standardised set of key measurements used to track changes in biodiversity over time, such as species populations, ecosystem structure, and genetic diversity. They act as a bridge between raw ecological data and policy-relevant indicators, with the aim to help scientists and decision-makers monitor and respond to biodiversity loss at local to global scales.

# 1.4 Biodiversity data governance

Tackling biodiversity loss and ensuring sustainable livelihoods requires decision-making that is grounded in high quality, comparable, reliable, relevant and timely data and evidence (Schmeller *et al.*, 2017; Stephenson *et al.*, 2017). However, persistent challenges in data collection, access, management, infrastructure and capacity continue to undermine the strength of the evidence base (Han et al., 2014). This is due in part to the widespread absence of credible science-policy interfaces, spaces where scientists and decision-makers can work together to understand on-the-ground issues, identify the evidence needed to inform decisions, and articulate the respective needs of data providers and users (Young *et al.*, 2014; Sarkki *et al.*, 2025). There are local and global efforts to collate biodiversity data in databases to facilitate accessibility and use, such as the Global Biodiversity Information Facility, the WWF/ZSL Living Planet Index and the IUCN Red List of Threatened Species, yet much of the data that exists is still fragmented between institutions and held locally, with little sharing between them (Stephenson *et al.*, 2017).

Regardless of the frameworks or policies established to assess biodiversity, decision-makers require data that are accessible and easy to interpret (Schmeller *et al.*, 2017; Stephenson *et al.*, 2017). This means presenting information in formats that are clear, user-friendly, decision-relevant and suitable for non-scientific audiences (Josse and Fernandez, 2021). Achieving this, however, depends on effective communication between data providers and users, as well as communication training for data providers. Without these, the uptake of evidence in decision making will remain limited (Geijzendorffer *et al.*, 2016; Stephenson *et al.*, 2017).

There is a clear disconnect between information being generated and its use in policy and decision making, with producers and users operating with different expectations, standards, and priorities and socio-economic and environmental priorities often seen as conflicting (Stephenson *et al.*, 2017). Until this disconnect is resolved, the impact of biodiversity monitoring data will remain limited, the effectiveness of conservation actions will be reduced, and alignment between scientific evidence and national biodiversity strategies will remain constrained (Josse & Fernandez, 2021).

The growing emphasis on high-quality biodiversity data has also brought increased attention to the principles that govern how such data are managed, shared, and used. The FAIR principles set out that data should be Findable, Accessible, Interoperable, and Reusable (Wilkinson *et al.*, 2016). In the context of biodiversity monitoring, this means ensuring that datasets are well-documented, stored in accessible repositories, use standardised formats, and can be readily integrated across platforms and studies. Applying FAIR principles enhances transparency, enables reproducibility, and allows data to be more effectively mobilised for research, policy, and conservation action at multiple scales. Complementary to this are the CARE principles that consideration should be given to the Collective Benefit, Authority to Control, Responsibility, and Ethics of data (Jennings *et al.*, 2023). These principles emphasise the importance of Indigenous Peoples' relationships and rights to data, and centres Indigenous communities and their knowledge as integral to biodiversity research rather than something additional to be incorporated.

However, the effectiveness of these governance principles ultimately relies on the ability to generate high-quality data at scale.

# 1.5 Biodiversity monitoring technologies

Advances in technology are transforming the capacity to generate biodiversity data at the scales and resolutions required for effective governance and decision-making. Tools such as artificial intelligence (AI), satellite imagery, autonomous aerial vehicles (UAVs), automated sensors, molecular tools, and cloud computing, are expanding the temporal and spatial scales that monitoring can be carried out on, while improving the resolution and precision with which data can be collected (Marvin *et al.*, 2016; Stephenson, 2020).

As the price of hardware continues to drop, technology can increasingly reduce the cost of monitoring. For example, the cost of a camera trap halved between 1998 and 2011, while performance and battery life increased, this lead to cost savings of 10-20% when compared to manual approaches, such as foot patrols, mainly due to reduced person-power costs in the field (O'Brien, 2016). The benefits of technology vs manual methods are evident when considering long-term, repeated monitoring. A comparative case study of acoustic monitoring, camera traps, environmental DNA (eDNA), and traditional survey methods found that technology-based approaches can offer substantial long-term cost advantages, despite initial setup costs, as passive acoustic monitoring had lower person-power and costs per species detected over time (Bell and Malerba, 2025). Technologies can greatly reduce the time needed to process data, leading to faster action and decision making. Using networked camera traps combined with AI-based image classification, rather than traditional camera traps requiring manual image retrieval and processing, reduced monitoring costs by 81% in an invasive species monitoring programme (Smith *et al.*, 2024). When combined with lower-throughput approaches, citizen science and local and Indigenous Knowledge, these innovations offer a transformative opportunity to improve environmental insight.

Here we provide a background to the main biodiversity monitoring technologies, highlighting their capabilities, the challenges in using them, and their future potential.

## Camera traps

Camera traps are automated digital cameras triggered by motion or heat (typically passive infrared sensors) and most commonly used to document medium- to large-bodied terrestrial mammals (Tobler *et al.*, 2008) and birds (O'Brien and Kinnaird, 2008), with growing applications for arboreal (Moore *et al.*, 2021) and small species (Hopkins, Santos-Elizondo and Villablanca, 2024). They provide direct measures of species presence, behaviour, activity patterns, and habitat use by generating verifiable photo/video records (Cordier *et al.*, 2022). Camera trapping can also be used to estimate habitat occupancy and population distributions given that biases introduced by autocorrelation are accounted for (Goldstein *et al.*, 2024). Population abundance can be inferred from using distance sampling (Harris *et al.*, 2020), capture–recapture for individually marked species (Silver *et al.*, 2004) or detection/non-detection models for unmarked species (Gilbert *et al.*, 2021).

Camera trapping is widely applicable in woodlands, grasslands, and remote understudied areas, particularly where visual surveys are difficult (Agha *et al.*, 2018). Automated imaging devices are also more recently being applied for insect monitoring (eg. AMI system https://github.com/AMI-system, Insect Detect https://maxsitt.github.io/insect-detect-docs/) and aquatic environments (eg. NewtCAM, FishCam (Mouy *et al.*, 2020)). The method is increasingly valuable for behavioural ecology, disturbance assessments (Mori *et al.*, 2025), and detecting rare or elusive species (Thomas *et al.*, 2020).

The widespread commercial availability of camera-trapping hardware, combined with the long history of its use, has made the method both accessible and relatively low-effort. Cameras are easy to deploy and transport, and consumables such as SD cards and batteries are widely available (Glover-Kapfer, Soto-Navarro and Wearn, 2019). Although solar panel attachments can extend deployment time, field locations are still constrained by the need to replace SD cards and batteries regularly (Glover-Kapfer, Soto-Navarro and Wearn, 2019). More recent developments in image processing and transmission have reduced the time-lag between data collection and analysis, allowing for real-time conservation action (Whytock *et al.*, 2023; Nazir and Kaleem, 2024).

Data quality is highly variable. False positives are commonly triggered by moving vegetation, sunlight, or thermal interference, while false negatives arise from slow trigger speeds, short detection ranges, or species, particularly small-bodied or ectothermic animals, that emit weak thermal signatures (Glover-Kapfer, Soto-Navarro and Wearn, 2019). Camera traps also generate very large volumes of images and videos, meaning that large-scale studies require robust data-management systems, efficient image-labelling tools and, increasingly, machine-learning pipelines (Oliver *et al.*, 2023).

Despite declining hardware costs over time, the overall expense of camera trapping remains the biggest constraint reported by users (Glover-Kapfer, Soto-Navarro and Wearn, 2019). Sensor performance varies notably between models, forcing practitioners to choose between deploying many low-cost units or fewer high-quality devices. Cheaper units often come with trade-offs such as reduced image quality, shorter lifespan, and higher rates of false detections. Vandalism and theft are also frequently reported issues with common mitigation strategies including commercial or custom security housings, cable locks, camouflage (e.g., using natural cover like logs), and no-glow infrared flashes (Glover-Kapfer, Soto-Navarro and Wearn, 2019). However, their true effectiveness remains uncertain (Meek *et al.*, 2019). Efficient data management, especially rapid and accurate image classification, is also seen as a top challenge associated with camera trapping (Glover-Kapfer, Soto-Navarro and Wearn, 2019).

Future opportunities in camera trapping include reducing identification bottlenecks through improved automated species recognition using AI. Progress will depend on expanding open-access camera-trap datasets (e.g. Wildlife Insights (Ahumada *et al.*, 2020)) and classifier models (eg. DeepForestVision (Magaldi *et al.*, 2025), ClassifyMe (Falzon *et al.*, 2020)) that encompass a wide range of species and habitats. Several large-scale projects have also demonstrated the value of citizen science in processing camera-trap images (e.g. Snapshot Serengeti (Swanson *et al.*, 2015)), in some cases achieving over 96% accuracy compared with expert classifications (Swanson *et al.*, 2016).

There is also considerable opportunity to establish standardized methods and metadata frameworks for camera trapping that enable meaningful comparisons across sites and regions, supporting integration of datasets into global data repositories (Oliver *et al.*, 2023). Tools such as Camera Trap DP help enforce consistent metadata structures for camera-trap datasets (Bubnicki *et al.*, 2024), and similar standards are now being developed for other automated imaging systems. For example, InsectAI, an EU-funded COSTAction project, is creating metadata conventions tailored to image-based insect monitoring (InsectAI, Working Group 2 https://insectai.eu/working-groups/wg3/)

### Acoustic recorders

Bioacoustic surveys are a long-established method for monitoring biodiversity, making use of the acoustic signals produced by living organisms (Becker *et al.*, 2022). Because many of these sounds are species-specific, bioacoustics enables direct measurement of species presence or absence, activity, distribution (Frommolt and Tauchert, 2014), richness (Wimmer *et al.*, 2013), and density (Stevenson *et al.*, 2015). It also allows aspects of animal behaviour to be surveyed directly; research into vocal repertoires, communication patterns, and species interactions has been widely facilitated by bioacoustic techniques (Tobias *et al.*, 2014; Bang *et al.*, 2023). Although estimating abundance has traditionally been challenging, recent evidence shows strong relationships between the vocal activity rate index (VAR), defined as the number of songs per unit time for a species, and population census data which indicate promising potential for inferring abundance from acoustic surveys (Hutschenreiter *et al.*, 2024).

In contrast to bioacoustics, ecoacoustics encompasses both biotic and abiotic sounds, providing soundscapes that characterise entire ecosystems (Melo *et al.*, 2023). Acoustic indices, which are numerical summaries of sound energy, are used as proxies to investigate habitat health and ecological processes

(Bradfer-Lawrence *et al.*, 2023). Under certain circumstances, these indices can also be used to infer biodiversity metrics such as species richness and diversity (Zhao *et al.*, 2019).

Rapid development and commercialisation of automated recording units (ARUs) in recent years have expanded the range of taxa and habitats that can be surveyed (Becker *et al.*, 2022). These devices enable Passive Acoustic Monitoring (PAM), as they can be deployed in the field to record continuously or according to a pre-programmed schedule without supervision. This expansion has also led to new applications, including the detection of logging activity, monitoring of poaching (Astaras *et al.*, 2020), and the assessment of anthropogenic noise impacts on ecosystems (Pichegru *et al.*, 2022).

Bioacoustics is particularly effective for monitoring species that produce distinctive or frequent sounds, and is therefore commonly used for vocal birds, mammals, anurans, reptiles, fish, and insects. PAM is especially valuable for surveying wildlife that may be difficult to detect with traditional methods, such as nocturnal species, marine organisms, forest-dwelling animals, and elusive or rare species (Ross *et al.*, 2023). At present, bioacoustics is used most extensively in terrestrial and marine systems, while freshwater environments remain comparatively understudied (Becker *et al.*, 2022). Nevertheless, promising results have emerged for freshwater fish and macroinvertebrates (Desjonquères *et al.*, 2024).

One of the major advantages of PAM is its capacity for large-scale, long-term data collection. There are now many commercial and open-source hardware options available for research-use, often requiring little expertise to set up (Hill *et al.*, 2018; Heath *et al.*, 2024; *Wildlife Acoustics*, 2024; Kitzes *et al.*, 2026). Depending on the device model, recording schedule, and target frequency range, ARUs can operate continuously for days to months and offer high levels of objectivity and replicability, enabling comparisons across sites and over time (Mennill, 2024). AI-based classifiers have transformed the scale at which acoustic data can be processed, allowing automated detection of species at rates previously impossible (Kahl *et al.*, 2021).

Several challenges remain in bioacoustics. Acoustic surveys generate large volumes of raw data; for example, an AudioMoth recorder produces about 350 MB of audible-frequency audio per hour and roughly 1.8 GB per hour when capturing ultrasound (>20 kHz) (Hill *et al.*, 2018). Projects can accumulate hundreds to thousands of recording hours which need to be stored and processed, creating the need for large, long-term data storage and processing facilities (Kvsn *et al.*, 2020).

In addition, developing AI classifiers for species detection requires specialist expertise and large, labelled training datasets, resources that are difficult to obtain, particularly for rare or understudied species (Longdon, 2023). Data quality issues such as background noise, non-target biogenic noise or system-generated hum remain challenges that can affect processing performance of AI classifiers (Darras *et al.*, 2020). Signal quality also worsens as hardware deteriorates from age or environmental conditions which can further reduce result validity (Darras *et al.*, 2018).

Looking ahead, further development of species-specific AI classifiers will broaden the range of species and habitats that can be surveyed using bioacoustics. This will include expanding bioacoustic research into marine and freshwater environments and exploring acoustics in insect communities (Becker *et al.*, 2022; Chávez-Andrade *et al.*, 2023). There is also growing potential for establishing standardised protocols that support comparisons across sites and study systems (Bradfer-Lawrence *et al.*, 2023; Ross *et al.*, 2023). In parallel, emerging methods for localising calls and identifying vocalisations from individual animals have the potential to generate much-needed abundance estimates, further enhancing the ecological value of acoustic data (Yen *et al.*, 2022; Knight *et al.*, 2024).

The Cornell University–led Elephant Listening Project (ELP) has spent 15 years monitoring forest elephants in the Congo Basin. They use an extensive network of 50 autonomous recording units placed high in the forest canopy to track elephant populations and helped understand their responses to selective logging. They have also developed techniques to estimate demographic traits such as age and sex, link calling behaviour to resource use and breeding activity and even identify vocalisations from individual elephants. Using an acoustic array deployed around a forest clearing in Gabon, researchers were able to pinpoint the exact location of calls and measure how sound energy attenuates as it travels through the forest, providing valuable insights for improving detection models and scaling up acoustic monitoring for elephant conservation. Finally, the recording units are also used to detect poaching events and identifies movement corridors to inform targeted protection efforts (Elephant Listening Project, Cornell University https://www.birds.cornell.edu/ccb/elephant-listening-project/)

## Networked sensors

Sensor networks consist of multiple low-power, Internet of Things (IoT) enabled devices capable of capturing biodiversity data in real time. Using edge computing and wireless communication, these devices run on-device machine learning models and transmit processed outputs to the cloud (Besson *et al.*, 2022). This enables biodiversity monitoring with minimal human presence and reduces the volume of raw data that must be stored as only processed data is transmitted (Gallacher *et al.*, 2021). Their real-time communication supports new opportunities for biodiversity monitoring including responding quickly to ecological disturbances, wildlife crime, and other time-critical events (Liao *et al.*, 2025). Sensor networks also offer flexibility in their data collection: depending on the devices deployed such as acoustic sensors, camera traps, or LiDAR, they can collect a wide range of biotic and abiotic data (Friess *et al.*, 2019).

Major challenges in the adoption of sensor networks include the cost of devices and their sources of connectivity and power (Besson *et al.*, 2022). A stable mobile connection is necessary for data transmission (Sethi *et al.,* 2018), with 5G wireless systems showing the most promise to support IoT networks (Chettri and Bera, 2019). Even with event-triggered recording and on-device processing, data volumes often exceed available bandwidth, particularly in remote areas with limited connectivity. Unfortunately, many of the world's most biodiverse regions also have the weakest data infrastructure, constraining both deployment and long-term monitoring efforts (Peters, Onunga and Akwee, 2025).

Integrating data from heterogeneous sensors adds further complexity. Devices may operate at different sampling rates, produce different data formats, or capture information across varying spatial scales (Besson *et al.*, 2022). Aligning these data streams often requires advanced digital literacy (Peters, Onunga and Akwee, 2025). Moreover, when only processed outputs, not raw data, are transmitted, it becomes difficult to verify the reliability and accuracy of the underlying machine learning models.

Before we can rely on AI classifiers, especially for larger or less well-studied taxonomic groups, there is an option for sensor networks to adopt a two-stage classifier. On-board edge processing crop images to focus on regions of interest and then remove empty frames. By transmitting only the cropped detections, for example, images containing insects, verification becomes faster and more reliable while significantly reducing data transmission loads (Friess *et al.*, 2019).

Citizen science approaches can offer creative solutions to data-transfer challenges. Projects such as the Senso-Trail explore opportunistic data offloading, where members of the public help transport data from sensors to secure storage when traditional networks are unavailable or lack sufficient capacity (Friess *et al.*, 2019). More effective on-board edge computation are also being developed which will rely on lower bandwidth for processing and transporting data (Dutta and Bharali, 2021).

Multi sensor solutions offer another avenue for improving efficiency. In these systems, one sensor can act as an intelligent trigger for others, ensuring that high-energy devices operate only when needed. For instance, the BatRack system developed for the Nature 4.0 project enables practitioners to capture energy- and data-efficient video of bats. The system activates cameras and begins recording only when the ultrasonic detector identifies bat activity near the device, resulting in highly targeted data collection with minimal resource use (Friess *et al.*, 2019).

Sensor networks are not deployed at scale yet, however, Microsoft's AI for Good Lab is testing its Solar Powered Acoustic and Remote Recording Observation Watch (SPARROW) https://unlocked.microsoft.com/project-sparrow/. Powered by solar energy, SPARROW combines camera traps, acoustic sensors, and environmental monitoring devices to collect biodiversity data and is currently operating at the El Silencio Natural Reserve and Research Station in Colombia's MMV region. Data are processed locally on low-energy edge GPUs, and the resulting outputs are transmitted via low-Earth-orbit satellites directly to the cloud.

Bird@Edge is another sensor network being tested which streams audio from multiple microphones to a NVIDIA Jetson Nano station where bird species recognition takes place. These results are then transmitted to a backend cloud server for further analysis by researchers. An AI classifier was trained and optimised for operation on the NVIDIA station, and it was found that species detections from the microphones reached 95.2% mean average precision in the Marburg Open Forest (Höchst *et al.*, 2022).

### Biologgers/telemetry

The widespread use of technology for the collection of animal telemetry data emerged in the 1950s, and has developed from manual tracking to highly sophisticated satellite and GPS tracking. Animal telemetry provides empirical data by generating high-resolution spatial and temporal data to assess movement and behaviour (Cagnacci *et al.*, 2010; Kays *et al.*, 2015). Modern GPS, Argos satellite systems, and multi-sensor biologging platforms enable continuous tracking across diverse taxa and ecosystems, from marine megafauna to small terrestrial mammals and birds. Applications span conservation planning, migration ecology, predator–prey dynamics, and responses to environmental change. Biologging has become central to movement ecology by linking fine-scale behaviour with broader ecological processes (Hussey *et al.*, 2015; Kays *et al.*, 2015; Wilmers *et al.*, 2015). Data can be integrated into hierarchical state-space models, continuous-time movement models, and step-selection or integrated step-selection functions to estimate transition probabilities, behavioural state switching, and resource-dependent movement kernels (Patterson *et al.*, 2008; Avgar *et al.*, 2016; Jonsen *et al.*, 2019). These telemetry-derived data streams can enable the parameterization of models that quantify functional connectivity, identify movement corridors, and predict individual responses to dynamic environmental covariates or anthropogenic disturbance regimes (Nathan *et al.*, 2008; McClintock and Michelot, 2018). Advances in sensor miniaturization, on-board processing, and remote data retrieval have expanded the taxonomic and ecological breadth of telemetry datasets, facilitating multi-individual and multi-species modelling approaches that incorporate spatial heterogeneity, individual variation, and landscape resistance surfaces (Hooten *et al.*, 2017; Williams *et al.*, 2020). As a result, telemetry-informed models now play a central role in forecasting population-level consequences of habitat alteration, evaluating the robustness of conservation interventions, and supporting adaptive management through scenario-based simulations in complex socio-ecological systems (Schick *et al.*, 2008; Morales *et al.*, 2010).

However, animal telemetry is under-utilised in the Global South. For example, acoustic telemetry is transforming aquatic ecology, but its full value for conservation and management can only be realized through global collaboration, long term monitoring, and stronger links between research and policy (Matley *et al.*, 2022). In a recent review of fish telemetry in inland African it was used in only eight countries with radio telemetry (81%) being used more than acoustic telemetry (11%) and only 25 native and 2 non-native species were studied. This is despite the fact that in Africa the benefits derived from telemetry studies outweigh the costs and it can provide evidence-based data to manage scarce water resources in Africa (Burnett *et al.*, 2021).

Biotelemetry and biologging are also transforming endangered species research by providing essential data for threat assessments and conservation planning (Cooke, 2008). But globally research remains uneven and to support effective conservation management, taxonomic range and geographic coverage needs to broaden to more directly address applied ecological challenges (Robichaud *et al.*, 2025).

Animal telemetry continues to evolve rapidly, offering unprecedented insights into wildlife ecology. However, realising its full potential requires addressing practical deployment challenges, substantial cost and infrastructure demands, and analytical barriers. At the same time, technological advances and improved analytical tools present significant opportunities for more efficient, accurate and impactful telemetry research.

Deploying animal telemetry presents several practical challenges relating to data scale, volume, and quality. Large sample sizes are often required to generate reliable ecological inferences, with 80–130 tagged individuals necessary to capture population-level spatial patterns (Hebblewhite and Haydon, 2010). Modern GPS and satellite tags generate high-frequency, high-resolution datasets, resulting in substantial data storage and processing demands (Kays *et al.*, 2015). Data quality issues remain pervasive: fix success rates, environmental interference, and premature device failure has been reported in up to 48% of deployments which can compromise dataset completeness and accuracy (Latham *et al.*, 2015). Variation in location estimation algorithms across manufacturers further can also complicate comparability between studies (Frair *et al.*, 2010).

Animal telemetry systems require substantial financial and logistical investment. Tag costs vary widely depending on sensor type, battery life, and communication technology, with GPS–satellite units often exceeding the budgets of small projects due to high manufacturing and data-transmission expenses (Kays *et al.*, 2015)(. Beyond the devices themselves, funding is needed for capture operations, specialist personnel, and long-term maintenance. Infrastructure requirements include reliable data acquisition platforms, such as satellite networks, VHF receiver arrays, or automated base stations, each demanding technical expertise and ongoing servicing (Hussey *et al.*, 2015). Large-scale deployments also require robust data management systems capable of storing, processing, and securing high-volume, high-frequency datasets.

Transforming animal telemetry data into meaningful ecological information is hindered by several challenges. Telemetry datasets are often large, heterogeneous, and irregularly sampled, complicating data cleaning and integration (Kays *et al.*, 2015). Location error, variable fix success, and sensor-specific biases introduce uncertainty that has to be modelled explicitly to avoid misleading ecological inferences (Frair *et al.*, 2010). Differences in device types, sampling schedules, and processing algorithms complicate comparisons made between studies, which could limit synthesis across studies (Hebblewhite and Haydon, 2010). Additionally, converting raw movement paths into behavioural or ecological metrics requires relatively advanced analytical skills and computational capacity, which may create a barrier for research teams with limited technical capacity (Joo *et al.*, 2020).

Near-term opportunities in animal telemetry are continually arising especially from rapid advances in sensor technology, data integration, and analytical tools. Improvements in battery efficiency, miniaturisation, and multi-sensor packages are enabling deployments on smaller species and extending tracking durations (Kays *et al.*, 2015). Enhanced satellite and other communication networks (e.g. mobile phone apps) are expanding real-time data transmission, supporting responsive conservation actions such as anti-poaching interventions and conflict-mitigation systems (Hobbs and Brehme, 2017). Increasing adoption of open-data platforms and standardised workflows is improving data accessibility and cross-project synthesis (Joo *et al.*, 2020). Machine-learning approaches also offer new opportunities to infer behaviour, detect anomalies, and integrate telemetry with environmental datasets at larger scales to support evidence-based wildlife management.

Hines, Glatzer, Ghosh, and Mitra (2023) present a data-driven analysis of elephant movement across Sub-Saharan Africa, focusing on how seasonal ecology, rainfall patterns, and landscape change shape movement behaviour. The authors attempt to understand migration drivers to inform conservation strategies. Hines, Glatzer, Ghosh, and Mitra (2023) demonstrate that elephant movement in Sub-Saharan Africa is shaped by the interplay of seasonal ecology, rainfall variability, and landscape condition highlighting the ecological and climatic drivers of elephant movement.  As a short-format conference paper, however, it lacks methodological depth, detailed data transparency, and comprehensive model validation.

Müller *et al.* (2023)  show how advances in biotelemetry and genomic technologies are increasingly being combined to understand how animal movement shapes gene flow, population structure, and evolutionary processes. The authors synthesized 139 studies and demonstrated that integrated telemetry–genetics approaches are now rapidly expanding and transforming ecological and conservation research. This gained impetus after 2010, when  studies have increasingly used integrated approaches of telemetry and genetics enabling a more robust landscape-genetic models that can strengthen conservation applications (Müller et al., 2023).

## Spatial & aerial observation technologies

The utility of spatial and aerial observations lies in the integration of remote sensing technologies to acquire data and the analytical frameworks, the most prominent of which is currently GIS (Geographical Information System), used to store, manage and display these data (Swetnam and Reyers, 2011). This pipeline has expanded in recent years to include machine learning and AI tools to assist in the transformation and analysis of the large datasets and raw data associated with these approaches (Hu *et al.*, 2023; Straffelini, 2024). Modes of data acquisition can vary from passive sensors (such as Landsat, (Ganem *et al.*, 2022)) to active sensors (including LiDAR (Light Detection and Ranging), sonar and drones/UAVs (Unmanned Aerial Vehicles), (Linchant *et al.*, 2015; Olson, 2023; Kissling, 2024). Scaling can range from directly captured metrics including individual identifiers (Landeo-Yauri, 2020), species identification (Zhang, 2020), species counts in specific habitats (Valle, 2021; Varela-Jaramillo, 2023), large scale distributions of sedentary and widespread species (de Pablo *et al.*, 2021; Hu *et al.*, 2023) to inferred metrics such as seasonal land use (Chibeya, 2021), habitat disturbance (Lamboj, 2020) and characterisation of global landscapes (Straffelini, Luo and Tarolli, 2024).

Case-specific objectives and requirements are likely to dictate the scale of data collection employed with careful consideration required as to the scope of the EBVs to be included from local to global (Reddy, 2021; Skidmore *et al.*, 2021; Mangewa, 2022). Certain species require bespoke methods to capture enough accurate monitoring data for a meaningful analysis (Spaan, 2019; Sampaio, 2025). Data quality can be highly variable depending on the collection and analysis methods used (Valle, 2021; Wood *et al.*, 2021), though streamlining data processing and particularly synergies with AI and machine learning tools can be an effective means to improve accuracy and efficiency should a dataset be large enough to necessitate this approach (Marchowski, 2021).

Costs can vary greatly depending on the on the remote sensing employed (cost of launching a satellite vs. cost of launching a drone), the amount of data included in analysis (spatially and temporally) and tools used to perform analysis (Kuenzer *et al.*, 2014). Innovations continue to lower certain costs where for instance, LiDAR equipment which in the past has been mounted on planes can now be deployed on UAVs (Kissling, 2024), while costs in terms of computer processing power required to process the data acquired by LiDAR often remain high (Garzon-Lopez *et al.*, 2024). Small scale rapid deployment data collections can prove to be an effective means to reduce financial requirements, making them more accessible to a wider field of researchers (Valle, 2021).

Efforts to monitor biodiversity are spatially and temporally fragmented, taxonomically biased and lack integration (Høye *et al.*, 2023). Access to remote sensing data sets can be limited and the data are often provided in crude formats, that require extensive transformation, presenting further restrictions in the form of hardware, network speed and programming skills requirements (Kuenzer *et al.*, 2014). Inconsistencies due to a lack of harmonised and standardised collection approaches when data are freely available can require robust workflows, specialist software and collaborative networks (Kissling, 2024), as well as sufficient funding, expert knowledge both ecological and technical (Skidmore *et al.*, 2021) and the development of novel methodologies to effectively distil fragmented data sources and extract meaningful biodiversity indices that can inform management actions (Silveira, 2021). This is particularly true when data are generated in areas that are subject to poorly resourced regulatory practices and socio-political conflict (Araujo, 2021; Stachowicz, 2024). Counter to ever rapid advancements in the development of remote sensing technologies and data management tools, multiple barriers in the form of bureaucratic and regulatory hurdles, resource constraints, lack of expertise and insufficient data quality disproportionally affect under-resourced organisations, agencies and indigenous and local communities (von Essen *et al.*, 2025).

Continuous improvements in monitoring capabilities can offer cost effective and agile responses to conservation concerns (Hua *et al.*, 2022), examination of often overlooked ecosystems (Kandus *et al.*, 2018) and the implementation of strategies that aim to assess, address and mitigate losses of biological diversity through integrative approaches to natural resource management (Pettorelli *et al.*, 2014). Groups such as Earth Observations Biodiversity Observation Network and Remote Sensing for Biodiversity within the Committee on Earth Observation Satellites (CEOS), aim to improve interdisciplinary links between remote sensing experts and ecologists to more effectively coordinated research agenda that can reinforce biodiversity management and conservation policies (Pettorelli *et al.*, 2014). Further advancements, capacity building and reduction of barriers to progression are most likely to come from initiatives that increase communication, training, integration and accessibility.

In recognition of both the rich sum of biodiversity (60% of the global total) found in Latin America and the Caribbean and the threats to this richness in the form of overexploitation, pollution, climate change and land use, efforts have been made to address gaps and opportunities to expand biodiversity monitoring in these areas (Garzon-Lopez *et al.*, 2024). Recommendations from this work to capitalise on advancement in the adoption of remote sensing for biodiversity monitoring include investment in local research institutions, decolonised practices to promote access to publishing outlets and expansion of networks at both the local and global level. The use of drones has become increasingly common among Indigenous people and local communities in multiple countries and while the motivations behind this adoption of biodiversity monitoring technologies can be highly contextual and case specific, broadly it has potential for positive outcomes in terms of environmental protection, increasing the forms of knowledge that contribute to environmental governance and improvement of biocultural conservation outcomes (Sauls *et al.*, 2023).

## Molecular approaches

Molecular biodiversity monitoring requires the generation of newly acquired sequence data from environmental samples and the subsequent comparison of these sequences against curated (usually publicly available) databases to a) identify species; and/or b) estimate diversity metrics (intraspecific; interspecific; community; function). Species identification is primarily performed using ‘DNA barcodes’: a sequence of relatively conserved DNA that can be easily and reliably amplified using standard laboratory techniques (Antil *et al.*, 2023). When barcoding is applied to environmental DNA (eDNA, for example, soil or river water samples) in a method as ‘metabarcoding’, characterisation of entire communities, including presence and relative abundance of individual species, can be achieved at a speed, cost and resolution that would not be possible with traditional systematics approaches (Ficetola and Taberlet, 2023). Other approaches, such as genomics, can similarly be applied at an individual or community level, and functional diversity (Nam *et al.*, 2023) can be revealed via the use of databases such as KEGG (www.kegg.jp) or inferred through taxonomy. Finally, intraspecific diversity metrics may be estimated using a range of species-specific genetic markers (e.g. SSRs, AFLPs, (Nybom, 2004)). All approaches can be applied at defined spatial (population or range-wide) and temporal (regular repeated measures, or following disturbance, for example) scales to measure baseline and/or changes in biodiversity metrics. Creer *et al.* (2016) provides an excellent overview of the practicalities of sampling, generating and analysing DNA-based identification approaches.

Effective biodiversity monitoring relies on sampling over spatial (how does diversity vary with environment/region) and/or temporal (how has diversity changed over time?) scales. An additional consideration for DNA-based approaches is the depth of data generated (i.e. the number of reads/markers per sample, (Porter and Hajibabaei, 2018)). DNA-based approaches may be more convenient to deploy than many other monitoring methods: sampling is usually straightforward, if standardised protocols are available, and requires relatively little expertise. The main practical consideration for deploying molecular monitoring technologies is which species/community to target and whether there are existing genomic resources available to enable comparison with these new data.

Cost and infrastructure requirements for molecular-based approaches to biodiversity monitoring depend on the depth and breadth of sequencing required. Generally speaking, the overall cost per sample increases with increased depth and breadth of the sequencing technology applied, but this may be countered by the massive decrease in the effective cost per species achieved through these methods (Porter and Hajibabaei, 2018). Other considerations that could impact the complexity (and therefore often the cost) of DNA-based analyses may include (but are not limited to) the genome size, ploidy and database representation of the species/species within the focal community which might be particularly poor for regions/ecosystems for which there have been few molecular analyses to date (Perry *et al.*, 2022). Importantly, cost and infrastructure requirements are not limited to the sequencing process itself, but must also factor any bioinformatics and storage requirements of the data generated (which can be considerable). A major barrier to building in-country genomic capacity through sequencing labs within LMIC’s is the additional cost associated with importing reagents and consumables (Helmy, Awad and Mosa, 2016) and the lack of specialist equipment maintenance (Vilaça *et al.*, 2024) outside the Global North.

Barriers relating to the conversion of raw sequencing data to meaningful and reproducible information on biodiversity are present at every step of the process and encompass both practical and socio-political challenges. Despite (or perhaps, because of) the ease and rapidity with which sequence data can be generated, sampling is often subjective, inappropriate or lacking in necessary detail (Dickie *et al.*, 2018). Major consequences of this are an inability to repeat the method (essential for biodiversity monitoring) and contamination within the data. Another challenge is the choice of taxonomic group that is targeted for analyses: this may be relatively simple when targeting a single species (although questions remain regarding its representativeness for biodiversity monitoring), but when eDNA is collected, the choice of DNA barcode will necessarily restrict subsequent data to organisms within a single group (e.g., the marker COI is used for metazoans, ITS is used for fungi, (Antil *et al.*, 2023)). Ideally, all-taxa inventories would provide a holistic biodiversity assessment, but these holistic assessments are relatively rare (Ficetola and Taberlet, 2023). A final practical challenge is the degree to which eDNA-based methods are representative of biodiversity, given that they rely on traces of DNA and not live organisms. Furthermore, the detection of invasive species may have significant management implications (Jerde *et al.*, 2013) which can cause conflict where detection relies entirely on the presence of trace DNA.

Socio-political challenges relating to the use of molecular-based biodiversity monitoring centre on the inherent inequity embedded in the process of sampling, generating, processing, publishing and owning molecular data. For a comprehensive overview of these issues, see Shen *et al.* (2024). Challenges include (but are not limited to): the inequity of the location of sequencing and analytical labs; the subsequent lack of engagement and/or under-representation of local and indigenous communities in the design, sampling and publication of molecular studies (Handsley-Davis *et al.*, 2021; von der Heyden, 2023); associated devaluation of local and indigenous knowledge (Devictor and Bensaude-Vincent, 2016); and the current lack of provision within the Nagoya protocol for digital services information (Ambler *et al.*, 2021).
Given the recognised importance of biodiversity and the need to establish global baseline estimates of species and community diversity, DNA-based approaches have a powerful role to play in providing standardisable and scaleable biomonitoring frameworks. However, researchers and policy makers must be clear-eyed about the practical limitations of these approaches and their potential to exacerbate existing inequalities and inequities. Major near-term opportunities include: continual improvement in the resolution and sensitivity of the sequence data (including a greater number of studies using metagenomics, (Curto *et al.*, 2025)), reference databases and bioinformatics analysis and the integration of DNA-based methods with other technologies (e.g. remote sensing, (Çevik and Çevik, 2025)).

The African BioGenome Project (AfricaBP) Open Institute has equitable data- and benefit-sharing at the heart of its initiative to improve food systems and biodiversity conservation through genomics (Hayah *et al.*, 2025). Their Pan-African knowledge exchange platform "...aims to bridge local knowledge gaps in biodiversity genomics and bioinformatics and enable infrastructural developments". The initiative implements biodiversity genomics and bioinformatics workshops across the continent (Sharaf *et al.*, 2024), to provide hands-on training for African scientists. Efforts to assess genomic resource capacity in LMICs have also been performed for Brazil (Vilaça *et al.*, 2024) and across Asia (Getchell *et al.*, 2024) albeit in the context of genomic approaches to pathogen surveillance).

## Community-facing & participatory tools

Community-facing and participatory tools, such as mobile applications used in citizen science, enable members of the public to contribute biodiversity observations using smartphones or web-based platforms. Users typically record species occurrences, photographs, audio, behaviour, habitat context, and associated metadata such as date, time, and location. These tools can operate across taxa including birds, insects, mammals, plants, freshwater organisms, and urban biodiversity, and across terrestrial, freshwater, marine, and urban ecosystems (Schmeller *et al.*, 2017; Sheard *et al.*, 2024). Automated identification platforms use visual recognition to support monitoring, facilitating invasive species detection, endemic species tracking, and educational engagement (Bonnet *et al.*, 2020). Social media data harvesting has also been shown to increase biodiversity records in data-poor tropical regions, particularly for threatened species that are often underrepresented in formal databases (Chowdhury *et al.*, 2023). Citizen science can help reduce gaps in biodiversity data from underrepresented and biologically-rich regions, but only if supported by sustained capacity building, open data standards, and interoperable data infrastructures (Schmeller *et al.*, 2017).

The primary metric directly captured is species occurrence (Essential Biodiversity Variables (EBVs) relating to species population), most often presence-only records, though some platforms support structured presence-absence data and effort-based checklists. Direct measures may also include counts, phenological timing, and habitat descriptors. From these data, other metrics can be inferred, including species distributions, seasonal activity patterns, range shifts, and coarse population trends, provided that sampling effort and bias are explicitly addressed (Sheard *et al.*, 2024).

Contribution to Ecosystem Structure and Function EBVs is more indirect. Although habitat context can be recorded, ecosystem extent, integrity, and condition are generally more robustly monitored through other methods, e.g. remote sensing. Integration within hybrid monitoring schemes, e.g. combining citizen science with Earth observation and sensor networks (Høye *et al.*, 2023), is therefore likely to be necessary if citizen-generated data are to contribute meaningfully to ecosystem-level indicators.

Within the monitoring framework of the Kunming–Montreal Global Biodiversity Framework, citizen science aligns most clearly with Target 21 on knowledge generation and data accessibility, and with Target 22 on participation and rights (CBD, 2024a; Danielsen *et al.*, 2024). Citizen science may also support progress towards Target 4 on species conservation by expanding knowledge of species distributions relevant to Red List assessments and recovery planning. However, alignment with ecosystem integrity targets depends on the extent to which citizen-generated datasets are integrated into national reporting systems and land-use decision processes. In many contexts, such integration remains incomplete.

Mobile app-based citizen science is highly scalable, ranging from small community-based monitoring initiatives to continent-wide schemes. The development of apps such as BirdLasser has been associated with increased participation and data submission, particularly when features such as gamification and social sharing are integrated (Lee and Nel, 2020). A well-designed mobile app, which is fun and free to use, facilitates the flow of information from collection to databases and has been shown to be essential to maintaining long-term interaction compared to web-based platforms (Lee and Nel, 2020).

Data volumes can be substantial, particularly when image and audio files are included. This requires robust backend storage, validation workflows, and, ideally, automated pipelines. Incorporating contextual metadata, such as location, date, weather, and recorder experience, can improve automated identification accuracy, producing better classification than image-only approaches (Terry, Roy and August, 2020). However, integration of metadata requires structured data management and considerable computational infrastructure (Terry, Roy and August, 2020).

Data quality challenges include spatial bias toward urban or accessible areas, taxonomic bias toward charismatic species, and uneven observer expertise (Schmeller *et al.*, 2017; Sheard *et al.*, 2024). Evidence from community-based monitoring in LMIC contexts shows that participants with limited prior experience of digital tools can successfully contribute biodiversity data with ample training and facilitation (Omar *et al.*, 2025). To support use in low-connectivity settings, offline data capture, local language interfaces, and facilitator support are essential (Bonnet *et al.*, 2020).

While participant-level costs may be low, backend infrastructure and ongoing engagement needs can be considerable. Costs of implementation include app development, server infrastructure, cloud storage, automated validation systems, user support, and long-term maintenance (Høye *et al.*, 2023; Sheard *et al.*, 2024). Training, community facilitation, and stakeholder engagement are essential to the success of citizen science projects (Bonnet *et al.*, 2020). These institutional and human resource requirements may represent significant ongoing commitments alongside technical development.

Citizen science is seen as a key route to capacity building in biodiversity monitoring (Schmeller *et al.*, 2017). To increase the value of citizen science data in contributing to evidential data and decision-making, the data must be integrated alongside other novel technologies, e.g. remote sensing, sensor networks, eDNA, and bioacoustics, and readily translated into outputs for policy reporting. This will require considerable investment in interoperable data infrastructures and automation of workflows (Høye *et al.*, 2023). Furthermore, where citizen-generated data are intended to inform governance or legal processes, it is necessary to include additional infrastructure for data security, documentation, and evidentiary standards (Inyang, 2026).

The central technical challenge is converting opportunistic and heterogeneous submissions into robust ecological indicators. Uneven sampling effort, observer bias, and platform-driven behavioural change can distort inferences of trends. For example, changes in reporting behaviour associated with the adoption of the BirdLasser app suggest caution when comparing reporting rates due to increased participation after the app was introduced (Lee and Nel, 2020). Digital inequities, including uneven smartphone access, connectivity constraints and costs and digital literacy gaps, may also skew participation towards urban or higher-income groups (Ambole, Anditi and Oni, 2025).

Informal digital participation also introduces methodological complexity. Biodiversity records extracted from user-generated content on social media in Bangladesh showed substantial species coverage and highlighted threatened taxa, however extracting, validating and correcting bias in the information are not sufficiently developed (Chowdhury *et al.*, 2023). Automated identification systems can help to scale the generation of biodiversity records, however introduce dependencies on training data quality and transparency of algorithms. Although contextual metadata such as time, location and user experience can substantially improve model performance, particularly for difficult taxa, machine learning systems remain sensitive to biases (Terry, Roy and August, 2020).

The evidentiary status of citizen-generated data in regulatory or enforcement contexts is variable. Legal and institutional frameworks may not yet recognise such data as admissible or sufficiently standardised for compliance monitoring (Inyang, 2026). Without clear pathways into formal decision-making processes, datasets risk remaining parallel to policy rather than informing it.

Near-term opportunities include integration of citizen science platforms with contextual AI, automated workflows, and interoperable data infrastructures. Multi-input machine learning models that combine imagery with environmental metadata can produce step changes in identification accuracy and scale up verification capacity (Terry, Roy and August, 2020).

Capacity building frameworks emphasise combining volunteer monitoring with professional surveys and other technologies to create more complete monitoring systems rather than relying on any single approach (Schmeller *et al.*, 2017). Projects such as MAMBO demonstrate the potential of co-designed monitoring systems that integrate citizen science with remote sensing and policy reporting to create standardised, scalable monitoring systems (Høye *et al.*, 2023).

There is also increasing opportunity for citizen science to democratise biodiversity monitoring and deliver environmental justice through meaningful participation in environmental decision making. Biodiversity and environmental data generated by local communities can help to bridge monitoring gaps where state capacity is limited, provided that legal and institutional frameworks evolve accordingly to recognise citizen-generated data (Inyang, 2026). A proper understanding of technological restraints (e.g. lack of 3G or WiFi, use of less powerful devices) can be gained by a pre-assessment (Bonnet *et al.*, 2020; Inyang, 2026).

In rural Kalimantan, Indonesia, a community-based citizen science initiative engaged local communities in monitoring wildlife within village forests. Participants had limited technological experience and successfully used mobile applications combined with training workshops and surveys. A small payment-for-observations mechanism increased participation while fostering local stewardship and ownership. This initiative illustrates how participatory tools can simultaneously generate biodiversity data and strengthen community governance structures (Omar *et al.*, 2025).

In tropical Bangladesh, biodiversity data extracted from Facebook posts substantially expanded known species records compared with formal databases, and featured a high proportion of threatened species. Although spatial biases toward urban centres remained, social media records were more evenly geographically distributed than formal datasets. This case illustrates how informal digital participation can contribute to biodiversity knowledge generation in data-poor regions (Chowdhury *et al.*, 2023).

### Protected area management tools

Protected area management tools are digital systems designed to support the planning, implementation and evaluation of conservation actions within protected areas. Their importance has increased in light of the global commitment to conserve 30% of terrestrial, inland water, coastal and marine areas by 2030 under the Kunming-Montreal Global Biodiversity Framework (CBD, 2022). Achieving this target requires not only expanding protected area coverage but also ensuring effective management, for which appropriate tools are essential.

Traditionally, protected area management effectiveness has been assessed using scorecard-based approaches, such as the Management Effectiveness Tracking Tool (METT) (Namsrai *et al.*, 2019; Van, 2025). The METT produces rapid, high-level evaluations of management inputs and processes. However, such approaches have limited capacity to assess biodiversity outcomes directly (Stolton *et al.*, 2019). Newer tools adopt a broader and more data-driven approach. For example, the Spatial Monitoring and Reporting

Tool (SMART; (*SMART*, 2026)) and EarthRanger (*EarthRanger*, 2026) enable protected area managers to collect, manage and analyse detailed spatial and operational datasets. These systems help address the widespread problem of poor data management, which can undermine data quality and limit effective decision-making (Urbano *et al.*, 2023).

Protected area management tools support a wide range of applications. They facilitate monitoring of wildlife populations, including mapping species densities and ranges (Hötte *et al.*, 2016), and enable protected area managers to evaluate conservation strategies and identify priority areas for resource allocation. They are also used to monitor patrol effort and coverage and record enforcement actions (Hötte *et al.*, 2016), supporting targeted ranger deployment. Tools can generate alerts for human-wildlife conflict risks (Ojija *et al.*, 2025), assist with visitor monitoring to promote sustainable tourism (Muñoz, Hausner and Monz, 2019; Zejda and Zelenka, 2019) and integrate environmental data to provide drought and wildfire risk warnings (Chávez *et al.*, 2020).

Protected area management platforms offer relatively straightforward data ingestion and analytical workflows, providing an accessible gateway to more advanced forms of analysis and potentially to integration with AI-based systems. Many platforms are designed with field-based users in mind and typically feature dashboard interfaces, as seen in EarthRanger (*EarthRanger*, 2026). Data collection has been automated in recent years via mobile devices and GPS units, although manual entry from paper-based records is also an option. A major benefit of these tools is improved standardisation of data collection, analysis and reporting. This can enhance data quality (Stolton *et al.*, 2019), facilitate spatial and temporal comparisons (Coad *et al.*, 2015), and support interoperability and collaboration with other conservation initiatives (Urbano *et al.*, 2023). Robust data management also strengthens the verifiability of analyses and decisions (Stolton *et al.*, 2019).

However, significant challenges remain. Hardware shortages, including inadequate access to mobile devices, GPS units and reliable data storage infrastructure, are common in LMIC contexts (Wilfred *et al.*, 2019; Kavhu and Mpakairi, 2021). Limited technical skills and insufficient training can constrain effective implementation (Wilfred *et al.*, 2019; Urbano *et al.*, 2023). Staff often face limited time for data collection and other administrative tasks (Wilfred *et al.*, 2019; Kavhu and Mpakairi, 2021; Wilson and Anthony, 2023), and monitoring procedures may be perceived as a “tick-box” exercise (Carbutt and Goodman, 2013). Staff have also raised concerns about the use of systems such as SMART to monitor ranger behaviour (Kavhu and Mpakairi, 2021), as well as negative impacts on morale due to increased workload (Wilfred *et al.*, 2019). Challenging field conditions, including poor connectivity for data transmission and challenges associated with night patrols or adverse weather, further complicate implementation (Wilfred *et al.*, 2019; Kavhu and Mpakairi, 2021). More broadly, limited and declining budgets for protected area management constrain the effective implementation of tool-generated insights (Anthony and Kovács, 2023), as tools can only drive conservation outcomes if sufficient funding is available to act on their findings (Wilson and Anthony, 2023). Finally, differing information needs at local and global scales make it challenging to design tools that are simultaneously useful for site-level management and for benchmarking against global targets (Moreaux *et al.*, 2018).

In terms of costs and infrastructure, several major protected area management platforms, including EarthRanger and SMART, are free to use. Some platforms also offer free hosting and cloud storage options (e.g. SMART Connect; (*SMART*, 2026)) and providers often supply free training resources. Nevertheless, implementing these tools requires significant investment in hardware such as mobile devices, GPS units, cameras, sensors or tracking equipment, as well as staffing costs for rangers and ecological personnel. Reliable data storage solutions, cloud infrastructure and sufficient connectivity are also important considerations, particularly for real-time data transmission and centralised data management.

### Artificial intelligence/Machine learning

Artificial intelligence (AI) tools have transformed approaches to biodiversity monitoring in recent years and continue to develop rapidly. In this context, AI tools refer to computational models and algorithms that can learn patterns from large datasets such as images, audio recordings, or spatial data and use these patterns to automate tasks that would otherwise require substantial human effort. The most widely adopted application is species identification from camera trap images and acoustic recordings (Zhang *et al.*, 2024). Increasingly, however, AI systems are being applied to more complex ecological tasks, such as distinguishing between individual animals within a species (Zhang *et al.*, 2024) and identifying specific animal behaviours from video (Wiltshire *et al.*, 2023) and acoustic recordings (Sharma, Sato and Gautam, 2023). AI tools are also used to identify conservation threats, including detecting signs of poaching activity or deforestation in near real time (Lynam *et al.*, 2025).

Most AI biodiversity tools are currently distributed as command-line applications or software libraries, often requiring users to work in programming environments such as Python or R. However, some developers have introduced more accessible interfaces. For example, BirdNET Analyzer provides a user-friendly interface for analysing bird sound recordings (*BirdNET*, 2026), and AI-powered species identification is integrated into citizen science platforms such as iNaturalist (*iNaturalist*, 2026). These developments have helped broaden participation in biodiversity monitoring beyond specialist researchers.

The practical benefits of AI tools are substantial. They dramatically increase data processing speed and capacity, reducing the time and financial costs associated with manual classification of large image or acoustic datasets. This scalability facilitates the expansion of monitoring programmes across broader spatial and temporal scales. When raw data are retained, AI-assisted outputs can be verified and re-analysed, although this requires significant data storage capacity. AI systems can also generate real-time or near-real-time insights, which are particularly valuable for time-sensitive tasks such as threat detection. In addition, AI integration within citizen science applications lowers barriers to participation, enabling amateur naturalists to contribute wildlife records more easily and accurately (Truong and Van der Wal, 2024).

Despite these advantages, several challenges constrain the effective use of AI tools in biodiversity monitoring. A major issue is the lack of geographical representativeness in many biodiversity datasets (García-Roselló, González-Dacosta and Lobo, 2023), which can introduce biases into AI models and reduce their performance in underrepresented regions (Noriega *et al.*, 2025). For many taxa, there is also a scarcity of labelled training data and existing datasets may lack representative variation, such as differing non-target sounds present in acoustic data. As a result, manual verification remains necessary in most workflows. There is also concern about overreliance on AI solutions and the potential erosion of field-based taxonomic skills within the conservation sector (Sandbrook, 2025). Furthermore, it is currently difficult to compare performance across different AI models and implementation contexts or to determine appropriate confidence thresholds (Robin and Hasif, 2021). The development of standardised metrics and benchmarking datasets has been identified as a priority for consistent evaluation of AI models (Pereira *et al.*, 2024). Environmental impacts, including energy, water and land use associated with large-scale AI computation, are an additional concern (Sandbrook, 2025). Finally, many models remain inaccessible to non-technical users due to command-line interfaces and programming requirements.

The costs associated with implementing AI vary considerably. Some off-the-shelf solutions are freely available, such as BirdNET (*BirdNET*, 2026), while others operate on subscription models or charge per use. Many tools are open-source but require technical expertise to deploy and maintain. Developing bespoke AI models involves additional costs, including hiring data scientists, as well as investing in cloud computing or high-performance computing infrastructure for model training and deployment. Substantial data storage capacity is also required to retain raw datasets and model outputs, and reliable internet connectivity may be necessary for cloud-based processing and data transfer.

# 1.6 Socio-economic context of biodiversity monitoring technologies

Despite advances in technologies and analytical methods to improve biodiversity monitoring, a recent meta-analysis looking at the proportional uptake of technology since 2000, found that after an initial surge in use, this trend has not continued, levelling off slightly after 2010, with manual approaches remaining dominant (Lawson *et al.*, 2025). There are likely numerous reasons for this, including unsustainable financing and inadequate capacity building (Speaker *et al.*, 2022; McGeady *et al.*, 2023; Reynolds *et al.*, 2025), the requirement for benchmarking against traditionally used approaches (Borja et al. 2024), robustness of hardware, legal restrictions and impacts on animal welfare (MacWilliams, Kim and Trueman, 2024) and lack of expert labelled data for training machine-learning algorithms that are usually required in the analysis of big data (Wägele *et al.*, 2022; Rasmussen, Stowell and Briefer, 2024).

Barriers to the uptake of new technologies are particularly pronounced in low- and middle-income countries (LMICs). These challenges stem from funding constraints, limited in-country technical capacity, perceived skill gaps, wider infrastructural and governance limitations (Stephenson *et al.*, 2017; Speaker *et al.*, 2022; McGeady *et al.*, 2023), and the production of technology being predominately undertaken in higher income countries (Reynolds *et al.*, 2025). Whilst costs of hardware might be declining, issues of capacity, data-sharing, storage and analysis have increased with the introduction of technological approaches (Stephenson, 2020).

It is also vital to consider the impact of science and technology on different social groups within communities and societies. Whilst technological tools have the potential to transform biodiversity monitoring and conservation, they also risk exacerbating existing inequalities if deployed without attention to access, cultural context, or potential harms. Gendered norms shape who designs technology, who uses it, and who benefits from it, and therefore technology can exacerbate gender inequalities in conservation contexts (Simlai and Sandbrook, 2025). More broadly, technologies such as remote sensing platforms, AI, and mobile monitoring applications can unintentionally reinforce social inequities when communities lack the capacity or influence needed to shape how these tools are used (Tabor *et al.*, 2025).

These challenges are closely linked to the marginalisation of local and Indigenous knowledge in current biodiversity monitoring practices. Indigenous peoples and communities hold deep place-based ecological insight built through generations of close interaction with local ecosystems, with long-term observation allowing detection of change before sensors can (Alessa *et al.*, 2016). Yet mainstream conservation has frequently overlooked or undermined Indigenous knowledge, relying predominantly on Western scientific approaches (VijayKumar, 2019; Loomis *et al.*, 2024). This exclusion weakens conservation outcomes by overlooking holistic perspectives, cultural values, and sustainable practices that have supported biodiversity for centuries (VijayKumar, 2019).

As a result, integrating novel technologies into global and national monitoring frameworks, including National Biodiversity Strategies and Action Plans (NBSAPs), remains a significant challenge. The importance of addressing this challenge, through technology transfer, is underscored in its inclusion in the CBD frameworks (Böhm and Collen, 2015). For these technologies to be effective, they must be reliable and affordable and be designed in ways that genuinely incorporate and respect local knowledge systems and practical capacities. Understanding need and addressing barriers could unlock the potential of advanced technologies to support LMICs in tackling interconnected challenges of poverty, climate change, and biodiversity loss.

# 1.7 Innovate 4 Nature aims and objectives

Monitoring biodiversity is essential for understanding and protecting ecosystems on which human societies depend, yet significant challenges in data collection, coverage, capacity, infrastructure, availability and effective use continue to impede effective conservation outcomes. Despite containing much of the world's biodiversity, many LMICs remain critically understudied, largely due to constrained national resources and limited local technical capacity. Emerging technologies, and the data they generate, hold the potential not only to deepen environmental insight, but to catalyse new approaches to biodiversity monitoring in LMICs and strengthen decision-making across political and financial spheres. Yet these benefits will only be realised if technologies are deployed equitably, integrated appropriately, and scaled globally in ways that respect local contexts and capacities.

In response to these challenges, the Innovate 4 Nature (I4N) programme was established. The I4N project is led by the UK Centre for Ecology & Hydrology (UKCEH) and funded by Defra. Defra is the UK government's Department for Environment, Food and Rural Affairs. Defra is responsible for improving and protecting the environment and aims to grow a green economy and sustain thriving rural communities. Project partners for I4N are the Tropical Biology Association (TBA) (https://tropical-biology.org/).

The programme was designed to:

1. **Assess the demand** of those who currently use or stand to benefit from using these technologies and the data they generate. Including creating a typology of use cases, by understanding the current use of technologies and data.
2. **Assess the opportunity** by identifying the barriers that hinder the effective utilisation of technology or data across different use cases, and what is needed to overcome these.

Together, these efforts aim to ensure that improved biodiversity data and insights can ultimately enhance livelihoods, reduce poverty, attract investment, and strengthen ecosystem protection and restoration.
The programme focused on engaging with stakeholders and communities across LMICs to build the evidence base and to inform the design of longer-term interventions and actions. Actors across all areas and disciplines were considered, from those engaging directly with the environment or resource (e.g. community members, farmers, fishers) through to those with a research or conservation perspective (e.g. scientists, NGOs) and those using data or information to inform policy or business decisions (e.g. local governance, policy makers, nature finance). Key to the programme are considerations of equity and social inclusion, focusing on how perspectives will differ between groups.

Insights generated through Innovate 4 Nature will be used to:

1. **Inform the design of future projects, programmes and case studies**, improving the equity, integration, and scalability of biodiversity monitoring technologies and the data they produce.
2. **Leverage new funding opportunities**, including the creation of new initiatives or the strengthening of existing programmes.
3. **Embed key findings, lessons, and recommendations into ODA programming**, ensuring that development investments are informed by evidence and aligned with equitable, effective technology uptake.

# 2 Research methods


Figure 3 Summary of the evidence gathered through four methods that underpins the Innovate 4 Nature findings.

# 2.1 Rapid evidence assessment

A rapid evidence assessment was undertaken to provide an overview of the use of biodiversity monitoring technologies across low- and middle-income countries (LMICs). The evidence assessment followed an approach to capture literature related to two main questions, using systematic methods.

## 2.1.1 Research questions

The rapid evidence assessment was guided by two primary questions:
1) How are biodiversity monitoring technologies being deployed in LMICs?
2) What are the main barriers (technical, financial, institutional, socio-political) to use of biodiversity monitoring technologies and their data in LMICs?

Each main question is supported by a set of sub-questions, which were used to guide the extraction and synthesis of relevant information from the literature:

- What technologies are being used in LMICs to monitor biodiversity?
- What are technologies being applied to (e.g. taxa, outcomes)?
- Who is deploying the technologies?
- To what extent are technologies integrated with Traditional and Indigenous knowledge?
- What are the barriers faced when deploying biodiversity monitoring?

## 2.1.2 Scope

Evidence of biodiversity monitoring technologies was synthesised:

- All taxonomic groups and habitats
- All technologies involved in the collection of primary data e.g. technologies deployed in the field or used to extract data from images/sound/other sources - categories based on (Speaker *et al.*, 2022):
    - camera traps
    - GIS & remote sensing
    - AI tools
    - mobile apps
    - bioacoustics
    - biologgers
    - UAVs/drones
    - protected area management tools
    - networked sensors
    - eDNA and genomics
- Geographic range: All countries eligible for Official Development Assistance (ODA) funding (including least developed countries, low-income countries and middle-income countries)

## 2.1.3 Search strategy

Peer-reviewed and grey literature were searched for using multiple sources including academic databases (Web of Science, Scopus), websites of relevant organisations (e.g. conservation based NGOs, relevant funding bodies), and Google Scholar. Search strings were constructed and applied depending on the database/website. Where more complex search strings were appropriate, they combined elements of activity (e.g. biodiversity monitoring), technology, location, and barriers/enablers. Due to the differences in search capabilities and infrastructure amongst the sources searched for grey literature, we employed a more flexible approach. We used less complex search strings to maximise possible relevant returns, where appropriate we used filters for document types, keywords, and dates of publication.

Details of search locations, the strings that were used to identify relevant literature, and number of returned articles is included in Annexe 1. Searches were conducted between September and October 2025.

### 2.1.4 Screening process

All results were uploaded to Lean Library (https://sciwheel.com/?lg) for two stage collaborative screening process using the inclusion/exclusion criteria (Table 1).

- Stage one (LB): articles assessed for inclusion based on their titles
- Stage two (full team): articles assessed based on abstracts

Any relevant review articles (= literature review/meta-analysis of a particular biodiversity monitoring technology) were included and their reference lists were checked for **primary articles** (further reviews were not included) to be included in the study. Figure 4 shows the number of articles retrieved, screened, and included.

Table 1 Scope of the REA.

| Criterion | Inclusion | Exclusion |
| --- | --- | --- |
| Study focus | Any empirical study using technology to collect or generate primary biodiversity data*, including AI for species identification (e.g. from images or recordings), remote sensing for species identification or habitat mapping (including crops or in-situ managed populations e.g. fisheries) | Purely methodological with no field data (including species distribution modelling); opinion pieces; technology applied in ex-situ animal research e.g. veterinarian or livestock context; articles that report biodiversity data that isn't an EBV (e.g. indices) |
| Geography | Biodiversity data collection conducted in any country eligible for ODA funding**<br>For marine studies – some/all data collection within territorial sea (12nm from coastline) or exclusive economic zone (EEZ) of an ODA eligible country | Studies carried out in HICs.<br>Data collection exclusively from high seas. |
| Timeframe | 2010–present (to capture modern technological innovations) | Pre-2010 studies |
| Language | English (due to REA time constraints) | Non-English |

*Biodiversity data includes all types of Essential Biodiversity Variable (EBV): https://geobon.org/ebvs/what-are-ebvs/
**List of countries to be included : https://www.oecd.org/en/topics/oda-eligibility-and-conditions/dac-list-of-oda-recipients.html

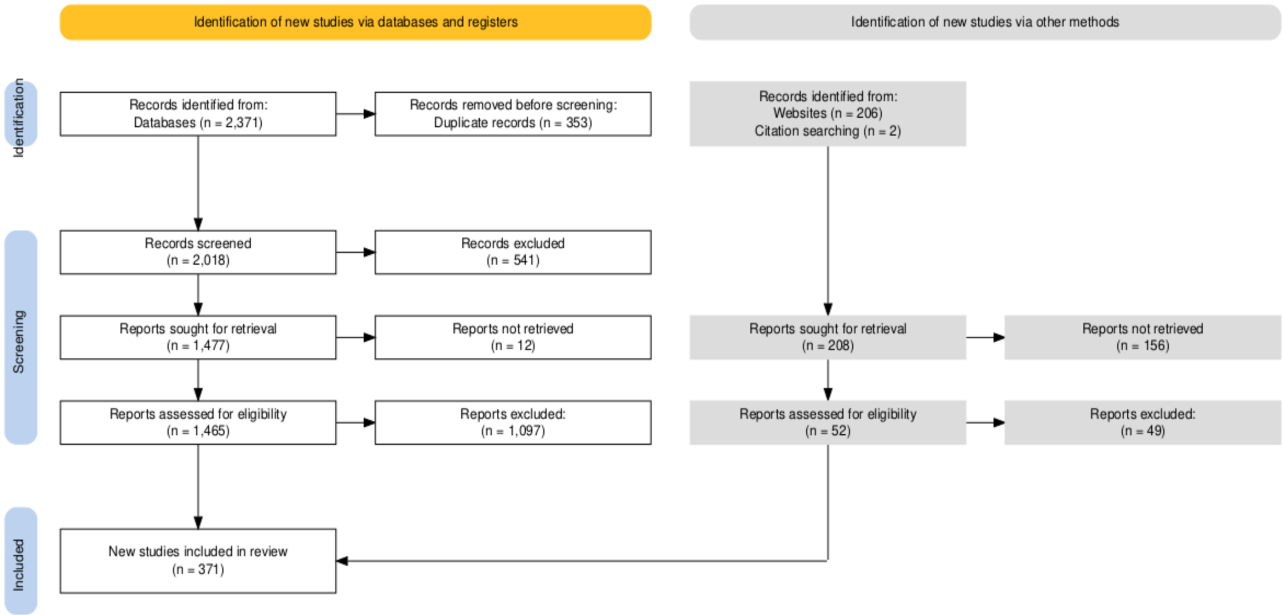



Figure 4 PRISMA-flow diagram showing the number of articles identified, screened, and included in the rapid evidence assessment.

### 2.1.5 Data extraction

Data from literature were extracted to a collaborative spreadsheet on KoboToolbox (https://www.kobotoolbox.org/). The main information extracted was the type of technology being used, how the technology was used (habitat and taxonomic focus; purpose of technology deployment), and aspects relating to technology adoption and capacity (any barriers or limitations; opportunities or novel deployments).

### 2.1.6 Data analysis

Studies identified through the rapid evidence assessment were analysed using a primarily descriptive approach. Key study characteristics and findings were extracted and summarised, and percentages were used to describe the distribution of biodiversity monitoring technology use across LMICs.

## 2.2 Questionnaire

### 2.2.1 Sampling strategy

To identify a sample for the targeted dissemination of the questionnaire, the UKCEH project team compiled a database of contacts. This included previous collaborators and colleagues, as well as researchers and organisations identified through literature or websites.

Invitations to participate in the survey were sent by email (over 100 emails sent to known individuals) and shared online (e.g. WildLabs discussion forum, Insect AI slack channel, LinkedIn posts), with encouragement of further sharing with the intent to use snowball sampling to reach a wider network of relevant participants.

### 2.2.2 Questionnaire design

The questionnaire was hosted using Microsoft Forms and collected anonymous responses. There was an offline version available which could be downloaded from the questionnaire landing page and was sent as an attachment in the participation invitation to contacts. The questionnaire was open from 27th October until 8th December 2025.

Before beginning, participants were required to give informed consent by reading statements about the study purpose, use and storage of data, and marking to confirm they had done so. Ethical approval was granted by the UKCEH Human Research Ethics Committee, reference 09920.

The questionnaire was developed by the research team with feedback from UKCEH and Defra colleagues. Questions were a mixture of multiple choice, Likert scale style and open text (full questionnaire in Annexe 2). The length of the questionnaire and accessibility of the language were key considerations when designing the survey. The final draft had an estimated completion time of 20-30 minutes and minimal technical language.

To minimise time spent on irrelevant questions, participants were first asked to select which type of respondent they were: someone collecting data themselves; someone not collecting data but using data collected by others; or neither collecting nor using data but someone (or representing those) who were interested in information about their local environment. This latter selection was primarily intended to capture the views of local communities, however a range of respondents selected this option.

### 2.2.3 Analysis

Questionnaire data were analysed using a mixed-methods approach. Responses to multiple-choice questions were summarised using descriptive statistics, with percentages calculated for each response option. Likert-scale items were analysed by examining the distribution of responses across scale categories and reporting the proportion of respondents selecting each option. Free-text responses were analysed using a simple thematic approach: responses were reviewed and grouped into recurring themes to identify common perspectives and key issues raised by participants. Quantitative and qualitative findings were then considered together to provide an overall interpretation of the questionnaire results.

## 2.3 Interviews

### 2.3.1 Method

This research component involved data collected via structured interviews and systematic extraction and analysis of data responding to the research objectives. Ethical approval was gained from the UKCEH Human Research Ethics Committee, reference 09920.

#### Data collection

Interviews were conducted face-to-face or virtually by social researchers based in the country of study, Kenya. The majority of interviews involved a single participant, although a small number included two participants from the same organisation. A topic guide was developed by the research team to address the main research objectives (see Annexe 3). This guide was used across interviews to support consistency in the themes explored, while allowing flexibility for respondents to elaborate on issues relevant to their experience.

Two consultants conducted interviews with different respondent groups using slightly different approaches to data collection and documentation.

Key informant interviews were conducted with individuals working in the biodiversity sector, including representatives from government agencies, research institutions, non-governmental organisations, and private sector organisations. These interviews were conducted either in person or virtually, depending on the availability and location of participants, and typically lasted between 20 and 30 minutes. With participants' consent, interviews were audio-recorded to ensure accuracy in capturing responses. Handwritten notes were also taken during interviews to capture key points and contextual information. Audio recordings were subsequently processed using the Microsoft Word Transcribe tool to generate initial transcripts. These transcripts were manually reviewed and corrected by the interviewer by cross-referencing the recordings and interview notes to address transcription errors and clarify terminology. Minor edits were made to remove filler words and correct spelling or grammatical errors before the transcripts were compiled and shared with the research team for analysis.

Additional interviews were conducted with community stakeholders across ten counties in southern, central, and coastal Kenya, selected due to their biodiversity significance. The counties included Narok, Kajiado, Laikipia, Kwale, Bomet, Lamu, Mombasa, Kilifi, Taita Taveta, and Nakuru. A total of 36 community members were interviewed, representing a range of community groups including conservancies, Community Forest Associations, Water Resource Users Associations, community research teams, and community elders. Respondents were selected through purposive sampling based on a preliminary assessment of their relevance to the study objectives. These interviews were conducted face-to-face using a structured questionnaire aligned with the study's research questions. In some cases, interviews were conducted in local languages. Where required, a local assistant was engaged to support translation between the researcher and participants. Following the interviews, responses were written up into structured summaries which served as the basis for analysis.

#### Analysis

Interview data relevant to each objective was identified, extracted into a single spreadsheet, and assigned a code capturing the viewpoint expressed. A coding frame developed iteratively, was used in this process. Three researchers independently reviewed two transcripts and created an initial coding frame following discussion and review. These codes were then applied by three researchers to a further 2 transcripts and the coding frame was reviewed again. The two interviewing researchers then applied this coding frame to the remaining transcripts, adding new codes if the existing coding frame did not reflect the data. Analysis of participants interviewed jointly separated the data from each participant.
It should be noted that the findings presented here are the personal viewpoints of participants and have not been verified.

### 2.3.2 Participants

We interviewed n=56 participants located in Kenya (Table 2). Approximately two thirds of participants were involved in community conservancy to some degree, with 4-6 from each of the other user groups. All perspectives identified by researchers are presented, including those mentioned by one participant only. However, we also identified those viewpoints shared by multiple participants, as well as the user groups represented. User group information is provided, however, caution should be applied when interpreting the importance of user group numbers as there was a much larger representation of community members.

Table 2 Number of interview participants across user groups.

| User Group | Count |
|---|---|
| Business/finance | 4 |
| Community conservancy | 37 |
| NGO | 5 |
| Research | 6 |
| Government agency | 4 |
| **Total participants** | **56** |

### 2.3.3 Limitations

Although data collection took the form of qualitative interviews, qualitative analysis of the data was not feasible within the available time thus a full understanding of the complexity and nuance of experience within individual participant contexts is not presented. The lack of availability of full, original transcripts prevents reporting of direct quotes at this stage and may limit the authenticity of ideas.

## 2.4 Workshop

A 2-day workshop in Nairobi, Kenya, was organised and led by project partners Tropical Biology Association (TBA).

### 2.4.1 Workshop aims

The workshop was designed to gather deeper insights around the use of technology and data in biodiversity monitoring, focusing on experiences from East Africa. The workshop enabled delegates to exchange experiences, discuss challenges, and share lessons learned to support better conservation outcomes, evidence-based decision-making, and smarter investment into nature.

Specifically, the workshop aimed to:

- Explore the potential for using technology in biodiversity monitoring to strengthen conservation, support evidence-based decision-making, and encourage investment in nature.
- Explore the needs of data users and barriers and potential solutions to their effective use in East Africa.
- Share case studies on technology in biodiversity monitoring and explore opportunities for scaling and increasing their impact.
- Stimulate South-South networks for technology exchange and collaboration.

### 2.4.2 Workshop participants

In attendance were 45 delegates (18 female (40%), 27 male) from a diverse mix of technology experts, conservation scientists, practitioners, and policymakers representing government and civil society in Kenya (27), Tanzania (4), Uganda (4), and the Democratic Republic of Congo (1) (Table 3).

The workshop blended knowledge exchange with collaborative problem-solving across all days, utilizing participatory methods to ensure diverse voices shaped the findings. The following section provides a breakdown of the workshop plan and structure.

Table 3 Number of workshop participants across institution types.

| Type of institution | Number of participants | | |
|---|---|---|---|
| | Delegate | Organising team | Total |
| Academic | 2 | | 2 |
| Community-based Organisation/Conservancy | 6 | | 6 |
| Government | 8 | | 8 |
| International Non-Governmental Organisations | 4 | 5 | 9 |
| Intergovernmental Organization | 1 | | 1 |
| National non-Governmental Organisations | 10 | 2 | 12 |
| Private Sector | 4 | 1 | 5 |
| Project Staff | | 2 | 2 |
| **Grand Total** | **35** | **10** | **45** |

## 2.4.3 Workshop activities

**Day 1: Context and Data-to-Impact Pathways.**

The workshop started with context-setting through plenary talks on global inequity and innovation systems thinking. Five ecosystem-specific case studies were presented, followed by participatory brainstorming to explored challenges and opportunities in technology for biodiversity monitoring. A second brainstorming discussed failures – and possible solution – across the 'data-to-impact' chain.

**Day 2: Informing Management, Decisions and Policy.**

Day 2 focused on how technology data informs management. Sessions covered platform development, and perspectives on biodiversity data use in (government) national planning and development, and within community conservancies. A multi-stakeholder panel discussion deepened insights on data use in decision making from local to national levels – including the role of different stakeholders. The workshop closed with a collaborative visioning exercise, with delegates co-creating a shared for an inclusive, effective, and impact-driven future of technology and data in biodiversity monitoring, building on insights from the workshop.

**Day 3: Technology Demonstration.**

This optional, half-day session provided hands-on learning on a range of technologies used for biodiversity monitoring. These included LepiSense for insects monitoring, bioacoustics tools for monitoring bats and birds, and soil and freshwater organisms, and drones.

The workshop adopted a participatory approach that combined case studies, group discussions and exercises, and practical demonstrations. The use of facilitation tools such as fishbone analysis, cards, and poster templates, ensured a strong flow of ideas and meaningful outcomes from the workshop. See Annexe 4 for the Workshop programme.

[The full slide deck of case studies an talks presented during the workshop is available at this link: https://drive.google.com/drive/folders/1L6EMX7yn_Jxl-T257TQBp7eGsK2eWkwH]

# 3 Results from the rapid evidence assessment

## 3.1 Who is deploying technologies in LMICs?

Data was extracted from 371 articles, predominantly peer-reviewed journal articles, from studies carried out in 100 countries (Figure 5). Most of the articles (54%) were authored by both first and last authors based in low- and middle-income countries, a further 16% had one author (either first or last), while 30% had neither first nor last author affiliated with an institution or organisation based in a LMIC.

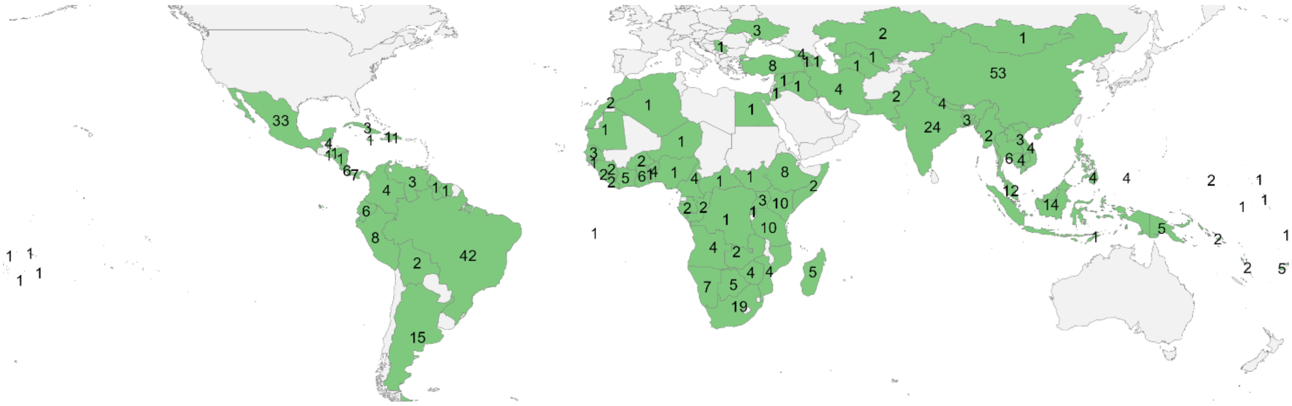
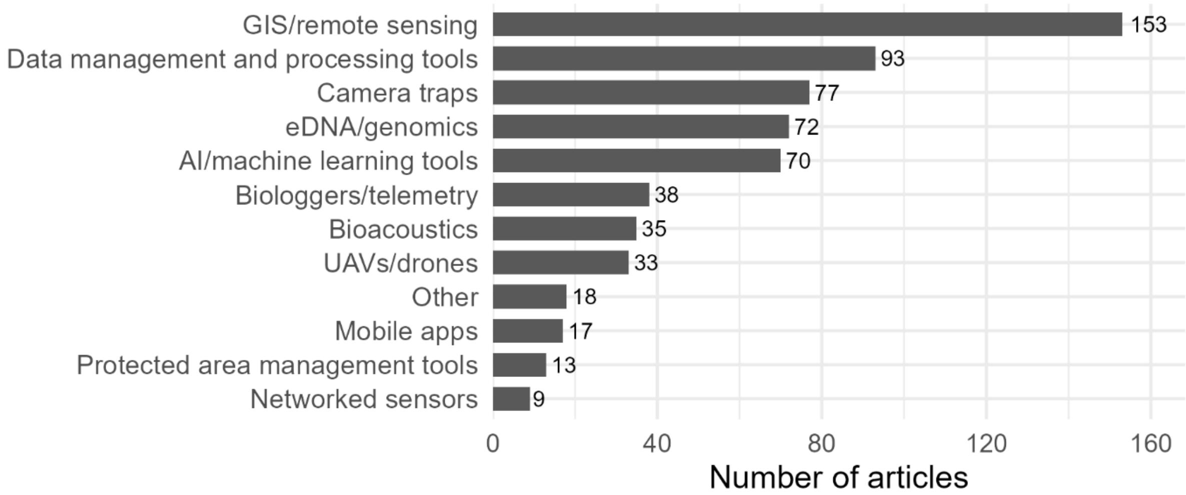


Figure 5 Number of studies from each country (n = 100) included in the rapid evidence assessment of biodiversity monitoring technology use across low- and middle-income countries.

## 3.2 What technologies are being used in LMICs to monitor biodiversity?

The technologies most frequently represented in the literature were GIS and remote (n = 153 articles, 41%), followed by data management and processing tools (25%), camera traps (21%) and eDNA/genomics and AI/machine learning tools (both categories with 19%). Figure 6 details the full representation of technologies across articles, including some of the reported technologies that fell outside our main categories. Data management and processing tools encompassed a wide variety of tools including biodiversity monitoring specific software (e.g. camera trap processing via Camelot or audio recordings via BirdNET) and some more generic data management and analysis tools.




Other technologies identified included: Underwater cameras (photo and video) (n = 4), biochemical tracers (n = 3), 3D imagery (n = 1), acoustic bathymetry (n = 1), thermal imaging (n = 1), Foldscope origami-based microscope supplemented with smartphone imaging n (= 1), triboelectric nanogenerator (self-powered sensor technology) (n = 1)

Figure 6 Representation of technologies across research articles (n = 371).

Between 2010 and 2025, the number of published studies using biodiversity monitoring technologies in low- and middle-income countries increased substantially (Figure 7), with the increase particularly noticeable from 2020 onwards. By 2024–2025, annual publication counts across most technology categories had increased several-fold compared to the early 2010s. The most consistent and widely used technology across the entire period was GIS and remote sensing, which is still one of the most frequently reported on technologies in 2025. The number of articles reporting camera trap use show steady long-term growth, reflecting their established role in field-based biodiversity monitoring. Other technologies, such as bioacoustics and UAVs/drones have increased in representation in the literature since 2020. However, the most rapid recent growth has occurred in data-intensive and computational approaches, particularly AI/machine learning tools, data management and processing tools, and eDNA/genomics. The technologies or the methods that were being used were predominantly established (n = 279 articles) vs novel (n = 80), in a number of cases it was unclear (n = 11). This information was based on what was stated by the authors articles, i.e. if they mentioned it was a trial or novel application of tools or methods.

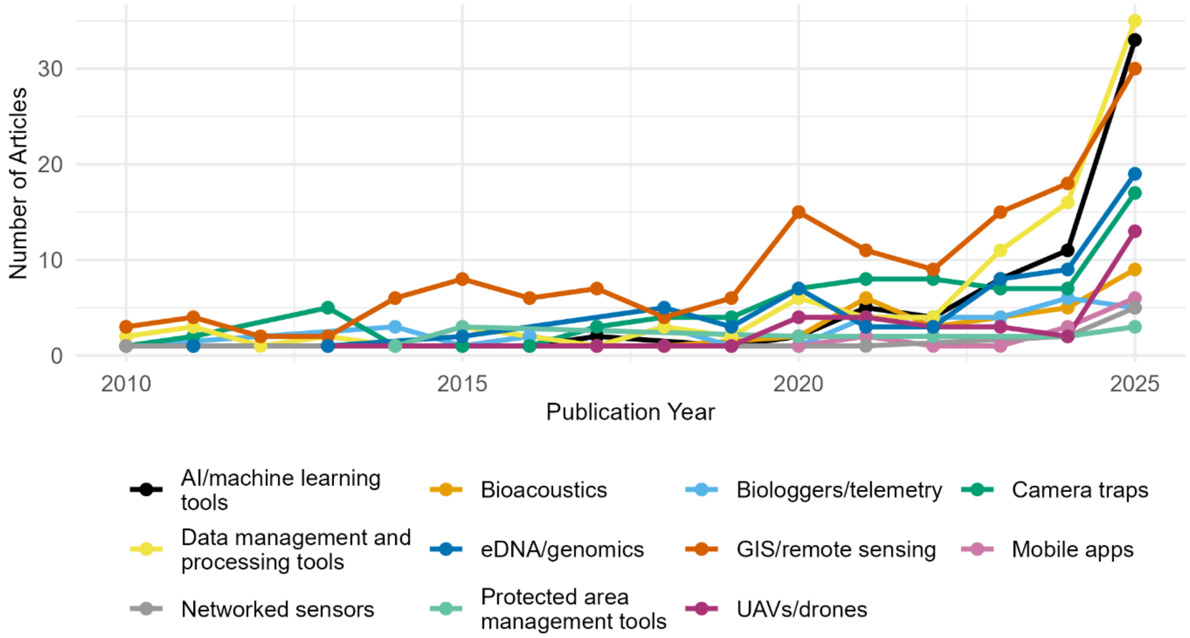



Figure 7 Trends in number of articles published per technology category over time (2010-2025 inclusive).

# 3.3 What are technologies being applied to?

### Application of technologies across taxonomic groups and habitats

The taxonomic group most frequently represented in the biodiversity monitoring with technology literature were land mammals (n = 115, 31%), followed by plants (n = 83, 22%), fish (n = 50, 14%) and birds (n = 44, 12%). Figure 8A indicates the representation of taxonomic groups across the articles we reviewed.

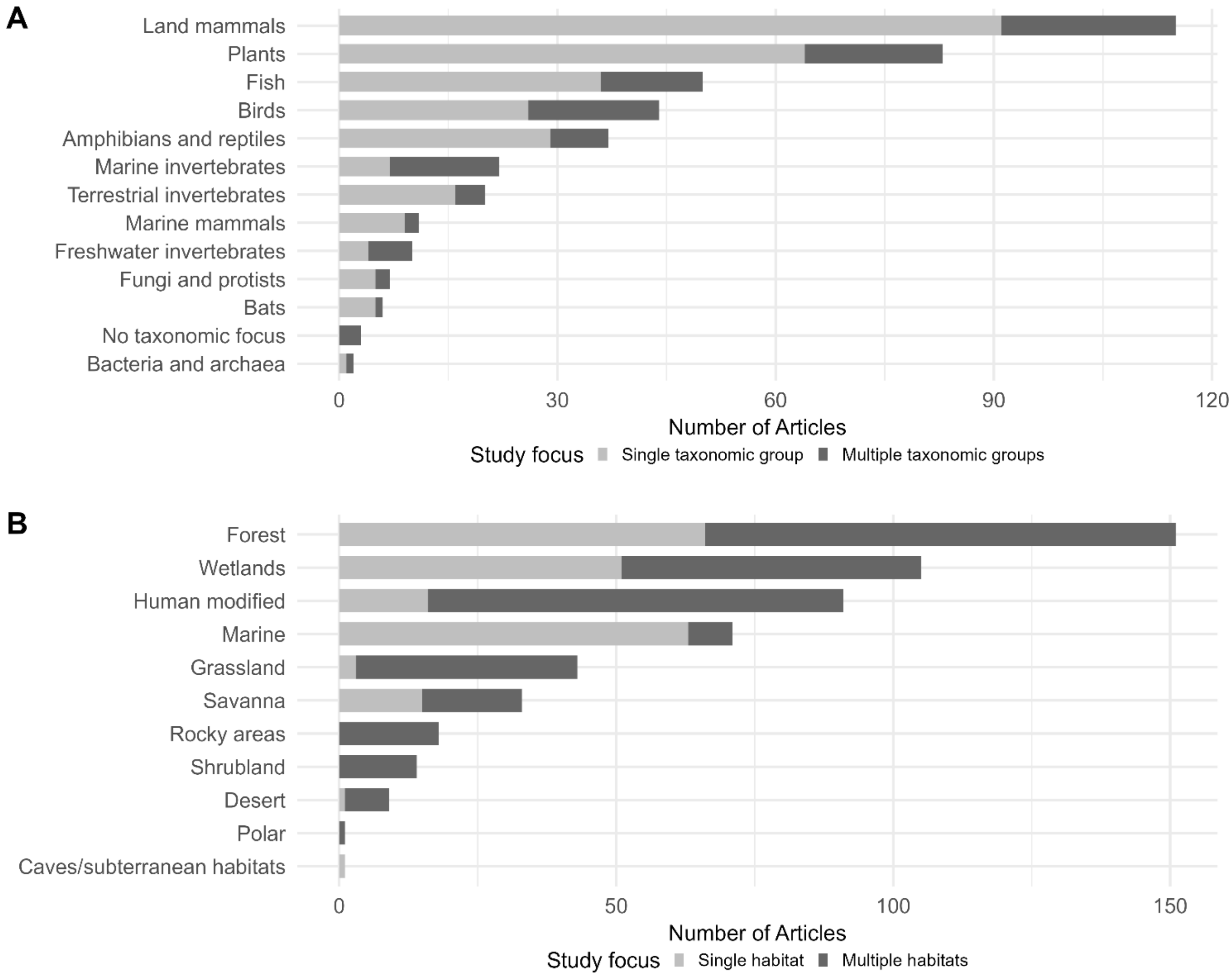



Figure 8 Representation of **A** taxonomic groups AND **B** habitats across the literature reviewed on biodiversity monitoring with technology in LMICs.”

Across the 371 studies reviewed, biodiversity monitoring using technology in LMICs is concentrated primarily in forested and freshwater habitats (Figure 8B). Forests account for the largest share of studies (n = 151, 41%), wetland systems, including rivers and streams, represent the second most common habitat focus (n = 105, 28%). Together, forest and freshwater ecosystems account for over two-thirds of all habitat-specific studies. Human-modified landscapes (including agricultural and urban areas) comprise 25% of studies (n = 91), while marine systems account for 19% of studies (n = 71).

Fewer articles included habitats such as grasslands (12%) and savannas (9%) show moderate levels of technological monitoring. Other habitats, such as rocky habitats (5%), shrublands (4%) and deserts 2%), were even less well represented in the literature we reviewed. A number of articles (n = 37, 10%) had no specific habitat focus, incorporating biodiversity monitoring across multiple habitat types.

## Monitoring objectives

Analysis on the articles we retrieved indicates that technologies are being applied across the Essential Biodiversity Variable (EBV) classes, with representation of classes varying. More than half of the studies (n = 212, 57%) focused on species population metrics such as species abundance and distribution. Ecosystem structure was captured in 115 articles (31%), while monitoring of community composition appeared in 111 articles (30%) and species traits in 73 articles (20%). Ecosystem function was represented in 54 articles (15%), while genetic composition was the least represented EBV class, appearing in 26 articles (7%). For each article, we assessed the aim or application of each of the technologies used, noting that some articles had multiple technologies applied to different aims. The majority of applications were focused on species or individual level identification (n = 224, 63%), while habitat assessments including quality and mapping were included in 175 articles (49%). In 40% of cases (n = 142), the technology or method was being tested. In 36% of articles, authors described the aim of technology use for informing a management or intervention decision, while risk prediction or threat detection were each indicated in 9% of articles.

## 3.4 Barriers and challenges

By far, the challenges or limitations of technologies most frequently reported in the articles we reviewed were technical related issues (n = 241, 65% articles). These included issues such as equipment failure in the field (e.g. camera traps), quality of the data collected (e.g. poor resolution of satellite images, variability in microphone quality), or other limitations to sampling such as low spatial representativeness of effort-intensive data collection e.g telemetry or high-resolution Structure from Motion (SfM) photogrammetry.

Capacity related challenges were the next most frequently mentioned, in 88 of the articles (24%), which were generally related to time or personnel constraints. These were referred to both in data collection, for instance in relation to remote or hard to access sampling locations, and data processing and analyses, for instance the need for specific expertise or computational resources. The effort needed for training and validation of remote sensing data and for species identification from audio and visual data was often mentioned, and lack of comprehensive reference libraries for eDNA and genomic studies were mentioned across numerous articles.

Financial constraints were referred to in 60 articles (16%), in relation to aspects such as cost of equipment or infrastructure, while socio-political and institutional issues were indicated in 32 and 18 articles respectively.

No challenge or limitation related to technology use was mentioned in 92 of the articles we reviewed (25%).

# 4 Questionnaire results

## 4.1 Questionnaire respondents

### 4.1.1 Geographic distribution of respondents

The Innovate 4 Nature project collected questionnaire responses from 65 participants, three of which were removed from the dataset as they were not working in a low or middle-income country context. The 62 responses we retained came from respondents with working expertise in 40 countries across eight geographical subregions (Figure 9; Table 4). The region with greatest representation amongst respondents' expertise were Sub-Saharan Africa (n = 32, 48%) and South-eastern Asia (n = 12, 19%). These were followed by Latin America and the Caribbean and Northern Africa (n = 9, 13% each). We had fewer respondents with expertise in Eastern Asia (n = 2, 3%), and one respondent for each of Eastern Europe, Southern Asia and Western Asia.

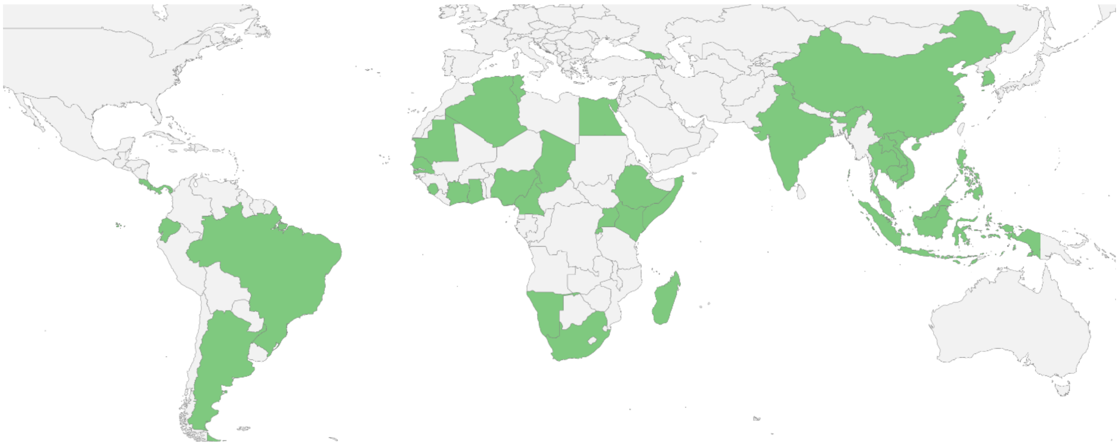


Figure 9 Countries of expertise represented by respondents.

Table 4 Regional focus of respondent's working expertise. Note that 5 respondents had expertise that spanned more than 1 region, and 1 respondent opted not to give their country of focus.

| Region | N = 67 |
|---|---|
| Sub-Saharan Africa | 32 (48%) |
| South-eastern Asia | 12 (19%) |
| Latin America and the Caribbean | 9 (13%) |
| Northern Africa | 9 (13%) |
| Eastern Asia | 2 (3%) |
| Eastern Europe | 1 (1.5%) |
| Southern Asia | 1 (1.5%) |
| Western Asia | 1 (1.5%) |

While all respondents had working expertise in LMIC contexts, not all respondents were living in a LMIC. Most respondents were living either in the country or a neighbouring country that they were carrying out biodiversity monitoring for, nine respondents were living in high income countries.

Most of respondents lived in urban locations (n = 43, 69%), while 16 (26%) lived in rural areas and other respondents chose not to give this information (n = 2, 3%) or did not know (n = 1, 2%).

### 4.1.2 Demographics of respondents

The majority of questionnaire respondents were men (n = 42, 68%), with 18 (29%) women responding and two respondents choosing not to give this information. Twenty (32%) of the questionnaire respondents identified as Indigenous, 34 (55%) did not and the remaining 8 respondents opted not to say (n = 5, 8%) or did not know (n = 3, 5%).

Respondents covered all but the lowest (18-24 yrs) age groups, with highest representation in 35-44 (n = 19, 31%), 25-34 (n = 17, 27%), and 45-54 (n = 15, 24%) age categories. This was followed by 55-64 (n = 6, 10%) and 65+ years (n = 3, 5%). Two respondents did not give this information.

Most respondents reported having no disability (n = 35, 56%), though each type of disability was represented by respondents that had some level of functional difficulty, we report this information in Table 5.

Table 5 Proportion of respondents reporting each level of functional difficulty by disability type (n, %). Percentages are based on the total sample (n = 62).

| Type of disability | Difficulty level | N = 62 |
|---|---|---|
| Difficulty seeing, even if wearing glasses | Prefer not to say | 1 (2%) |
| | No difficulty | 46 (74%) |
| | Some difficulty | 15 (24%) |
| Difficulty hearing, even if using a hearing aid(s) | Prefer not to say | 1 (2%) |
| | No difficulty | 57 (92%) |
| | Some difficulty | 3 (5%) |
| | A lot of difficulty | 1 (2%) |
| Difficulty walking or climbing steps | Prefer not to say | 1 (2%) |
| | No difficulty | 54 (87%) |
| | Some difficulty | 6 (10%) |
| | A lot of difficulty | 1 (2%) |
| Difficulty remembering or concentrating | Prefer not to say | 1 (2%) |

| | | |
|---|---|---|
| | No difficulty | 50 (81%) |
| | Some difficulty | 9 (15%) |
| | A lot of difficulty | 2 (3%) |
| Difficulty with self-care | Prefer not to say | 1 (2%) |
| | No difficulty | 58 (94%) |
| | Some difficulty | 3 (5%) |
| Difficulty communicating by speaking | Prefer not to say | 1 (2%) |
| | No difficulty | 56 (90%) |
| | Some difficulty | 5 (8%) |

### 4.1.3 Professional background of respondents and biodiversity monitoring involvement

Most respondents worked for universities or research institutes (n = 27, 44%), non-governmental organisations or charities (n = 15, 24%), and governmental or regulatory agencies (n = 11, 18%). Figure 10 provides the full breakdown of organisational affiliations.

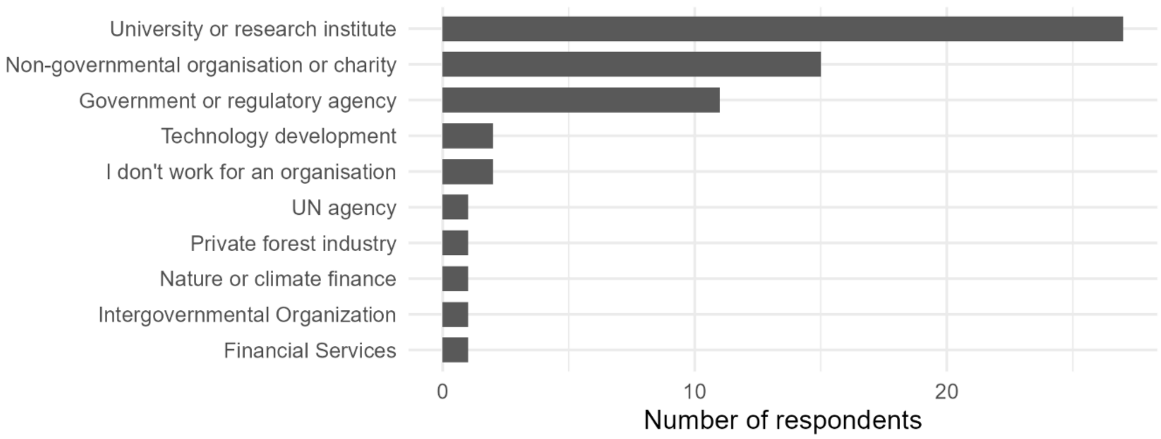



Figure 10 Organisational affiliation of respondents (n = 62).

For comparative analyses across questionnaire responses, organisation types were aggregated into broader user groups. Respondents working for NGOs or charities (n = 15), Intergovernmental Organization (n = 1), UN agency (n = 1) were combined into “NGO/IGO”. Those working in technology development (n = 2), nature or climate finance (n = 1), financial services (n = 1), private forest industry (n = 1) were grouped as “business/finance sector”. Universities and research institutes were retained as “research,” and government or regulatory agencies as “Governmental bodies.” The two respondents who reported not working for an organisation were classified as “Independent.”

Respondents included those collecting biodiversity data (37%, n = 23), only using biodiversity data (55%, n = 34), and five respondents (8%) who neither collected nor used biodiversity data but who represented communities interested in biodiversity data. Of the respondents who collected biodiversity data, 18 (78%) were also working with the data, giving a total of 52 responses (84% of all respondents) from people working with biodiversity data.

### 4.1.4 Decisions and actions informed by biodiversity monitoring

Most (83%, n = 43) respondents working with data were using it to inform decisions or actions including targeting interventions, designating protected areas and developing or enforcing environmental regulations (Table 6).

Table 6 Summary of the actions and decisions that respondents were using biodiversity data to inform. Percentages are based on the total number of respondents who reported using data for this purpose (n = 43).

| Types of actions and decisions | N = 43 |
|---|---|
| Measuring progress or change | 37 (86%) |
| Establishing baselines | 33 (77%) |
| Biodiversity inventories | 31 (72%) |
| Targeting interventions or actions | 30 (70%) |
| Education/outreach | 27 (63%) |
| Protected area designation | 23 (53%) |
| Developing/enforcing environmental regulations (incl. guiding law enforcement) | 22 (51%) |
| Natural capital/ecosystem services assessments | 21 (49%) |
| Land/sea-use planning | 20 (47%) |
| Environmental impact assessments | 1 (2%) |
| Face desertification | 1 (2%) |
| Policy development, standard setting and proposing | 1 (2%) |

We assessed the extent to which respondents from different organisations, as aggregated into our user groups, were involved in different decision making and action taking contexts. Small sample sizes in these subgroups means that responses should be interpreted carefully. Responses indicate that biodiversity data and technologies are used to support a range of decisions and actions across all user groups, though the relative emphasis varies.

Notably, measuring progress or change, establishing baselines, biodiversity inventories, and targeting interventions or actions were mentioned across all groups:

- Measuring progress or change was mentioned by 12 respondents (92.3%) in NGO/IGO contexts, and 11 (68.8%) researchers. It was mentioned by 100% of those working for government bodies (n = 8), as well as 100% of those in the business/finance sector (n = 3) and independent researchers (n = 2).

- Establishing baselines was selected by 81% of researchers (n = 13) and 85% NGO/IGO respondents (n = 11), and 50% of those working in governmental bodies (n = 4). It was also selected by 100% of business/finance (n = 3) and independent respondents (n = 2).

- Biodiversity inventories were reported by 8 respondents in the NGO/IGO group (61.5%), 11 researchers (68.8%), and 7 working in governmental bodies (87.5%). Also mentioned by 100% in the business/finance sector (n = 3) and independent researchers (n = 2).

- Targeting interventions or actions was reported by 11 respondents in research (68.8%), 10 in NGO/IGOs (76.9%), and 4 in governmental bodies (50%). Also, by all 3 respondents from business/finance (100%) and 50% of independents (n = 1).

Other decision types were also common across multiple groups. Overall, these results indicate strong similarities in how biodiversity data are applied, highlighting the cross-cutting relevance of biodiversity data across sectors.

# 4.2 Current use of biodiversity monitoring technology and data

### Taxa and habitats

Respondents using both technology and data reported conducting biodiversity monitoring across a wide range of taxa and habitats, with many respondents having more than one focus to their work (Figure 11). The most frequently represented taxa were plants (65%, n = 37), land mammals (44%, n = 25), terrestrial invertebrates (42%, n = 24) and birds (40%, n = 23). Amphibians and reptiles were monitored by 13 respondents (23%), fish by 10 (18%), and marine invertebrates by eight (14%). Marine mammals and freshwater invertebrates were each monitored by six (11%) respondents, bats by five (9%), and fungi and protists, and bacteria and archaea were each represented by three respondents (5%). Six respondents reported no specific taxonomic focus in their biodiversity monitoring work. Forests (70%, n = 40) were the habitat most respondents reported their biodiversity monitoring took place in, followed by human-modified landscapes (46%, n=26), and wetlands (40%, n = 23). Grasslands and savanna were both represented by 21 respondents (37%), with 20 respondents (35%) working with biodiversity in shrublands. Rocky areas were monitored by 13 respondents (23%), with 11 (19%) for marine areas, and 6 (11%) for deserts. Fewer respondents reported monitoring for caves and subterranean habitats (7%, n = 4). Four respondents reported no habitat focus to their work.

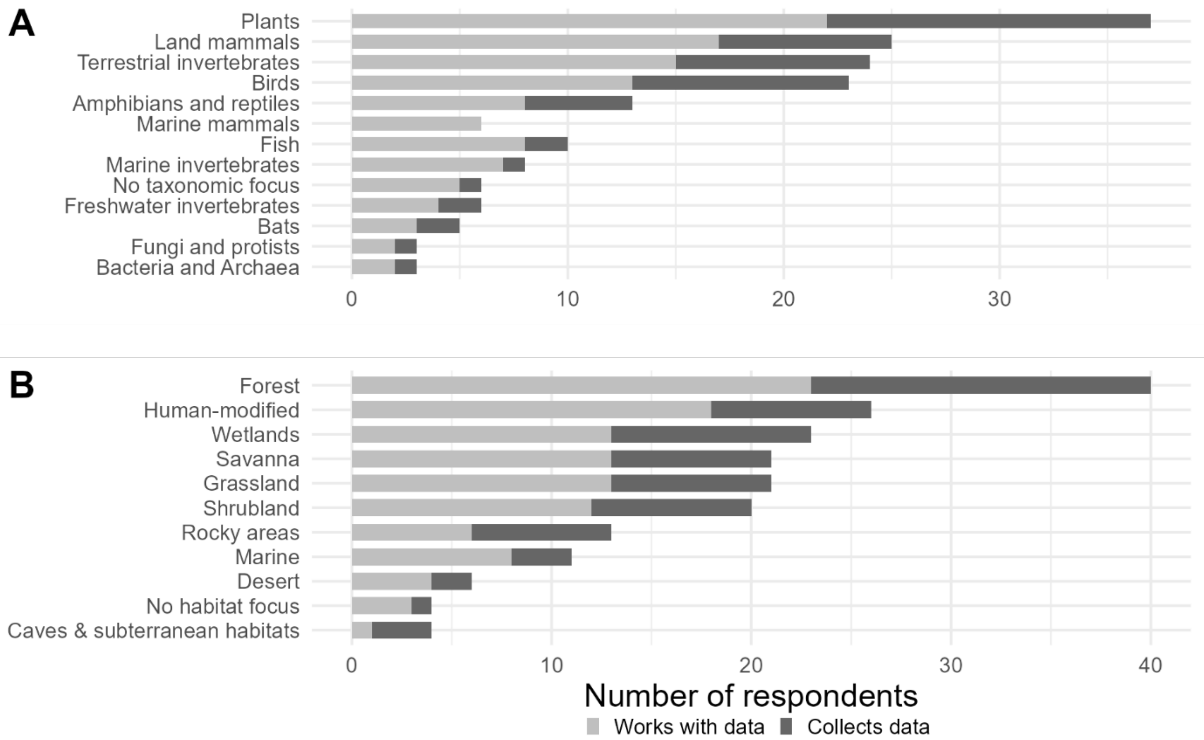



Figure 11 Number of respondents who reported working on each **A** taxonomic and **B** habitat group.

## Technologies being used

Survey respondents could select up to three technologies that either they used to collect biodiversity data or that was used by others to generate the data they work with. Most respondents selected more than one technology (Figure 12). The most commonly used technologies were camera traps and GIS/remote sensing, each selected by 26 respondents (46%). Mobile applications (32%, n = 18) were next, followed by acoustic devices and machine learning/AI with 17 respondents (30%), and UAVs/drones (21%, n = 12). Other technologies represented were protected area management systems (11%, n = 6), eDNA/genomics (9%, n = 5), and biologgers/tracking devices (5%, n = 3). Automated insect monitoring systems and BRUVs/RUVs were each reported by a single respondent. Three respondents who used biodiversity data did not know which technology had been used to collect it, and three respondents collecting data reported not using any technology.

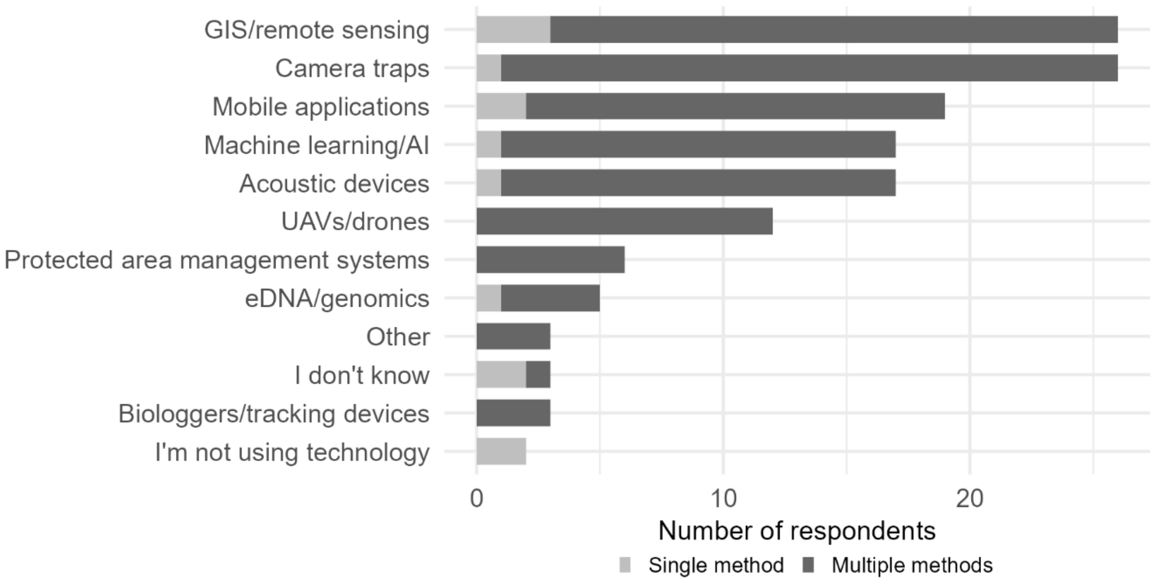



Figure 12 Technologies being used for biodiversity monitoring by questionnaire respondents.

# 4.3 Current perceptions of biodiversity monitoring technologies and data

We asked respondents to share their opinions on their current experiences with biodiversity monitoring technology and data (Figure 13). For both technology and data users, a higher proportion of respondents reported difficulty in access rather than finding it easy (Figure 10). Technology users reported difficulty both accessing (47%, n = 11) and using (35%, n = 8) technology. Difficulty of access was more prevalently reported than difficulty of use for data users (37%, n = 19 vs 19%, n = 10 respectively). Overall, similar proportions of respondents using technology and data felt positively about the ease of access and use (26% (n = 6) of technology users and 27% (n = 14) of data users for both questions).

Fifty-six percent of technology users (n = 13) agreed with the statement “The biodiversity monitoring technology that is available to me meets my needs”, while 41% of data users (n = 21) felt the data available to them met their needs. Similar proportions of technology and data users disagreed or strongly disagreed with the statements about their needs being met (30% (n = 7) for technology users, 31% (n = 16) for data users).

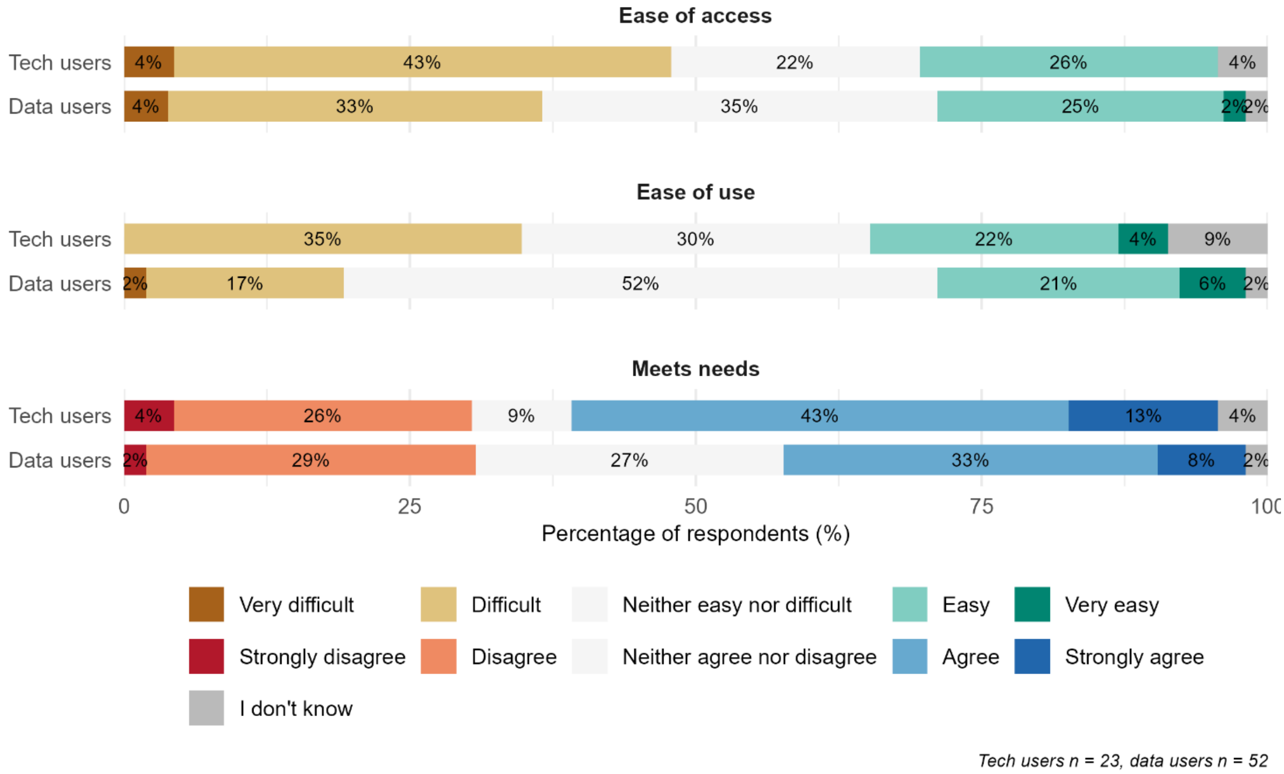



Figure 13 Breakdown of respondents' perceptions on ease of access and use of technology and data for biodiversity monitoring, and on how well current biodiversity technologies and data meet their needs.

# 4.4 Challenges and barriers to access and use of biodiversity monitoring technologies and data

To understand what was preventing the access and use of technology and data for biodiversity monitoring, we asked respondents to select the greatest three challenges they were facing from pre-determined list. There was also the option for respondents to select *Other* and enter their own challenges if they were not represented. An open text question allowed respondents to give further information about these barriers.

## Barriers to technology access and use

The two most frequently selected barriers were the upfront costs of technology, chosen by over 60% of respondents (n = 14), and lack of access to technology (57% of respondents, n = 13) (Figure 14). Other barriers common amongst respondents were a lack of training or knowledge around technology (39%, n = 9), and costs of repair or maintenance of technologies (35%, n = 8). Other issues experienced by respondents included limited or unreliable computing infrastructure (22%, n = 5), technology not being suited to local environment (22%, n = 5), and difficulties coordinating with other groups or stakeholders (17%, n = 4).

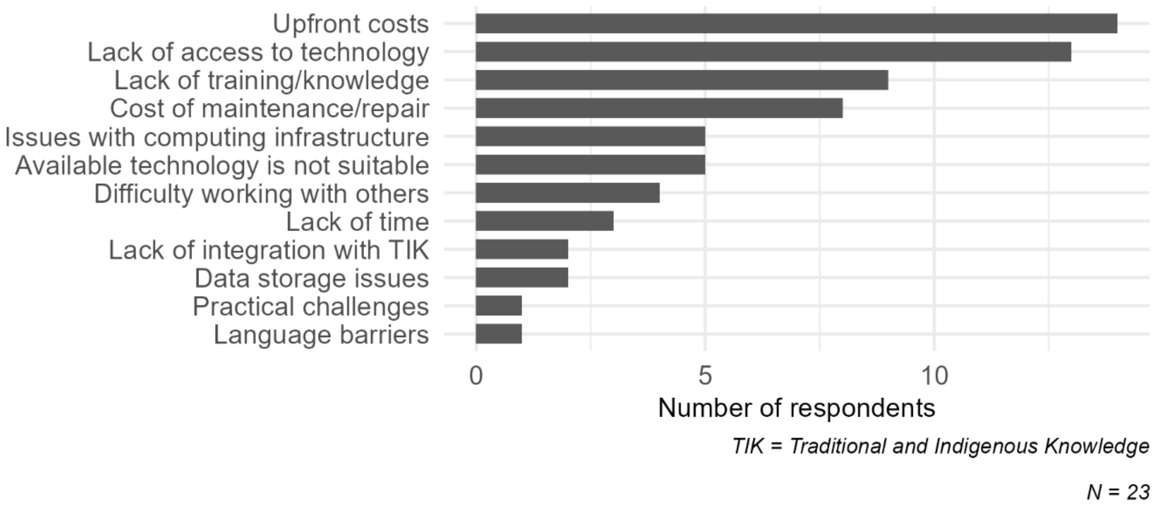



Figure 14 Respondents' experiences of barriers to accessing and using biodiversity monitoring technology. Y-axis labels have been shortened from the original challenge as represented in the questionnaire or reported by respondents. Note that each respondent (n = 23) could select up to 3 challenges.

In the free-text responses, respondents gave more context to their experiences of these barriers. Notably, few respondents mentioned the performance of the technologies themselves, though four respondents mentioned the poor performance of species level classifiers and the need for manual identification. These comments were specifically in reference to plant, insect and fish species identification.

Some statements highlighted the challenges that the high volume of data that can be generated by technology can raise, particularly where computing infrastructure is lacking for example *"Some of the countries in the region don't have adequate computing infrastructure to handle heavy data such as satellite imagery and drone data."*. This was linked by one participant to a reliance on other countries for data processing: *"There is a dependence on external processing systems—the data we receive will need to be processed on servers outside the country (e.g., in the UK)".*

Other themes of external reliance were reflected in comments about where technologies are developed, both in terms of hardware and software or AI algorithms. One respondent remarked on *"complicated and expensive import processes"* while another respondent's comment highlighted the balance between financial costs and having technology that best serves its local purpose *"Our project has largely relied on volunteer citizen scientists using mobile apps developed by other institutions for data collection. Adapting and updating the apps to meet emerging local needs wasn't always easy and straightforward. We have considered and are working on building apps locally, but … maintenance costs for the apps but largely also for the data hosting infrastructure have been challenging to steadily secure."*

## Barriers to data access and use

There was less consensus amongst respondents regarding barriers to data use, with no single challenge selected by the majority (Figure 15). Again, upfront costs were the most frequently selected barrier, chosen by 40% of respondents (n = 21). The next most frequently reported challenges were data not being available (e.g. not published or digitised) and hard to access (e.g. hard to find, located across multiple sources, difficult to use data portals), selected by 31% (n = 16) and 29% (n = 15) of respondents respectively. Respondents also reported that data did not meeting their needs in terms of spatial coverage or resolution (27%, n = 14) and taxonomic coverage (25%, n = 13).

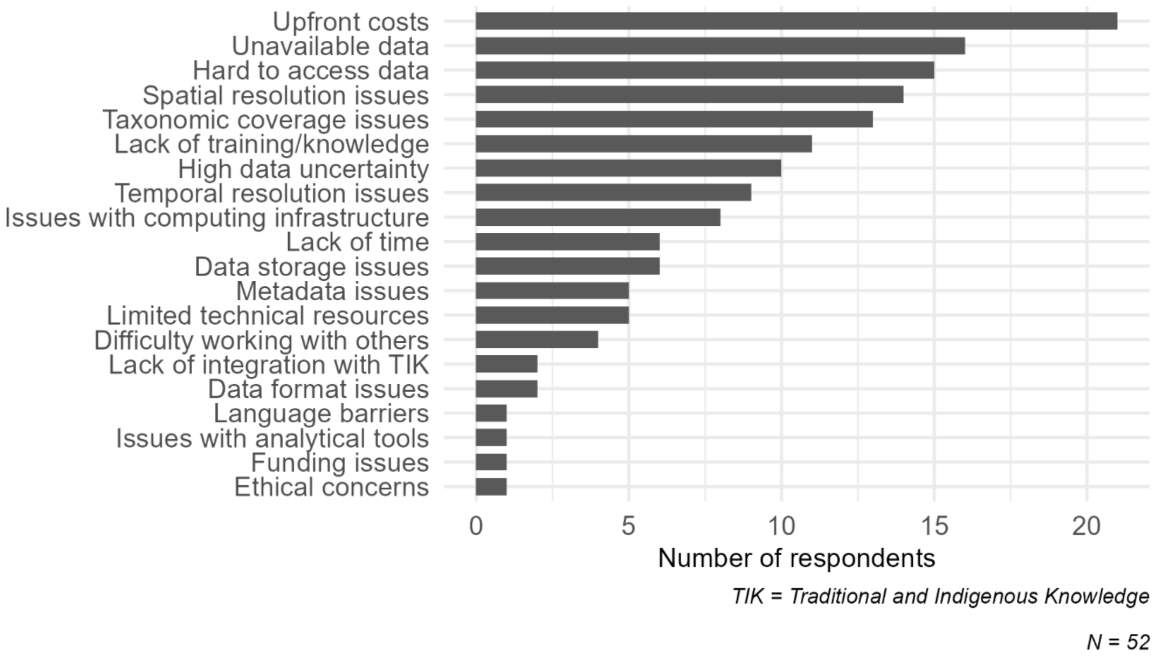



Figure 15 Respondents' experiences of barriers to accessing and using biodiversity data. Y-axis labels have been shortened from the original challenge as represented in the questionnaire or reported by respondents. Note that each respondent (n = 52) could select up to 3 challenges.

In written responses, participants highlighted issues of data availability, whether a case of not data not being shared or being overly expensive. From one respondent, a data scientist working in an intergovernmental organisation, their barrier was an "*absence of data sharing policies among the data providers*" and from a project officer in a government agency *"The information mostly sit within different institutions and access to the data can be very difficult at times."* Cost of data storage, need for good computing for data processing, and a shortage of time or skills for data analysis were mentioned as barriers by respondents. A respondent working as a project officer in Tanzania noted their location specific challenges *"The data I use is not trusted at international standard levels. For example, there are no established databases of species identification keys to match my location. Water quality labs are not accepted at international levels."*

## Barriers across user groups

We examined the differences in challenges with biodiversity data as reported by respondents from different user groups (Figure 16). For this we omitted the two independent research respondents.

Across user groups, several challenges related to data are reported consistently. Upfront costs are widely reported, affecting 2 business/finance respondents (40%), 4 respondents from governmental bodies (36%), 6 from NGOs/IGOs (35%), and 8 researchers (30%). Hard-to-access data is another common challenge, with 3 out of 5 respondents (60%) from the business/finance sector, 3 from governmental bodies (27%), 6 respondents from NGO/IGOs (35%), though only 2 researchers (7%).

Some differences are apparent between groups. Unavailable data is a greater concern for researchers (n = 8, 30%) than for those in governmental bodies (n = 1, 9%). Conversely, lack of training or knowledge is more notable for governmental bodies (n = 11, 27%) compared with Research (n = 4, 15%). Issues with computing infrastructure are mainly reported by those working for governmental bodies (n = 5 46%), with fewer mentions by respondents from NGOs (n = 2, 12%) and research (n = 1, 4%). Issues of lack of integration of Traditional and Indigenous Knowledge (TIK) was mentioned only by respondents from governmental bodies and NGO/IGOs (1 respondent from each).

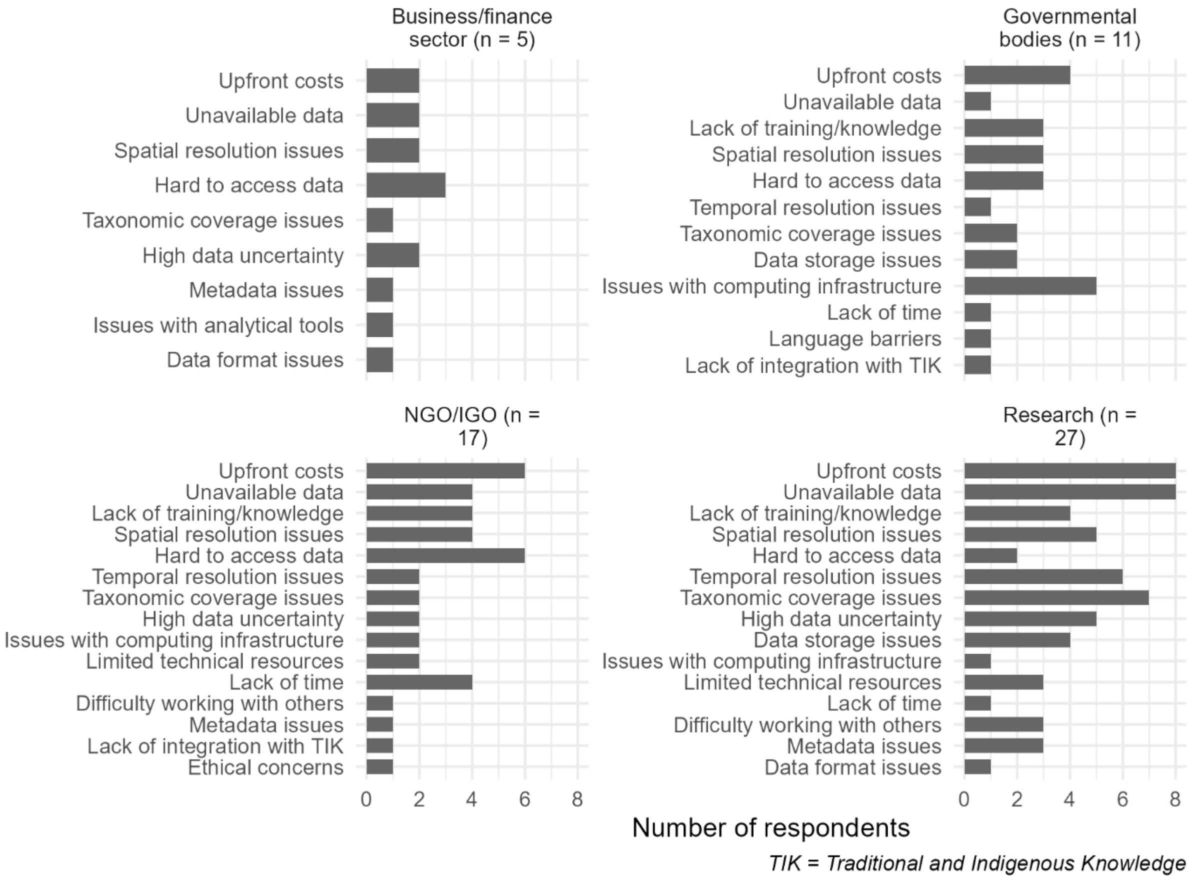



Figure 16 Respondents' experiences of barriers to accessing and using biodiversity data, broken down by user group. Y-axis labels have been shortened from the original challenge as represented in the questionnaire or reported by respondents. Note that each respondent (n = 43) could select up to 3 challenges.

## Data to inform actions and decisions

The main challenge raised by respondents using data to inform decisions and actions was a lack of standardisation of biodiversity data, an issue raised by over 50% of respondents (n = 22) (Table 7). Other barriers frequently selected by respondents related to challenges of data integration (44%, n = 19), funding issues (44%, n = 19) and poor data quality (40%, n = 17). Many of the free-text responses reflected on these data standards, quality and accessibility issues, such as this respondent's statement *"there is a lack of clear frameworks or standardized guidance for data integration and interpretation. As a result, combining data from different sources or methodologies is challenging, and decision-makers may struggle to translate raw or fragmented biodiversity information into actionable conservation strategies."* Respondents frequently linked their data related issues to funding, such as for data management and storage *"Biodiversity data management is often an afterthought and is usually the first item to be cut from a budget when funds are needed elsewhere"* and the process from data collection to analysis *"Limited funding restricts access to advanced monitoring tools, analytical software, and adequate data storage capacity, as well as training opportunities needed to process and interpret large datasets efficiently."*

Challenges related to collaboration, both in terms of lack of data sharing and communication between different actors, were highlighted by respondents. In particular the disconnect between data collection and policy was apparent through statements such as the following two comments from people working in different roles within government or regulatory agencies, from a data scientist: *"there is still limited clarity around the information needs of decision-makers and policymakers"* and someone working as a project officer: *"Data collected is not made available by scientists, does not have explanation to understand the data and is not the data we need"*.

Table 7 Respondents' experiences of barriers to using data to inform actions and decisions.

| **Barriers experienced** | **N = 43** |
|---|---|
| Lack of standardisation in biodiversity data (e.g. collection methods, reported metrics) | 22 (51%) |
| Lack of clear guidance or frameworks for data integration | 19 (44%) |
| Lack of funding | 19 (44%) |
| Data quality is not high enough | 17 (40%) |
| Insufficient capacity or expertise in data analysis | 16 (37%) |
| Difficulty communicating/collaborating with other groups or stakeholders | 9 (21%) |
| Lack of trust in data sources | 5 (12%) |
| Mismatch between monitoring outputs and decision timelines | 5 (12%) |
| Limited or unreliable computing infrastructure (e.g. unstable power supply, slow internet, outdated hardware) | 4 (9%) |
| The data available doesn't help guide decisions or actions | 4 (9%) |
| Insufficient capacity for analysis (no problem with expertise) | 1 (2%) |

# 4.5 Considerations of Traditional and Indigenous knowledge

We asked respondents to consider the extent to which Traditional and Indigenous knowledge (TIK) was integrated into the biodiversity monitoring they were involved in (Figure 17).

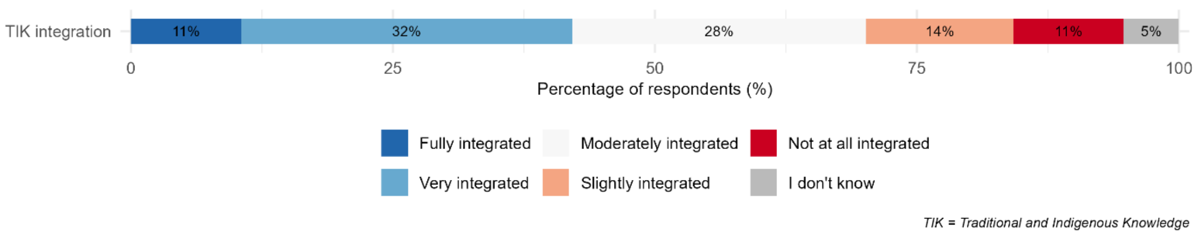



Figure 17 Respondents' reporting of how well Traditional and Indigenous Knowledge is integrated into their biodiversity monitoring work.

Respondents were asked for their opinion on the three main challenges in including Traditional and Indigenous knowledge into biodiversity monitoring. A breakdown of responses is shown in Figure 15. Most respondents highlighted lack of access (n = 31, 54%) and collaboration (n = 29, 51%). Other frequently selected challenges included issues of data ownership or ethics (n = 22, 39%), institutional support (n = 20, 35%) and unclear guidance on how to integrate (n = 19, 33%).

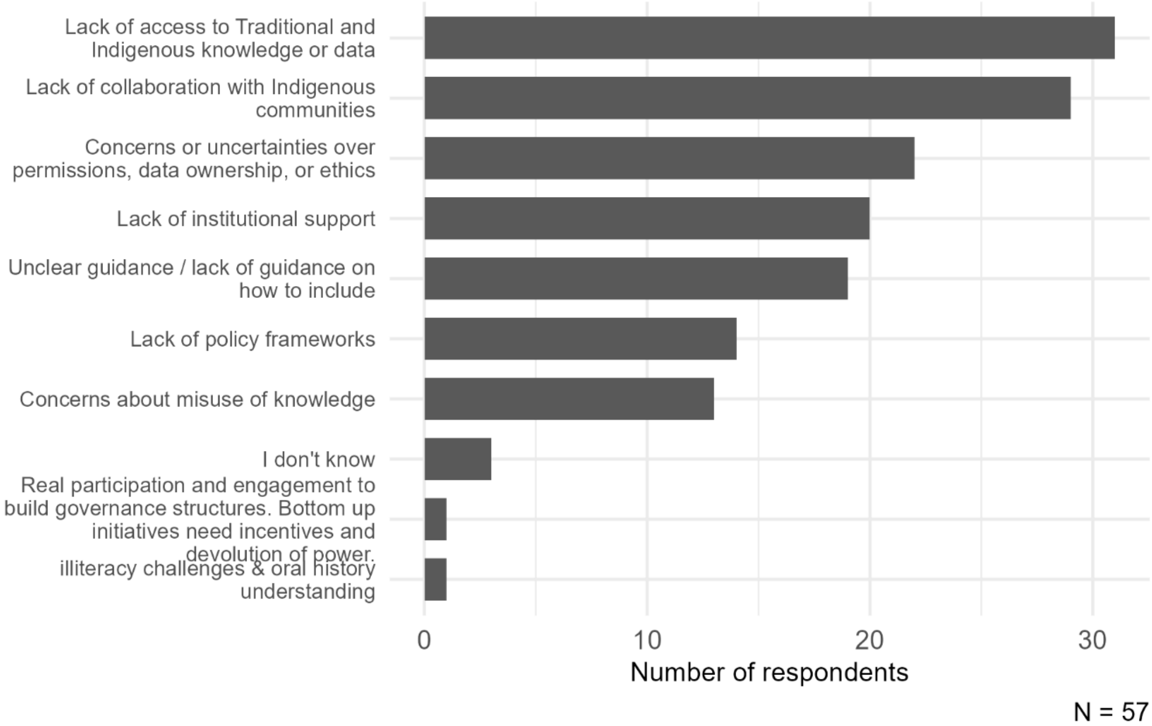



Figure 18 Respondents (n = 57) opinions on the challenges to integrating Traditional and Indigenous Knowledge into biodiversity monitoring.

In free-text answers, respondents highlighted the value of TIK and the importance of inclusion in biodiversity monitoring. They raised issues of lack of collaboration and communication, mistrust and concerns of misuse or exploitation of information and knowledge. Also mentioned were the lack of guidance or frameworks to combine different information sources, and a need for systems for *"combining local observations, stories, and seasonal indicators with scientific data to create more holistic and culturally grounded biodiversity monitoring"*. Respondents gave answers that spoke to the need for co-production of these systems, as well as mutual benefits from the outputs.

# 4.6 Views on technology markets and development

We asked respondents if they thought the demand for technology was growing in their region, with 81% of respondents agreeing it was. Respondents were also asked to estimate how much money their organisation had spent or invested in biodiversity monitoring technology over the past 5 years (Table 8). While most respondents did not know, 23 respondents gave estimates, which ranged from £0 to almost £7 million (median = £47,500).

Table 8 Amount (in GBP) spent/invested in biodiversity monitoring technology over a 5-year period, as estimated by questionnaire respondents (n = 23).

| Organisation type | Number of estimates | Median GBP |
|---|---|---|
| Research | 9 | £39,500 |
| NGO/IGO | 8 | £59,250 |
| Governmental bodies | 4 | £119,178 |
| Business/finance sector | 2 | £428,950 |
| Independent | 0 | N/A |

We asked respondents about how they would rate the readiness or deployment level of each technology for their specific biodiversity monitoring. The technology most highly ranked in terms of development was GIS and remote sensing, while eDNA technologies were least highly ranked (Figure 19).

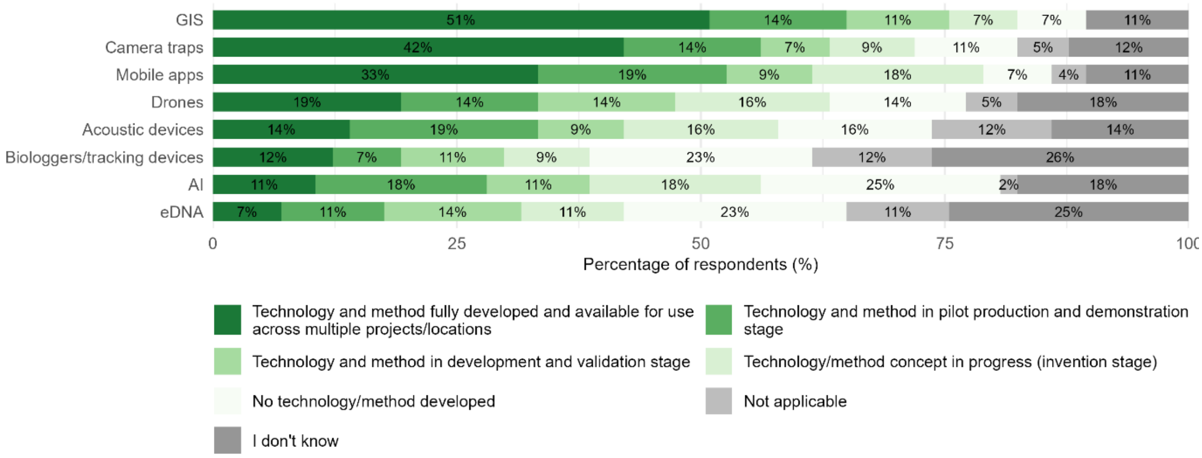



Figure 19 Readiness of different technologies to address the monitoring work undertaken by each respondent (n = 62).

# 4.7 Opportunities identified and interventions needed – the future of biodiversity monitoring technologies

## Opportunities

We asked respondents about the opportunities they saw for new or improved technologies to have the biggest impact on collecting or improving biodiversity data. Some respondents gave specific technologies they wanted to see improvements in, some respondents gave areas of research or monitoring where they wanted to see improved application of technologies, and some respondents gave more general hopes for the future of biodiversity monitoring. Many respondents mentioned opportunities for technology in data management and sharing, with data standardisation and integration frequently mentioned.

Specific areas mentioned by respondents:

- AI and machine learning to improve speed and ease of data analyses
- Improving spatial (eg remote areas) and temporal (eg real-time) sampling
- lower cost of high-resolution imagery, including detailed imagery from LIDAR and hyperspectral sensors
- developments in field-based eDNA protocols and sampling methods

## Interventions

We asked questionnaire respondents to select the three most important improvements or interventions to help biodiversity technologies and data better suit their needs. Respondents across both data collection and use identified long-term funding, capacity building, and improved access to tools as priority areas to better support biodiversity technologies and data systems.

For those using technology to collect data, the most frequently identified requirement was support for long-term monitoring, with 13 respondents (57%) highlighting the need for sustained funding, staffing, or other resources to maintain monitoring efforts over time (Figure 20). Respondents also emphasised the importance of more affordable technology or components and greater access to training or technical support, both selected by 11 respondents (48%).

A smaller proportion of respondents identified needs related to the usability and performance of technologies. Six respondents (26%) wanted technologies that are easier to use, while the same number requested improved performance. Additionally, five respondents (22%) indicated a need for greater access to a wider range of technology options, and four (17%) expressed interest in more customised technologies tailored to their specific requirements.

Some respondents highlighted needs related to data management and analytical capacity. Three respondents (13%) reported a need for better access to data analysis tools or expertise, while two respondents each (9%) pointed to improved data storage, enhanced computing infrastructure, and better information-sharing or collaboration platforms.

Finally, a small number of respondents noted broader systemic or partnership-related needs, including greater support for or integration with Traditional and Indigenous knowledge and stronger partnerships with researchers or institutions, each mentioned by one respondent (4%).

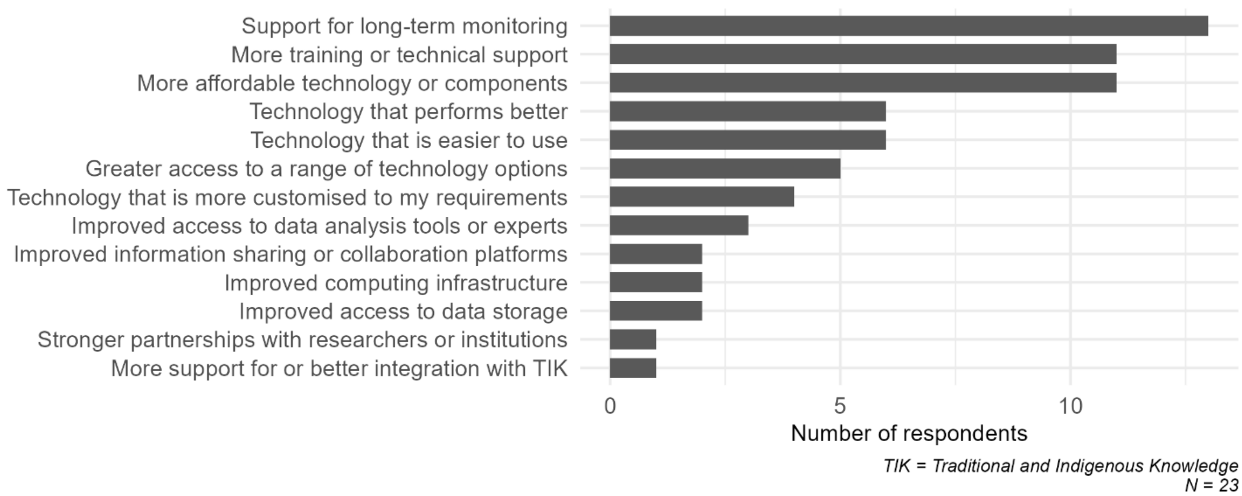



Figure 20 Needs identified by questionnaire respondents collecting data with biodiversity monitoring technologies (n = 23).

Survey responses from participants who use biodiversity data highlight a range of needs related to data access, technical capacity, and supporting infrastructure (Figure 21). The most frequently reported needs were improved access to data management and processing tools or software, improvements in biodiversity monitoring technology, and more training or technical support, each identified by 17 respondents (34%). Access to data was also a prominent theme. Fifteen respondents (30%) reported a need for greater access to currently available data, while 13 respondents (26%) indicated a need for additional data.

Respondents also highlighted needs in terms of the processing and application of data. Both improved access to analytical tools and guidance on integrating biodiversity data into policy or planning were selected by 13 respondents (26%). Infrastructure-related needs were also noted, including improved access to data storage (n = 9, 18%), improved computing infrastructure (n = 6, 12%), and consistent internet access (n = 1, 2%).

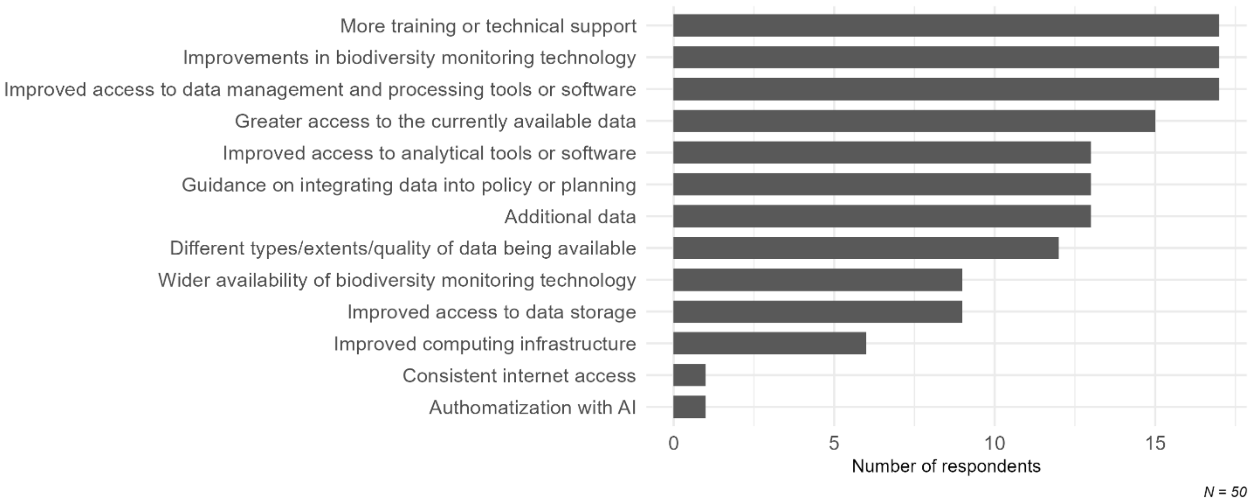



Figure 21 Needs identified by questionnaire respondents working with biodiversity data (n = 50).

## Future of biodiversity monitoring technologies and data

In free-text responses, respondents indicated that solutions beyond technological innovations were important for biodiversity monitoring, particularly the involvement and co-development of monitoring alongside local people and communities. Developing local capacity was highlighted as a need for sustained improvement of monitoring efforts, and frameworks and systems for standardising national and regional level biodiversity monitoring were also suggested as priorities. As stated by one questionnaire respondent, *"the future lies in developing affordable, locally adaptable, and open-source tools supported by AI models trained on regional species. Integrating automation, citizen science, and remote sensing can make biodiversity data more inclusive and actionable. Ultimately, monitoring should become community-driven, empowering local people to use data for sustainable conservation decisions."*

# 5 Interview results

## 5.1 Technologies currently being used, their application and their perceived benefits

The use of technologies varied within and between respondent user groups (Figure 22). Mobile applications and camera traps were both mentioned by 30 respondents (53.6%), mobile applications used by most respondents from community conservancies (n = 23, 62.2%).

Other widely used technologies included GIS/remote sensing (n = 17, 30.4%) and tracking devices (n = 14, 25%). Other technologies such as eDNA/genomics and spectroscopy for soil analysis were mentioned by fewer respondents (n = 3, 5.4% and n = 2, 3.6% respectively).

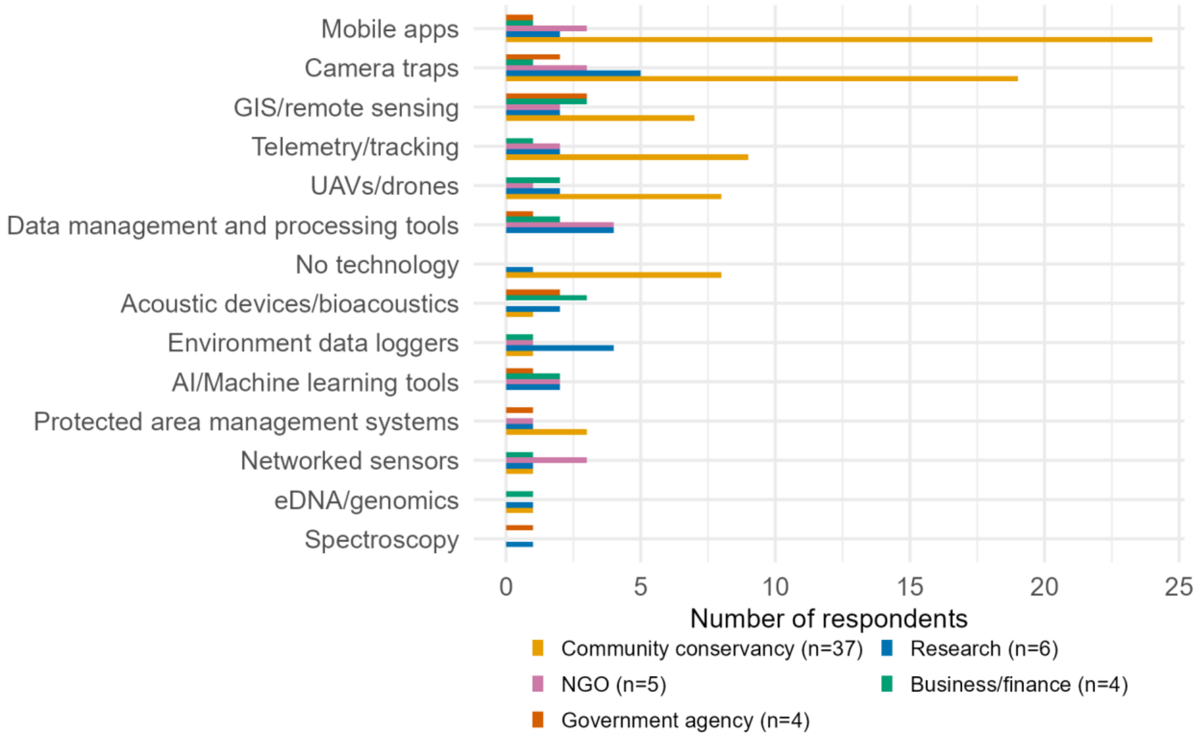



Figure 22 Number of respondents per user group who mentioned using each technology for biodiversity monitoring

### Application of technologies

Interview participants reported using technologies in a range of ways to support conservation and management activities (Table 9). The most common use was to inform management actions and interventions, cited by 37 respondents (66%). The majority of respondents across all user groups mentioned this application of technology. Technologies were also widely used to support or enhance decision making, reported by 31 respondents (55%), indicating their importance in guiding planning and operational choices. Many respondents described applications related to ecosystem monitoring. Monitoring ecosystem functioning was reported by 20 respondents (36%), while monitoring ecosystem structure was mentioned by 17 respondents (30%). Technologies were also used for monitoring species populations, noted by 15 respondents (27%).

Several participants highlighted uses related to human–wildlife interactions and enforcement. Understanding human–wildlife conflict was reported by 13 respondents (23%), and tracking illegal or unsustainable activity by 9 respondents (16%). Less frequently mentioned applications included understanding species traits (8 respondents, 14%), managing personnel or rangers (6 respondents, 11%), and understanding community composition (6 respondents, 11%). A small number of respondents reported using technologies for early-warning data (3 respondents, 5%) and transparent and verifiable measurement and reporting (1 respondent, 2%).

Table 9 Uses of technology for biodiversity monitoring across respondents.

| Use of technology | Total respondents | User Group | User group respondents (% of total user group response) |
|---|---|---|---|
| To inform management actions and interventions | 37 | Business/finance | 3 (75%) |
| | | Community conservancy | 20 (54.1%) |
| | | Government agency | 4 (100%) |
| | | NGO | 5 (100%) |
| | | Research | 5 (83.3%) |
| Support/enhance decision making | 31 | Business/finance | 3 (75%) |
| | | Community conservancy | 13 (35.1%) |
| | | Government agency | 4 (100%) |
| | | NGO | 5 (100%) |
| | | Research | 6 (100%) |
| Monitoring ecosystem functioning | 20 | Business/finance | 3 (75%) |
| | | Community conservancy | 4 (10.8%) |
| | | Government agency | 4 (100%) |
| | | NGO | 4 (80%) |
| | | Research | 5 (83.3%) |
| Monitoring ecosystem structure | 17 | Business/finance | 2 (50%) |
| | | Community conservancy | 3 (8.1%) |
| | | Government agency | 3 (75%) |
| | | NGO | 3 (60%) |
| | | Research | 6 (100%) |
| Monitoring species populations | 15 | Business/finance | 2 (50%) |
| | | Community conservancy | 4 (10.8%) |

| | | | |
|---|---|---|---|
| | | Government agency | 2 (50%) |
| | | NGO | 4 (80%) |
| | | Research | 3 (50%) |
| Understanding human-wildlife conflict | 13 | Business/finance | 3 (75%) |
| | | Community conservancy | 6 (16.2%) |
| | | NGO | 3 (60%) |
| | | Research | 1 (16.7%) |
| Tracking illegal or unsustainable activity | 9 | Community conservancy | 7 (18.9%) |
| | | Government agency | 1 (25%) |
| | | Research | 1 (16.7%) |
| Understanding species traits | 8 | Business/finance | 1 (25%) |
| | | Community conservancy | 3 (8.1%) |
| | | Government agency | 1 (25%) |
| | | NGO | 1 (20%) |
| | | Research | 2 (33.3%) |
| Managing personnel/rangers | 6 | Community conservancy | 5 (13.5%) |
| | | NGO | 1 (20%) |
| Understanding community composition | 6 | Community conservancy | 1 (2.7%) |
| | | Government agency | 2 (50%) |
| | | NGO | 1 (20%) |
| | | Research | 2 (33.3%) |
| Early-warning data | 3 | Business/finance | 1 (25%) |
| | | Government agency | 1 (25%) |
| | | NGO | 1 (20%) |
| Transparent and verifiable measurement and reporting | 1 | NGO | 1 (20%) |

## Perceived benefits

Participants identified diverse ways in which technology for monitoring biodiversity is a benefit. They talk about these in terms of three key functions: the quality of the data produced, the resource savings made, and changes to the capacity or ability to use the data produced via technology. It is notable that the most commonly cited benefits relate to how technology improves the processes of data collection, or the future use of that data. The low number of participants identifying reduced costs as a benefit is reflected in later analysis of the resources required for implementation, in which the majority of people stated that funding was needed. Further, we could speculate that the low number of people citing a reduction in human resource may be linked to the identified need for training for successful implementation.

- Data quality: Some participants from across all user groups valued the improved quality of data through technology use. This was expressed as potential for a reduction in bias (27%, n=15), the increased transparency and verification of measurements (32%, n=18),

or the standardisation of monitoring systems. It should be noted that, as a proportion of each user group, these benefits were expressed more often by individuals in Business/finance or Research.
- Resource savings: Reductions in human (n=4) and financial resource (n=6) also featured in discussions with a small number of participants. These were from user groups more likely to be commissioning or delivering monitoring (e.g. Government agencies) rather than collecting data (such as from the community conservancy sector)
- Capacity and ability to collect and use data: Three quarters of participants referred to the ease and efficiency technology brings to data collection. These participants were from across the board including community conservancy, NGO, business and government agencies who are perhaps more likely to be responsible for on-the-ground data collection than researchers who may be more often responsible for applying or utilising the data. Technology as a tool to improve data integration and reporting was mentioned by almost half of participants (46%, n=26), perhaps, unsurprisingly, greater representation from researchers over Community members. Improved spatial (30%) and temporal (21%) coverage were also considered important. Other cited benefits from technology related to how data could be better used: enhancing decision making, providing continuous data streams and real-time data. Again, benefits relating to the application and utilisation of data are more likely to be cited by government, research organisations or NGOs who are more likely to be *currently** using data. (*recognising that communities may also potentially use data but are not necessarily doing at this stage).
- Some participants stressed that the benefit of technology lies in supporting traditional data gathering methods rather than replacing them.

# 5.2 Challenges and barriers to using technologies and data

We asked participants what barriers and challenges they and others experienced in using biodiversity monitoring technologies and data. Almost all challenges had representation across the organisation types, indicating these issues have wide representation.

### Technology use

Participants spoke about the challenges of using technology in six broad ways: capacity, infrastructure and resources, characteristics of technology, the value of outputs, governance of knowledge and data, and social aspects including user perceptions and trust. The breakdown of these themes and the number of respondents who mentioned them are presented in Table 10.

The barrier and challenges most often mentioned related to capacity, reported by a total of 35 respondents (62.5%) and across all five user groups. This shortage of skills was referred to in different contexts but frequently in reference to lack of capacity in local communities to deploy technologies, an absence of local technical knowledge to repair and maintain technologies, and limited knowledge on how to analyse the data that was being collected.

Challenges related to inadequate network coverage or power supply were the next most frequently reported. A total of 30 interview participants (53.6%) across all organisation types referred to these issues. Other issues related to resources included the lack of sustained investment (n = 20, 36%), and lack of access to the technologies (n = 4, 7.1%).

Barriers related to the characteristics of the technology themself related to cost (n=24, 43%), that technology is not reliable (n = 15, 27%), and too complex (n = 13, 23.2%). These barriers were mentioned by multiple respondents across organisation types. A number of individual technology related issues were reported by interview participants, for instance that technology can impact species behaviour. The example given by this respondent was elephants wearing GPS collars becoming more aggressive and causing issues for communities.

Over 20% of participants (n = 12) mentioned technologies had limited effectiveness for the biodiversity monitoring they were carrying out. Other barriers related to the perceived value of data generated by technologies included outputs that were not accessible or useful (n = 6, 10.7%) and that technologies did not improve upon existing monitoring approaches conducted without technology (n = 6, 10.7%). Participants spoke of barriers related to knowledge governance in terms of the lack of integration of technologies into monitoring frameworks (n = 8, 14.3%) and policy (n = 3, 5.4%). Also mentioned were limited community involvement and resulting lack of community benefit (n = 6, 10.7%), and insufficient integration of Traditional and Indigenous Knowledge (n = 2, 3.6%).

Participants also reported barriers related to trust, perceptions, and inclusivity. These included resistance to or fear of technology (n = 7, 12.5%) and uncertainty or limited understanding of the value of new technologies (n = 5, 8.9%). These were raised in the community conservancy context in terms of having to repeatedly introduce new technology to local communities due to a rapidly evolving technology scene. Some participants also highlighted issues of trust, including trust in external organisations (n = 4, 7.1%) and trust in the technologies themselves (n = 2, 3.6%). Gender-related barriers were mentioned by one participant (n = 1, 1.8%). This participant highlighted a lower literacy rate in women in their area, and that technology should be designed specifically with this in mind.

Table 10 Barriers to access and use of technologies as mentioned by interview participants, grouped by thematic area.

| Barrier | Total respondents | User Group | User group respondents (% of total user group response) |
|---|---|---|---|
| *Capacity* | | | |
| Skills shortage | 35 | Business/finance | 3 (75%) |
| | | Community conservancy | 18 (48.6%) |
| | | Government agency | 4 (100%) |
| | | NGO | 5 (100%) |
| | | Research | 5 (83.3%) |
| Time limitations for personnel | 2 | Business/finance | 1 (25%) |
| | | Community conservancy | 1 (2.7%) |
| *Infrastructure and resources* | | | |
| Inadequate network/mobile coverage OR inadequate power/energy options | 30 | Business/finance | 1 (25%) |
| | | Community conservancy | 20 (54.1%) |
| | | Government agency | 3 (75%) |
| | | NGO | 4 (80%) |
| | | Research | 2 (33.3%) |
| Requires sustained investment/expenditure | 20 | Business/finance | 2 (50%) |
| | | Community conservancy | 9 (24.3%) |
| | | Government agency | 2 (50%) |
| | | NGO | 3 (60%) |
| | | Research | 4 (66.7%) |

| | | | |
|---|---|---|---|
| Infrastructure or resource issues prevent access | 4 | Community conservancy | 4 (10.8%) |
| Lack of access to/availability of technology | 4 | Community conservancy | 4 (10.8%) |
| *Characteristics of technology* | | | |
| Technology too expensive | 24 | Business/finance | 2 (50%) |
| | | Community conservancy | 15 (40.5%) |
| | | Government agency | 2 (50%) |
| | | NGO | 2 (40%) |
| | | Research | 3 (50%) |
| Reliability: poor quality and difficult to maintain technology | 15 | Community conservancy | 10 (27%) |
| | | Government agency | 1 (25%) |
| | | NGO | 2 (40%) |
| | | Research | 2 (33.3%) |
| Technology too complex | 13 | Business/finance | 1 (25%) |
| | | Community conservancy | 6 (16.2%) |
| | | Government agency | 2 (50%) |
| | | NGO | 2 (40%) |
| | | Research | 2 (33.3%) |
| Difficult terrain compromises tech efficiency | 1 | Government agency | 1 (25%) |
| Technology components bulky | 1 | Government agency | 1 (25%) |
| Technology impacts on species behaviour | 1 | Community conservancy | 1 (2.7%) |
| *Value of data and outputs* | | | |
| Limited effectiveness of technology for more detailed biodiversity monitoring | 12 | Business/finance | 1 (25%) |
| | | Community conservancy | 3 (8.1%) |
| | | Government agency | 2 (50%) |
| | | NGO | 2 (40%) |
| | | Research | 4 (66.7%) |
| Outputs not accessible or useful | 6 | Community conservancy | 3 (8.1%) |
| | | Government agency | 2 (50%) |
| | | Research | 1 (16.7%) |
| Redundancy of technology | 6 | Community conservancy | 3 (8.1%) |
| | | Government agency | 1 (25%) |
| | | NGO | 1 (20%) |
| | | Research | 1 (16.7%) |

| | | | |
|---|---|---|---|
| Data produced is not what is needed or is not useful | 1 | Research | 1 (16.7%) |
| *Knowledge governance* | | | |
| Lack of integration of technology | 8 | Business/finance | 2 (50%) |
| | | Government agency | 3 (75%) |
| | | NGO | 1 (20%) |
| | | Research | 2 (33.3%) |
| Lack of involvement or benefit to community | 6 | Community conservancy | 3 (8.1%) |
| | | NGO | 3 (60%) |
| Data privacy and rights concerns | 3 | Community conservancy | 1 (2.7%) |
| | | NGO | 1 (20%) |
| | | Research | 1 (16.7%) |
| Policy/framework challenges | 3 | Business/finance | 2 (50%) |
| | | Government agency | 1 (25%) |
| Integration of traditional or local knowledge | 2 | Community conservancy | 2 (5.4%) |
| *Social factors* | | | |
| Resistance to or fear of technology | 7 | Business/finance | 1 (25%) |
| | | Community conservancy | 5 (13.5%) |
| | | Government agency | 1 (25%) |
| Uncertainty about/limited understanding of the value of [new] technologies | 5 | Business/finance | 1 (25%) |
| | | Community conservancy | 3 (8.1%) |
| | | Government agency | 1 (25%) |
| Trust in external organisations | 4 | Business/finance | 1 (25%) |
| | | Government agency | 1 (25%) |
| | | NGO | 2 (40%) |
| Trust in technology | 2 | NGO | 1 (20%) |
| | | Research | 1 (16.7%) |
| Gender | 1 | Community conservancy | 1 (2.7%) |

## Data use

The broader themes that came up when participants were asked about the challenges that limit the use and sharing of biodiversity data were data governance and policy, accessibility and usability of data, and capacity and resources. The challenges and the number of respondents who mentioned them are presented in Table 11.

The most frequently mentioned challenges related to data governance and institutional frameworks. Nearly half of participants (n = 24, 42.9%) expressed concerns around data ownership and governance, highlighting uncertainty about who controls and can use biodiversity data. Similarly, 21 participants (37.5%) noted the absence of clear pathways or policies for applying data to decision-making or conservation impact, and 20 participants (35.7%) described operating in silos or fragmented working as a barrier to effective data use. Risk aversion in data sharing and management was also raised by 14 participants (25%).

Participants also highlighted challenges related to data accessibility and usability. Fourteen participants (25%) reported that data were difficult to access, while 13 participants (23.2%) mentioned issues around the format of data. Nine participants (16.1%) noted that the data produced were not what was needed or were not useful.

Ten participants (17.9%) reported a lack of financial or material resources, and the same number (n = 10, 17.9%) highlighted insufficient technical capacity for data management and analysis. Data storage limitations were spoken about by six participants (10.7%).

Table 11 Barriers to access and use of biodiversity data as mentioned by interview participants, grouped by thematic area.

| Barrier | Total respondents | User Group | User group respondents (% of total user group response) |
|---|---|---|---|
| *Data governance and policy* | | | |
| Concerns around data ownership/governance | 24 | Business/finance | 3 (75%) |
| | | Community conservancy | 11 (29.7%) |
| | | Government agency | 4 (100%) |
| | | NGO | 4 (80%) |
| | | Research | 2 (33.3%) |
| Pathways and policies for application of data/routes to impact is missing | 21 | Business/finance | 4 (100%) |
| | | Community conservancy | 10 (27%) |
| | | Government agency | 1 (25%) |
| | | NGO | 3 (60%) |
| | | Research | 3 (50%) |
| Operating in silos/fragmented working | 20 | Business/finance | 2 (50%) |
| | | Community conservancy | 6 (16.2%) |
| | | Government agency | 2 (50%) |
| | | NGO | 5 (100%) |
| | | Research | 5 (83.3%) |
| Risk aversion | 14 | Business/finance | 3 (75%) |
| | | Community conservancy | 2 (5.4%) |
| | | Government agency | 2 (50%) |
| | | NGO | 3 (60%) |
| | | Research | 4 (66.7%) |
| *Data accessibility and usability* | | | |
| Data accessibility | 14 | Business/finance | 2 (50%) |
| | | Community conservancy | 3 (8.1%) |

| | | | |
|---|---|---|---|
| | | Government agency | 3 (75%) |
| | | NGO | 3 (60%) |
| | | Research | 3 (50%) |
| Format of data not appropriate | 13 | Business/finance | 2 (50%) |
| | | Community conservancy | 3 (8.1%) |
| | | Government agency | 3 (75%) |
| | | NGO | 4 (80%) |
| | | Research | 1 (16.7%) |
| Data produced is not what is needed or is not useful | 9 | Business/finance | 1 (25%) |
| | | Community conservancy | 2 (5.4%) |
| | | Government agency | 3 (75%) |
| | | NGO | 2 (40%) |
| | | Research | 1 (16.7%) |
| Complexity of biodiversity data | 3 | Community conservancy | 2 (5.4%) |
| | | Government agency | 1 (25%) |
| *Capacity and resources* | | | |
| Lack of resources | 10 | Community conservancy | 7 (18.9%) |
| | | Government agency | 1 (25%) |
| | | Research | 2 (33.3%) |
| Lack of technical capacity for data management and analysis | 10 | Business/finance | 1 (25%) |
| | | Community conservancy | 5 (13.5%) |
| | | Government agency | 2 (50%) |
| | | Research | 2 (33.3%) |
| Storage limitations | 6 | Business/finance | 1 (25%) |
| | | Community conservancy | 1 (2.7%) |
| | | Government agency | 2 (50%) |
| | | NGO | 2 (40%) |

# 5.3 Needs related to technologies and data

Participants spoke about what is required for the successful implementation of technology in monitoring in five ways: funding and resources, the need for capacity building, the way that technology and related knowledge are created and shared, improved governance and integration of technologies, and changes to the nature of the technology itself (Table 12).

The two needs most frequently mentioned were related to funding (n = 38, 67.9%) and training (n = 37, 66.1%). Other topics that many participants spoke about related to increased collaboration in terms of partnerships (n = 20, 35.7%) and co-development approaches (n = 11, 19.6%). Further needs that were expressed by interview participants related to better policy support (n = 10) and embedding the use of technologies in frameworks (n = 9, 16.1%). Another aspect of capacity that was raised was the need for development of local technical support (n = 9, 16.1%). Aspects related to technology themselves were mentioned by relatively few respondents, but this was mentioned in terms of technology adapted to local environmental needs (n = 7, 12.5%), easier to use (n = 5, 8.9%) and cheaper technology (n = 4, 7.1%).

Table 12 Needs expressed by interview participants for successful biodiversity monitoring.

| Need | Total respondents | User Group | User group respondents (% of total user group response) |
|---|---|---|---|
| *Funding and resources* | | | |
| Funding for technology | 38 | Business/finance | 4 (100%) |
| | | Community conservancy | 21 (56.8%) |
| | | Government agency | 4 (100%) |
| | | NGO | 3 (60%) |
| | | Research | 6 (100%) |
| Improved infrastructure | 1 | Community conservancy | 1 (2.7%) |
| *Capacity building* | | | |
| Training | 37 | Business/finance | 3 (75%) |
| | | Community conservancy | 22 (59.5%) |
| | | Government agency | 4 (100%) |
| | | NGO | 4 (80%) |
| | | Research | 4 (66.7%) |
| Availability of technical specialists for support | 9 | Business/finance | 2 (50%) |
| | | Community conservancy | 3 (8.1%) |
| | | Government agency | 1 (25%) |
| | | NGO | 2 (40%) |
| | | Research | 1 (16.7%) |
| *Greater collaboration* | | | |
| Partnerships and knowledge exchanges | 20 | Business/finance | 2 (50%) |
| | | Community conservancy | 10 (27%) |
| | | Government agency | 2 (50%) |
| | | NGO | 3 (60%) |
| | | Research | 3 (50%) |
| Co-development approaches | 11 | Business/finance | 1 (25%) |
| | | Community conservancy | 8 (21.6%) |

| | | | |
|---|---|---|---|
| | | NGO | 2 (40%) |
| Cross institutional/interdisciplinary working, from community to science to government and across ecosystems | 8 | Business/finance | 2 (50%) |
| | | Community conservancy | 1 (2.7%) |
| | | Government agency | 1 (25%) |
| | | Research | 4 (66.7%) |
| Community buy-in and clear understanding of benefits or value of involvement and technology | 2 | Community conservancy | 1 (2.7%) |
| | | NGO | 1 (20%) |
| Integration of traditional knowledge into decision making | 2 | Business/finance | 1 (25%) |
| | | Community conservancy | 1 (2.7%) |
| *Governance and integration* | | | |
| Policy support | 10 | Business/finance | 3 (75%) |
| | | Community conservancy | 2 (5.4%) |
| | | Government agency | 2 (50%) |
| | | NGO | 1 (20%) |
| | | Research | 2 (33.3%) |
| Technology use/monitoring to be embedded in institutions and frameworks | 9 | Business/finance | 2 (50%) |
| | | Community conservancy | 1 (2.7%) |
| | | Government agency | 3 (75%) |
| | | NGO | 2 (40%) |
| | | Research | 1 (16.7%) |
| Standardisation of systems | 6 | Business/finance | 1 (25%) |
| | | Community conservancy | 1 (2.7%) |
| | | Government agency | 2 (50%) |
| | | Research | 2 (33.3%) |
| *Improvements to technology and outputs* | | | |
| Technology fit for use in location | 7 | Community conservancy | 6 (16.2%) |
| | | Government agency | 1 (25%) |
| Technology that is easier to use | 5 | Business/finance | 1 (25%) |
| | | Community conservancy | 3 (8.1%) |
| | | NGO | 1 (20%) |

| | | | |
|---|---|---|---|
| Cheaper technology | 4 | Community conservancy | 2 (5.4%) |
| | | Government agency | 1 (25%) |
| | | Research | 1 (16.7%) |

### Resources available locally to support implementation

Participants were asked about resources already available within their locality which could support the use of technology. Much of what was mentioned referred to better involvement of local communities at all stages of biodiversity monitoring. Local resources were spoken about in terms of the activities that could, or do, take place. For example, citizen science, collective action and organised community participation in monitoring. There were frequent mentions of the place-based knowledge and observations of change over time that was held by community members, particularly elders, which is currently underutilised and overlooked. Engaging young people in monitoring was also spoken about by multiple participants.

Community-based decision making and ownership were mentioned as strengths which could be drawn on to support monitoring. Also identified were stewardship of both monitoring and the data produced.

# 5.4 What are the future opportunities

Participants identified diverse future opportunities both for using technology and for the use of monitoring data (Table 13). They talked about opportunities in terms of how technology could be better applied, the potential applications of data produced through technology, in terms of the data that is being captured and in terms of how data processing or collection may develop. A small number of participants also mentioned technology improving collaboration and standardisation.

The most prominent idea for the future of technologies was a desire for them to be applied to real world conservation challenges, rather than focusing primarily on technological development itself (n = 24, 43%). This view was expressed across all organisation types, including all business/finance respondents (n = 4; 100%), all NGO respondents (n = 5; 100%), and all research respondents (n = 6; 100%), as well as 3 government agency respondents (75%) and 6 community conservancy respondents (16%). Other commonly mentioned priorities were the development and use of early-warning data systems and the role of technology and data in informing finance and investment frameworks, both mentioned by 15 respondents (27%). The frequency of reference to these opportunities by respondents varied between organisation type, but both were mentioned across all organisations. In addition, 10 respondents (18%) discussed the opportunity that technologies provided in linking biodiversity outcomes to socioeconomic outcomes, and several participants emphasised the potential for integration of Traditional Knowledge into decision making (n = 9, 16%).

Participants also highlighted the importance of improving how conservation data are collected and integrated. The most frequently cited priority was the integration of multiple data types and sources, reported by 27 respondents (48%). Many felt that providing continuous data streams was possible via technology (n = 20, 36%), also discussed was the possibility that technology provided in terms of capturing landscape-level information (n = 19, 34%) and long-term data trends (n = 13, 23%).

The opportunity for technologies to improve to governance and coordination was mentioned by some respondents. Partnerships and collaboration were mentioned by 6 respondents (11%), all of whom were from community conservancies (6; 16%).

Table 13 Future opportunities for technology in biodiversity monitoring, as spoken about by interview participants.

| Opportunities | Total respondents | User Group | User group respondents (% of total user group response) |
|---|---|---|---|
| *Application of technology, data and information* | | | |
| Technology to inform real world conservation challenges, not just continuous technology development | 24 | Business/finance | 4 (100%) |
| | | Community conservancy | 6 (16.2%) |
| | | Government agency | 3 (75%) |
| | | NGO | 5 (100%) |
| | | Research | 6 (100%) |
| Early-warning data | 15 | Business/finance | 2 (50%) |
| | | Community conservancy | 4 (10.8%) |
| | | Government agency | 3 (75%) |
| | | NGO | 4 (80%) |
| | | Research | 2 (33.3%) |
| To inform finance/investment frameworks e.g. measurement of biodiversity for biodiversity credits | 15 | Business/finance | 4 (100%) |
| | | Community conservancy | 3 (8.1%) |
| | | Government agency | 3 (75%) |
| | | NGO | 1 (20%) |
| | | Research | 4 (66.7%) |
| Improved application of AI | 13 | Business/finance | 2 (50%) |
| | | Community conservancy | 4 (10.8%) |
| | | Government agency | 2 (50%) |
| | | NGO | 1 (20%) |
| | | Research | 4 (66.7%) |
| Linking biodiversity to socioeconomic outcomes | 10 | Business/finance | 3 (75%) |
| | | Community conservancy | 3 (8.1%) |
| | | NGO | 1 (20%) |
| | | Research | 3 (50%) |
| Integration of Traditional | 9 | Community conservancy | 5 (13.5%) |

| | | | |
|---|---|---|---|
| Knowledge into decision making | | Government agency | 1 (25%) |
| | | NGO | 1 (20%) |
| | | Research | 2 (33.3%) |
| Technology for farmers | 4 | Community conservancy | 3 (8.1%) |
| | | Research | 1 (16.7%) |
| Transparent and verifiable measurement and reporting | 3 | Business/finance | 1 (25%) |
| | | Community conservancy | 1 (2.7%) |
| | | NGO | 1 (20%) |
| Technology supporting traditional data gathering methods rather than replacing | 1 | Business/finance | 1 (25%) |
| *Developments in data collection and integration* | | | |
| Integration of multiple data types and from different sources | 27 | Business/finance | 2 (50%) |
| | | Community conservancy | 11 (29.7%) |
| | | Government agency | 3 (75%) |
| | | NGO | 5 (100%) |
| | | Research | 6 (100%) |
| Providing continuous data streams | 20 | Business/finance | 1 (25%) |
| | | Community conservancy | 6 (16.2%) |
| | | Government agency | 3 (75%) |
| | | NGO | 4 (80%) |
| | | Research | 6 (100%) |
| Landscape-level information | 19 | Business/finance | 2 (50%) |
| | | Community conservancy | 4 (10.8%) |
| | | Government agency | 3 (75%) |
| | | NGO | 5 (100%) |
| | | Research | 5 (83.3%) |
| Long-term data that can indicate trends | 13 | Community conservancy | 3 (8.1%) |

| | | | |
|---|---|---|---|
| | | Government agency | 3 (75%) |
| | | NGO | 3 (60%) |
| | | Research | 4 (66.7%) |
| Invasive species monitoring | 3 | Business/finance | 1 (25%) |
| | | Government agency | 1 (25%) |
| | | Research | 1 (16.7%) |
| Capturing population genetics | 2 | Business/finance | 1 (25%) |
| | | Community conservancy | 1 (2.7%) |
| *Governance and collaboration* | | | |
| Partnerships/collaboration | 6 | Community conservancy | 6 (16.2%) |
| Standardisation of systems | 1 | Business/finance | 1 (25%) |

# 6 Findings from the workshop

## 6.1 Current use of technology in biodiversity monitoring

Participants showcased context-appropriate applications of technology in biodiversity monitoring, where technology integrates with existing knowledge systems. These cases converged around three key themes of success:

### Theme 1: Informing national planning and policy (Data Infrastructure)

A Uganda freshwater biodiversity portal highlighted how integrated data systems strengthen evidence-based national planning. Built from eDNA research, the portal integrates occurrence data for over 130 freshwater fish species. This enables spatial analysis of threats to critically endangered species during infrastructure planning.

**Key insight:** "*Without this portal, developers couldn't assess whether proposed infrastructure projects would impact vulnerable species*". The system directly supports national Environmental Impact Assessment (EIA) processes.

**Regional Tech Organizations:** Represented by the Regional Centre for Mapping of Resources for Development (RCMRD), a Technical Support Centre (TSC) of the Convention on Biological Diversity, highlighted their role in providing open access data, data expertise, tools and other resources to support planning and policy processes. These efforts are backed by formal agreements with data contributors.

**Critically, a monitoring-evaluation gap emerged**: when asked how technologies are actually working beyond dissemination, it emerged that the TSC must independently mobilize resources to deliver on its obligation.

### Theme 2: Strengthening community conservation (Ownership and Deployment)

Two community conservancy-led initiatives highlighted how integrated data systems empower community-driven monitoring and conservation action:

**Conservancies Data Hub:** The "One Container, One View" approach centralizes incident data from multiple conservancies. Outputs enable coordinated responses across landscapes.

**Key insight:** "*Integration and data governance create more value than new tools*."

**Mobile patrols for REDD+ Safeguards:** In Kenya's Kasigau Corridor, rangers use a mobile app to record species sightings and threats in near real-time. Integrated patrol-biodiversity data **revealed spatial mismatches**: high-conservation-value species avoided human-access routes where threats clustered. This informed **smarter ranger deployment**, ensuring resource and rangers optimization.

**Critical Lesson:** "*Every system is only as good as its user. Invest in the user, not just the technology.*"

## Theme 3: Technical adaptation in complex environments (Innovation & Reality)

**Camera Traps + AI in Serengeti:** Facing 2.4 million unprocessed images from 200 camera traps, a conservation organization partnered with universities to develop AI tools data processing. As a result, image processing time dropped from months to days while maintaining accuracy. The issue of "garbage images" emerged: a presenter noted that "80 - 90% of images may be empty, and reducing grass cover 10 – 15m in front of cameras and adjusting heat sensitivity cuts false triggers." Upon debating the issue, participants concluded that long-term archives of "garbage images" could reveal habitat changes invisible within short study periods.

**eDNA for freshwater systems:** In Tanzania, eDNA sampling revealed hidden fish diversity in aquaculture ponds, detected invasive species, and informed pre-dam biodiversity baselines. Constraints included limited local sequencing facilities, complex Nagoya Protocol permitting, and the absence of regional genomic reference databases. The case study also highlighted that **analytical infrastructure lags behind field data-collection capacity**. The researcher recommended *"investing in strong reference databases, without which, species identification remains guesswork*."

**Marine monitoring realities**: A marine conservation specialist stressed that underwater technology (e.g., camera systems), require extensive prototyping due to the complexity of marine environment. Limited knowledge of the distribution patterns of some marine species also makes biodiversity monitoring challenging. For example, months of monitoring sharks in shallow waters using Baited Remote Underwater Video Systems (BRUVS), detected no individuals, necessitating a shift to surveys at depths of **150m** to establish baseline data. Equipment importation delays can also exceed six months.

**Key insight:** "*For aquatic systems, budget project time for optimization. Failure rates are high; you cannot treat marine technology like terrestrial*." As a results, coastal and marine areas, are lagging in the technology race.

Together with hearing case studies on how technology is being used for biodiversity monitoring, participants were introduced to innovative monitoring tools during the technology demonstration session (day 3 of the workshop as shown in Figure 23).

Figure 23 Participants learn first-hand about diverse monitoring tools during the technology demonstration session

# 6.2 Key opportunities and challenges of technology for biodiversity monitoring

Successful technology applications consistently showed three key traits: (1) technologies are chosen based on clearly defined management needs rather than novelty, (2) they are integrated into existing workflows, and (3) they include rapid feedback loops.

The key challenges identified include: fragmented data ecosystems where multiple incomplete platforms prevent cross-agency sharing; significant capacity asymmetries, with training narrowly focused on data collection rather than synthesis or interpretation; infrastructure gaps including limited local sequencing facilities and the import delays for equipment; policy misalignment where monitoring is not integrated into regulatory frameworks; and equity concerns around who controls, benefits from, and has access to data.

The main opportunities to bridge these barriers include: integrating data systems through harmonized national platforms; empowering community-based monitoring with formal recognition and feedback mechanisms; improving data to decision pathways by embedding data analysts with government agencies; scaling emerging technologies such as AI-assisted image processing and eDNA; and investing in long-term monitoring infrastructure including reference libraries and repair capacity.

# 6.3 From data to impact: barriers to decision-making and possible solutions

Workshop participants examined the “data to impact pathway” to identity key failure points, their route causes and solutions (Figure 24). Three of the four critical failures occurred with the data-to-impact chain, while the fourth related to coordination across local and national levels (Table 14).

Table 14 Data-to-Impact chain failure points and proposed solutions

| Break point | Evidence from workshop | Proposed solution |
|---|---|---|
| Collection ⇨ Management | Multiple incompatible platforms; lack of cross-agency technology and data sharing mechanisms | Harmonized schemas with tiered access (public/ private/ security layers) |
| Analysis ⇨ Interpretation | Scientists produce complex outputs that decision-makers cannot use; lack of "translators" and analysts to re-package the information for non-expert users | Co-produce policy briefs, understand objectives before data collection; embed data officers in county governments |
| Evidence ⇨Action | Lack of accountability for acting on findings; monitoring becomes a compliance exercise | Mandatory feedback loops requiring managers to document how data informed decisions |
| Cross-level coordination (operate across the chain not within a single link) | Community data rarely feeds into national databases or policy, leading to misaligned economic outcomes | Formalize community resource assessors as recognized data contributors |

*"We need enduring systems where technology serves people, and people, in turn, steward biodiversity for generations."* **Workshop participant**


Figure 24 Participants co-created the data-to-impact pathways and highlight common break points (top right), and discussed to root causes of failures in the data to impact chain (left)

# 6.4 Underlying causes of failure: data-to-impact analysis

Table 15 shows what the participants diagnosed as the main reasons **why** biodiversity monitoring data fails to inform decisions, and what needs to change. Critically, these causes intersect: fragmented systems worsen capacity gaps, Western-designed tools ignore context, while short-term funding undermines ownership.

Table 15 Root causes of failures across the data-impact chain, and corresponding shift required

| Root causes | Evidence from the workshop | Shift required |
|---|---|---|
| **Context-blind technology design** | Tools developed for Global North contexts often fail in African ecosystems due to differing socio-economic realities. | Design **with** communities from day one. Prioritize practicality and affordability. |
| **Fragmented data ecosystems** | Conservancies use incompatible systems (SMART, EarthRanger, WhatsApp, paper). | Harmonize schemas; create single biodiversity dashboards. |
| **Capacity asymmetries** | Training focuses narrowly on data collection and less on synthesis and analysis. Lack of "data translators" that can repackage the information into informative and usable formats. | Shift training to interpretation and policy brief development. |
| **Weak science-policy interfaces** | Corridors get fenced because planners don't see wildlife data. | Mandate regular science-policy interfaces. |
| **Unsustainable funding models** | Pilot projects end when funding stops; tools become shelfware | Shift from pilots to financing **monitoring ecosystems**. |
| **Extraction without ownership** | Technology introduced without community co-design creates shelfware. | Prioritize local ownership. Co-create tools with communities. |
| **Policy misalignment** | Africa possesses policy frameworks but lacks mechanisms to domesticate global tools | Champion economic framing. Lobby for adaptive regulatory sandboxes. |

# 6.5 Informing management and policy with data

Technology-generated biodiversity data is increasingly informing decisions on development, planning, and natural resource management across East Africa. However, impact could be enhanced, if monitoring systems are designed with context, and not merely transferred to it.

Participants co-identified foundational principles for enduring monitoring systems, as summarized in Table 16. By enduring monitoring system, we mean long-term, sustainable structures and processes supported by continuous funding, capacity building, maintenance, and strong institutional integration, ensuring they remain functional and impactful beyond funding cycles.

Table 16 Foundational principles for enduring monitoring systems

| Workshop Observation and insight | Workshop Emphasis/ Ideal Situation | Implication for Future Practice |
|---|---|---|
| **Context is non-negotiable** | Social-economic realities differ dramatically across regions. | Design **with** communities from day one, not for them. Integrate local context into every development phase. |
| **Practicality > technical complexity** | Affordability and durability matter more than AI sophistication. | Prioritize “frugal technology”: tools repairable locally and usable with minimal training. |
| **Technology for WHOM?** | *"Without responding to user needs, technology becomes obsolete. Technology is a business needing investment and return."* Tools developed without market alignment become shelfware within project cycles | Co-define value with end-users. |
| **Adoption = innovation** | Novelty without uptake delivers zero conservation impact. | Measure success by sustained use, not deployment metrics. |
| **Capacity is irreplaceable** | It's about people asking the right questions. Combine OLD knowledge with NEW methods | Train experts that can interpret and translate technical data into accessible and actionable information for diverse stakeholders; integrate Indigenous knowledge with technology |

| | | |
|---|---|---|
| **Local ownership = sustainability** | Community institutions sustaining monitoring independently demonstrated true ownership. | Separate data **ownership** (communities) from **custodianship** (trusted entities). |
| **Ecosystem gaps persist** | Marine and coastal monitoring significantly lags terrestrial efforts. | Budget for project time enhance focus and funding for marine and coastal environments. |
| **Domesticate, don't import** | Africa lacks mechanisms to domesticate global tools to local contexts. | Adapt global tools to local contexts and regulations. |

# 6.6 Leveraging technology for impact

A multi-stakeholder panel explored how biodiversity monitoring technologies and data can strengthen decision-making from local to national level (Figure 25). The dialogue moved beyond technical specifications to address systemic barriers in finance, policy, and data governance (see Annexe 4 for questions raised during the session).


Figure 25 Panellists discussing the use of technology and biodiversity data in decision-making.

The session surfaced a critical consensus on context, ownership, and value. Table 17 summarizes the key debates, points of agreement and way forward.

Table 17 Critical debates and consensus points from the panel discussion

| Debate | Points of Agreement | Path Forward |
|---|---|---|
| **Data ownership vs. open science** | Communities must control primary data; aggregated insights enable regional learning. | Communities must control primary data; aggregated insights enable regional learning. |
| **Private sector engagement** | Businesses depend on ecosystem services (e.g., breweries rely on water towers). | Package data showing ecosystem risk to business continuity; create blended finance |
| **Beyond species counts** | We monitor elephants but ignore habitat degradation driving invasive species. | Pilot multidimensional biodiversity indices capturing cultural values and ecosystem services. |
| **Restoration agenda** | Degradation, not just climate change, is the primary driver of invasive species. | Champion restoration alongside climate agendas; healthy ecosystems buffer climate impacts. |

Five key outcomes from the panel discussion

1. Technology Must Serve People (Context is Key): Social-economic realities vary significantly across East Africa; solutions must be designed with these variations, not despite them. Practicality and affordability matter more than technical sophistication. Tools must function reliably with limited infrastructure rather than showcasing cutting-edge features that fail when power fluctuates. The consensus was that context determines design, and technology must solve specific management questions in specific landscapes.

2. Capacity Development is Irreplaceable: Success requires combining indigenous knowledge with technological innovation. Training must shift from data collection to interpretation and policy brief development. Institutions that sustain monitoring independently after external funding ends demonstrate that local ownership creates resilience beyond perpetual external financing. Capacity building must be institutionalized to withstand staff turnover.

3. Private Sector Engagement Requires Value Demonstration: Technology has become a business needing investment and return. Without responding to market needs, new tech becomes obsolete. The private sector holds significant capital but requires data packaged as risk assessment. For example, industries dependent on water towers need data on ecosystem risk to business continuity. The path forward is to leverage emerging frameworks like nature-related financial disclosures to unlock blended finance.

4. Policy Domestication Over Policy Absence: Africa isn't lacking policy, but mechanisms to domesticate technology. Relevant policy frameworks exist, but there is a lack of mechanisms to adapt global tools to local contexts. The focus should be on creating ecosystems where the right tools, in the right hands, at the right time, drive action. This includes streamlining permitting processes and establishing joint research permits to reduce delays.

5. Data Governance and Custodianship: To build trust and enable sharing, a model that allows ownership to remain with the producer of the data while sharing custodianship with trusted entities was recommended. This separates data ownership (remaining with communities or collectors) from custodianship (trusted entities managing storage), ensuring access without compromising sovereignty.

# 6.7 Visioning the future of technology and data in biodiversity monitoring

Participants co-designed aspirational future ideas for technology-enabled biodiversity monitoring in East Africa. Outputs converged around the need for **technology that serves people and ecosystems through long-term people centred systems, not isolated tools**. One group visualized this as a "Smart Conservation Tree" (Figure 26), where healthy soil (capacity, funding, infrastructure) grows a strong trunk (interoperable data systems), bearing fruits of sustainability.

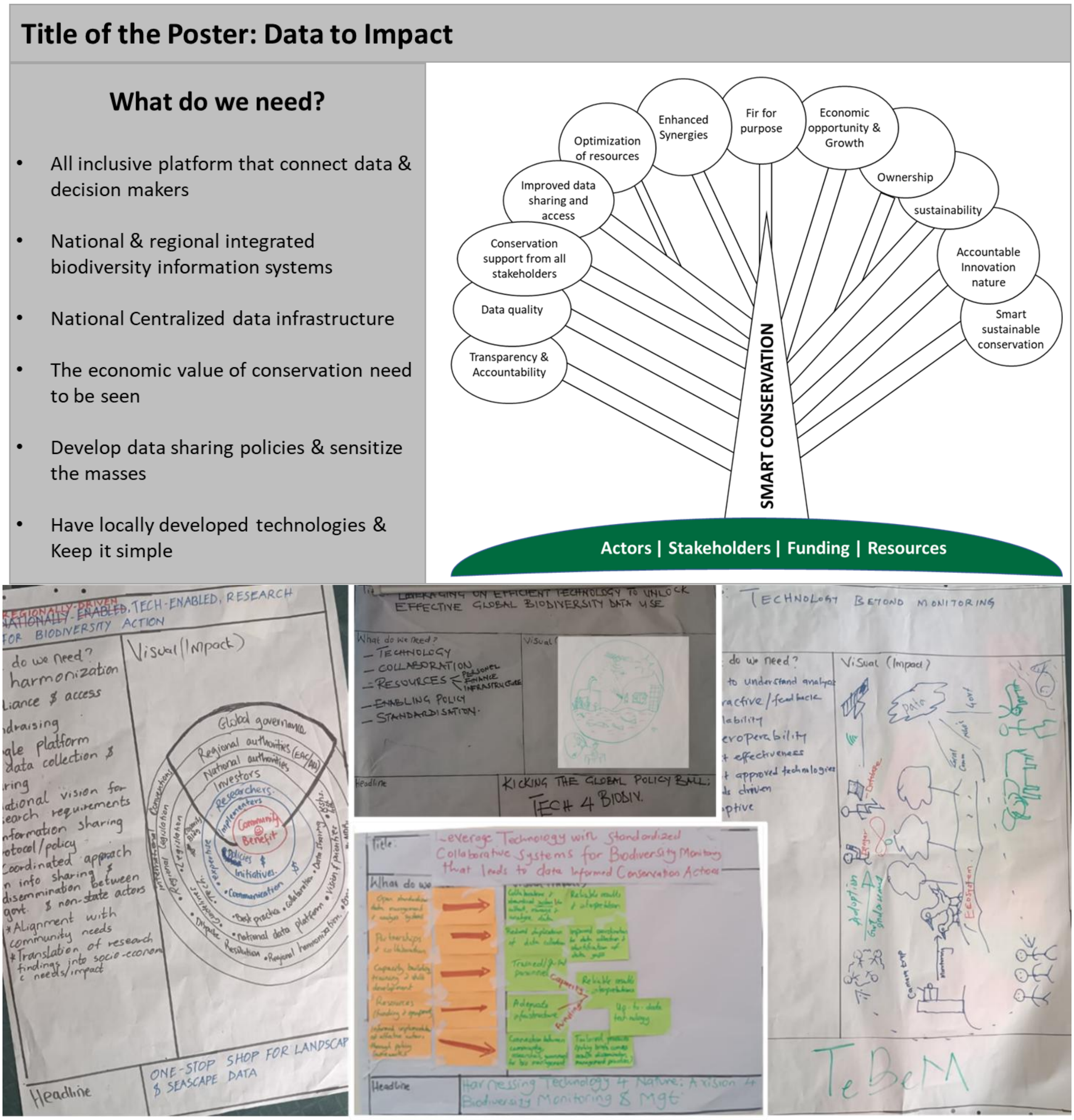



Figure 26 Visioning exercise outputs, including a ‘reconstructed’ "Smart Conservation Tree" (top), and the other ideas that the delegates co-created (bottom).

## Proposed visions ideas for Technology and Data in Biodiversity Monitoring in East Africa

Responding to the question, "*what does success look like for technology and data in biodiversity monitoring in East Africa*?", workshop participants came up with following four vision ideas:

| | |
|---|---|
| **"Smart Conservation" (Data to Impact)**<br><br>- Group 1 - | This group visualized the journey from data to impact as a tree: the "Smart Conservation Tree" rooted in actors, stakeholders, funding, and resources. Their vision centred on an inclusive data platform that connects data to decision-makers, with needs including: a regional integrated biodiversity information system; centralized data infrastructure shared across agencies; locally developed technologies that reflect indigenous and local knowledge; and stronger data-sharing policies. The sticky-note branches of the tree captured cross-cutting themes of sustainability, cross-sector collaboration, and community ownership. |
| **"Tech 4 Biodiv: Kicking the Global Policy Ball"**<br><br>- Group 2 - | This vision focused on leveraging efficient technology to unlock effective global biodiversity data use. Their visuals depicted a thriving landscape, forests, water, and wildlife, as the desired impact. Key needs identified were: technology, collaboration, resources (personnel, finance, infrastructure), enabling policy, and standardization. The headline message, "Kicking the Global Policy Ball" captured the ambition to use biodiversity data to actively drive global policy change rather than simply report to it. |
| **"One-Stop Shop for Landscape and Seascape Data"**<br><br>- Group 3 - | The group envisioned a community-enabled, tech-enabled research ecosystem for biodiversity action. Their visual used concentric rings radiating outward from community at the centre through researchers, national authorities, regional authorities, and global governance, all connected by communication, data platforms, and regional harmonization mechanisms. Key needs included: data harmonization and open access; a single integrated platform for data collection; a shared national vision for research requirements and data sharing; a coordinated multi-stakeholder approach linking government, NGOs, and non-state actors; alignment with community needs; and translation of research findings into actionable, context-relevant outcomes. |
| **"TeBioM: Technology Beyond Monitoring"**<br><br>- Group 4 - | This group pushed the vision beyond data collection towards technology as a driver of community empowerment and ecosystem stewardship. Their illustrated poster depicted people, animals, and landscapes connected through technology, with rangers, farmers, and researchers all participating in a shared monitoring and decision-making system. Key needs included: tools to understand and analyse data; interactive and feedback-ready interfaces; adaptability and effectiveness; locally appropriate and community-approved technologies; and inclusive, adaptive governance. The name "TeBioM" itself signals that the vision extends beyond monitoring into action, stewardship, and impact. |

The common threads that emerged across these visions were: the need for integrated, accessible data systems; community ownership and co-design; multi-stakeholder collaboration across local to global levels; and technology that goes beyond collection to drive decisions and action. These are synthesized in Table 18.

Table 18 Priority actions across Four Pillars

| Pillar | Priority Actions | Why It Matters |
|---|---|---|
| **Inclusive capacity** | Train "data translators"; shift from collection-only to interpretation; co-design tools with communities. | Prevents shelfware; ensures data informs decisions. |
| **Strengthened data hubs** | Harmonize national reporting into single dashboards; provide regional centres with sustainable core funding. | Ends duplication; enables cross-agency learning. |
| **Catalytic partnerships** | Engineer-science collaborations (e.g., sustainable robotics for environmental work); South-South Technology exchange (e.g., Tanzania eDNA → Uganda lakes); private sector engagement on ecosystem dependencies | Leverages global innovation centering on African contexts |
| **Diversified funding** | Fund infrastructure (libraries, repairs); finance maintenance not just pilots; package data for private sector value. | Ensures longevity beyond donor project cycles. |

# 6.8 Overall reflections from the workshop

Table 19 summarise six cross-cutting themes that consistently emerged from the workshop, all reflecting persistent challenges and opportunities in biodiversity monitoring technology adoption.

Table 19 Cross-Cutting Themes in Biodiversity Monitoring Technology Adoption

| Theme | Key Insights | Points of Agreement |
|---|---|---|
| Barriers to technology | Costs, import delays, infrastructure gaps, analytical capacity deficits. | Barriers extend beyond hardware. |
| Data access | Multiple incompatible platforms; lack of standardization; security concerns. | Need harmonized schemas with tiered access. |
| Capacity building | Training focuses on collection, neglecting interpretation. | Capacity must extend to analysis. |
| Policy/institutional issues | Absence of science-policy interfaces; conflicting policy mixes. | Need regular forums where researchers/policymakers co-design monitoring around policy questions. |
| Equity and inclusion | Representation gaps (women, Indigenous); knowledge extraction. | Communities must co-design tools- not just be end-users. |
| Sustainability and scaling | Pilot projects end when funding stops; tools become "shelfware." | Fund ecosystems (maintenance, training, benefit-sharing), not just pilots. |

# 7 GEDSI analysis

A Gender Equality, Disability and Social Inclusion (GEDSI) responsive approach is an important aspect to integrate into project planning, implementation, monitoring and evaluation. It allows societal contexts to be considered and facilitates projects and initiatives in delivering positive outcomes and in minimising unintended negative consequences for all involved or affected, as well as nature. Innovate 4 Nature follows guidance outlined by UK International Climate Finance (ICF) on delivering the project with a GEDSI responsive approach. Additionally, the project's GEDSI Action Plan has also been informed by guidance from the UK Foreign, Commonwealth & Development Office.

Women and Indigenous minorities are underrepresented within STEM professions and there are notable challenges faced by women in conservation careers that may impact their perceived barriers to and opportunities for increasing the uptake of biodiversity monitoring technology (James *et al.*, 2023; Cheryan *et al.*, 2025; Shrisunder *et al.*, 2025). By collecting data on participants' gender, age and Indigenous status, response data can be disaggregated to reveal patterns in how different demographic groups respond. This can aid in identifying common experiences and possibly highlight disparities not previously considered. This allows better understanding of how barriers for the uptake of biodiversity monitoring technology may be linked to GEDSI-related factors and how taking a GEDSI-responsive approach to addressing opportunities and interventions may support objectives to increase use and ease of access of such technology.

The GEDSI analysis carried out prior to inform the GEDSI Action plan (see Annexe 5), revealed remaining inequalities in the studied countries, highlighting who is most at risk of being left behind, with gender, poverty, education, disability, and digital access emerging as key intersecting factors. Gender inequalities in political representation continue to be substantial, limiting women's influence in decision-making. Intersecting factors such as disability, economic disadvantage, and Indigenous identity compound these inequalities and can worsen disadvantages in opportunity and participation. Here, we focus on

## 7.1 GEDSI representation

### 7.1.1 Questionnaire respondents

There was a higher representation of men amongst the questionnaire respondents (n = 62), with 68% men and 29% women. Most respondents reported no disability (n = 35, 56%), though all disability categories had at least some representation. 32% of respondents identified as Indigenous, while 55% did not. The remaining 13% either selected 'do not know' or 'prefer not to say'. This provides a reasonable level of Indigenous representation within the sample. These representations of different demographic groups differ slightly when responses are broken down by respondent category, such as technology users or data users, with some categories showcasing larger gaps in representation.

The imbalance of respondents making up the different GEDSI related groupings should be considered when interpreting the results, as the perspectives of men, non-disabled, and non-Indigenous participants make up the majority which may skew results. It is particularly important to keep this in mind when examining gender-disaggregated results, as the smaller cohort of women limits the strength of comparisons and may reduce the reliability of conclusions drawn about gender differences in responses. Given the relatively small overall sample size (n = 62), these restrictions are further amplified and should be acknowledged when interpreting any GEDSI category differences. However, qualitative insights gathered through interviews can help support and elaborate on the inferences drawn from the questionnaire data. Though a number of factors may contribute to the GEDSI imbalances within the sample, the lesser number of women, Indigenous respondents, and individuals reporting a disability represented in the sample of questionnaire respondents, likely reflects existing inequities in the area of biodiversity and conservation work, suggesting that these groups may already face barriers to participation that are represented in the sample.  Due to the small sample size, to ensure anonymity; this report does not detail proportions of responses given by different intersections (e.g. Indigenous women who are also 65+); however, it is noted that certain intersections are likely to face more disadvantage in within the STEM sector and with access to technology. This is also the case for the countries/regions that participants were responding from, due to unequal representation we do not disaggregate GEDSI groupings geographically.

### 7.1.2 Interview participants

Similarly to the questionnaire respondents, the interview participants (n = 56) also had a higher proportion of men (59%) compared to 39% women and the rest who selected ‘prefer not to say’. Conversely, at the interview stage there was a higher proportion of participants who identified as Indigenous with 62.5%, compared to 37.5% of participants who didn’t. The majority of participants identified as having no disability (68%) however there was representation within all the disability categories except difficulty with hearing. The majority of participants were aged between 25-34 years old but there was representation in all categories except 65+.

## 7.2 GEDSI analysis on the use of biodiversity monitoring technologies and data

As previously noted, the relatively small questionnaire sample size limits the reliability of GEDSI disaggregated findings. However, it remains important to analyse the data in this way alongside the interview results to identify any GEDSI-specific barriers or opportunities, for example, how gender or Indigenous identity may influence individuals’ use of biodiversity monitoring technology. Limited sample sizes or missing information prohibited the analysis of data in relation to geography, poverty, education or other factors that are likely to influence access and use of technologies. While questionnaire data relates to global findings, interview respondents were all from Kenya.

### 7.2.1 Gender-related findings

When asked about barriers to using or accessing biodiversity monitoring technology, there was slight difference between men and women’s responses. Most notably, a higher proportion of women (11% of n = 6) were more likely report the barrier ‘available technology is not suitable’, when compared to men 4.35% (n=16). Some common themes captured in the interviews on this topic describe technology not suited for the technical literacy of the user or for internet or electricity access available on sites. Considerations for gender in relation to tech literacy was also highlighted at the interview stage. Conversely, men were more likely to report ‘upfront costs’ as a key barrier with 26% (n=16) of responses from men compared to only 11% (n=6) of those from women. This pattern may be partly attributable to the underrepresentation of women in middle and senior management positions globally, especially those with responsibility for organisational resources (Stojmenovska, Steinmetz and Volker, 2021; Hanna et al., 2023). At the interview stage men also highlighted monetary reasons for barriers more than women however both upfront costs and the need for sustained investment were notably cited in both groups.

Amongst the questionnaire respondents, there was no clear difference in confidence levels with biodiversity data use between genders however, slightly more women self-reported their confidence level as ‘expert’ with 20% (n=10) of respondents compared to just 4.17% (n=24) of respondents. Within the cohort of respondents who addressed questions on biodiversity data use, a substantial gender disparity is evident. Consequently, the interpretation issues associated with gender-disaggregated data parallel those found in the cohort responding to questions on biodiversity monitoring technologies.

When asked about the barriers they face in accessing and using biodiversity data, men were more likely than women to identify ‘upfront cost’ as a barrier, with 15.89% (n=37) of men’s responses compared with 9.67% (n=14) of women’s responses. Men were also more likely to report ‘temporal resolution issues’; 7.48% compared with 2.44%. Conversely, women were more likely to indicate issues with data storage, with 9.76% of responses selecting this barrier compared with 1.87% of men. Women were also more likely to report ‘lack of time’ as a barrier, with 7.32% of responses compared with 2.8% from men. At the interview stage, the theme of concerns around data ownership and governance was highlighted more by the men who were interviewed than by women.

Amongst the questionnaire respondents, when asked about what interventions/improvements would help adoption or advance the use of biodiversity monitoring, women were more likely to select ‘technology that is more customised to my requirements’ with 11.11% (n=6) compared to 2.17% (n=16) of men’s responses. This corresponds to the higher tendency of women to report that the suitability of technology was a key barrier, as previously stated. At the interview stage, women more notably referenced a need for more training in biodiversity monitoring technology, quoting ‘capacity development’ and highlighting the need for training not just younger team members. Respondents in the youngest age group (25–34) were less likely than older age groups to select ‘technology that is easier to use’ as a priority intervention/improvement. This may reflect the broadly observed trend that younger generations generally have higher levels of digital fluency, due to increased exposure to technology from a young age in education and everyday scenarios. When discussing future opportunities for biodiversity monitoring technology and data use at the interview stage, women more frequently highlighted the importance of continuous data streams, whereas men more often emphasized the potential for expanded partnerships and collaboration.

### 7.2.2 Indigenous identity related findings

Questionnaire respondents who identified as Indigenous tended to report lower levels of self-assessed confidence compared with those who did not identify as Indigenous. Among Indigenous respondents (n = 12), 0% rated themselves as ‘expert’, and 50% identified as either ‘novice’ or ‘beginner’. In contrast, among non-Indigenous respondents (n = 10), 20% assessed themselves as ‘expert’, while only 10% identified as ‘beginner’ and none selected ‘novice’. However, the interview responses showed similar response in rates in both groups for citing ‘skills shortage’ as a barrier for the use of biodiversity monitoring technology. Additionally, Indigenous respondents were more likely to report ‘lack of access to technology’ as a barrier compared with non-Indigenous respondents, with rates of 23.53% (n=3) and 16.67% (n=2) respectively. Furthermore, Indigenous respondents were more likely to report ‘difficulty working with others’ as a barrier with 11% (n=12) in comparison to none of the 10 non-Indigenous respondents, who were more likely to report ‘cost of maintenance/repair’, ‘issues with computing infrastructure’, lack of integration with TIK’ and ‘available technology is not suitable’ as barriers. Both groups, however, significantly reported ‘upfront costs’ as a barrier that they face when accessing or using biodiversity monitoring technology which was similarly reflected in the interviews.

When disaggregating the response data on opportunities for interventions/improvements, respondents who identify as Indigenous were more likely to claim that ‘more training or technical support’ would support such improvements with 23.53% (n=12), compared to 6.67% (n=10). This observation is also reflected in the interview responses, where it emerged as a more prominent theme among Indigenous interviewees, particularly their emphasis on the need for training in data analysis, training delivered in local languages, and broader capacity building and empowerment. Conversely non-Indigenous respondents were more likely to select the response ‘technology that performs better (e.g. higher quality, more robust)’ 13.33% (n=10) when compared to Indigenous respondents’ responses, 5.88% (n=12). Furthermore, the non-Indigenous group were more likely to select ‘more affordable technology or components’, 23% compared to 11.76%. Interview responses from Indigenous interviewees reflected a stronger focus on integration of multiple data types and from difference sources, identifying this as a key future opportunity for advancing biodiversity monitoring technology and data use.

Disaggregating the data by Indigenous identity shows that ‘upfront cost’ was the most frequently reported barrier across both groups. Indigenous respondents were notably more likely to report challenges related to ‘lack of training/knowledge’ (15.38%, n=14) and data storage (10.26%), compared to 4.17% (n=32) and 2.08% respectively among non-Indigenous respondents. This is supported by the interview responses with the common theme of lack of resources notably highlighted by Indigenous participants, when compared to the non-Indigenous participants.

Respondents who identified as Indigenous were more likely to indicate that ‘improved access to data management and processing tools and software’ would help biodiversity data better meet their needs, with 17.95% (n=14) selecting this option compared with 10.47% (n=32) of non-Indigenous respondents. Conversely, non-Indigenous respondents were more likely to report that ‘additional data (i.e., the quantity of data currently available is insufficient)’ would be beneficial, accounting for 11.63% (n=32) of their responses, compared with only 2.56% (n=14) among Indigenous respondents.

A higher proportion of respondents who identified as Indigenous reported that TIK is ‘fully integrated’, with 22.22% (n=18) selecting this option compared with just 3.03% (n=33) of non-Indigenous respondents. However, the majority of non-Indigenous respondents still considered TIK to be ‘very integrated’. At the interview stage, integration of TIK into decision making was highlighted as by both groups when asked about future opportunities for technology and data, with reference to simplifying technology and involving communities with design as well as digitising TIK, and enhancing citizen science efforts.

When asked about the main challenges to including TIK into biodiversity monitoring, ‘Lack of access to TIK or data’ was the most common response from questionnaire respondents that identify as Indigenous with 23% of responses (n=18) whilst the most common response from those who do not as identify was ‘lack of collaboration with Indigenous communities’ accounting for 19.54% of responses. Indigenous respondents were more likely to be select ‘concerns or uncertainties over permissions, data ownership or ethics’ with 17.65% of responses listing this as a main challenge compared to just 11.49% of responses from non-Indigenous individuals. However, non-Indigenous respondents were more likely to select ‘unclear guidance/lack of guidance on how to include’ with 14.94% of responses compared with 9.8%, and ‘lack of policy frameworks’ with 10.34% compared with 5.88%, than Indigenous respondents. At the interview stage, interviewees noted several key considerations for incorporating TIK into biodiversity monitoring. They highlighted the importance of empowering Indigenous communities through access to appropriate technologies, involving them as co creators in the development and design of biodiversity monitoring technologies, and ensuring that they are accessible and delivered in local languages.

# 7.3 GEDSI considerations for interventions

While based on a small sample, the GEDSI-related patterns identified provide a foundation for informing the design of interventions that support more inclusive access to and use of biodiversity monitoring technologies and data, thereby strengthening overall effectiveness. Taking into account an increased digital literacy in younger age groups, training in both the use of technology and biodiversity data should be made encouraged in across age groups and stages in career to increase empowerment and technical skills across the whole workforce. Additionally access to training and resources for Indigenous communities should be increased in order to tackle disparities in confidence levels and technical capabilities with using technology and associated data. Such training should be made available in local languages and have a focus on increasing empowerment with both data collection and analysis. Accessibility of technology, data and data management tools amongst Indigenous individuals should also be addressed by increasing focus on co-development of tools and in local languages, to better incorporate and harness local knowledge in the design of technology. It is also important to account for the disadvantages experienced by women, ensuring their perspectives inform the design of technologies so that said tools are suitable for all genders. Collaborating with women’s groups to expand training opportunities in the use of biodiversity monitoring technologies and associated data can further support uptake, confidence, and empowerment.

# 8 Cross cutting findings

This section explores the cross-cutting findings from the rapid evidence assessment, questionnaire, interviews and workshop, broken down by current use and benefits of technology and future opportunities, followed by an analysis of the barriers, needs and proposed interventions and recommendations for each cross-cutting theme. All the information included in each section is taken directly from answers and statements made by participants, with recommendations made based of this information, combined with interpretation and experience of authors. We present a use case typology, which summarises the barriers and needs for each type of user group associated with biodiversity monitoring. Figure 27 shows the key challenges and solutions along the data to decision pipeline.

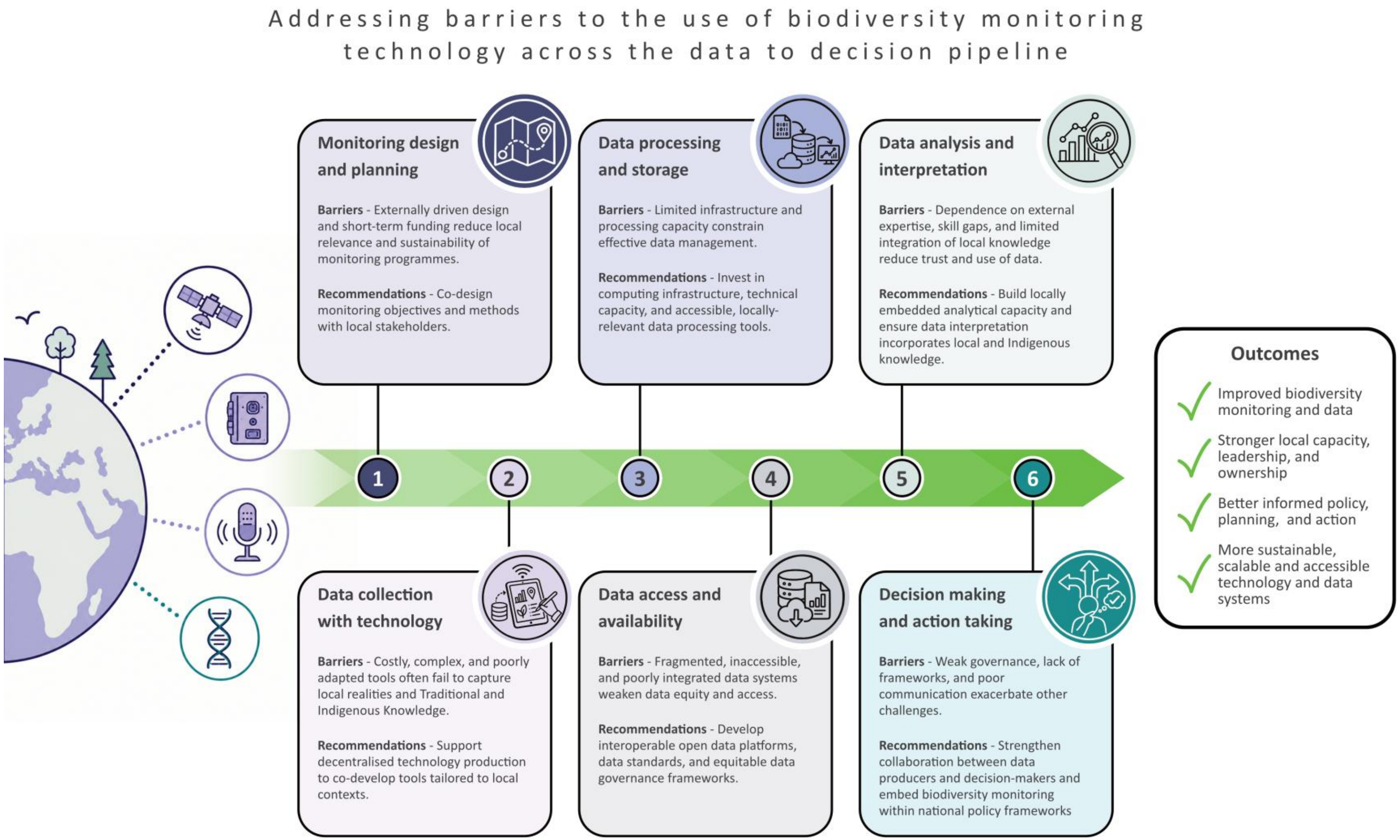



Figure 27 The key barriers along the data capture to decision making pipeline, as identified during the Innovate 4 Nature programme, and recommendations to overcome these challenges.

# 8.1 Current use of technology

A range of technologies applied to different aspects of biodiversity monitoring were captured in our evidence base. From the REA, it was clear that the number of articles reporting on technology use in LMICs has risen between 2010 to 2025, with a greater increase in more recent years. In a recent study that looked at global uptake of technology between 2000-2022, the largest increases were between 2000-2010, with small but insignificant increases since 2010 (Lawson *et al.*, 2025). This suggests that LMICs may have been behind in the uptake of technology. 81% of questionnaire participants thought demand for technology was increasing in their region, suggesting that these increases will continue over time.

By far the most popular technologies currently being used were GIS and remote sensing (REA- 41% and questionnaire- 46%), followed by camera traps (REA- 21% and questionnaire- 46%). Among workshop participants, GIS and remote sensing and camera traps were the 2nd and 3rd most popular technologies used. Mobile applications were the most popular technology used by workshop participants and third most common technology from the questionnaire respondents (32%). Mobile applications scored very low in the REA, possibly due to mobile applications being utilised in the field, but the data not being published in the academic literature. Interestingly, respondents from the questionnaire also highlighted GIS and remote sensing, camera traps and mobile applications as the most ‘ready’ technologies when assessing against the NASA readiness scores, with eDNA and AI being the least developed.

In their global survey, Speaker et al. (2022) found similar trends of technology usage, and perceptions of technologies were also similar in terms of eDNA being one of the lowest ranking technologies in terms of performance. This highlights this area as ripe for development to enable this monitoring technique to be fully utilised.

Land mammals were strongly represented across both the REA and questionnaire results, a pattern that is well documented in the literature (Clark and May, 2002; Di Marco *et al.*, 2017; Lawson *et al.*, 2025), More surprising was the strong representation of fish-based studies in the REA (14%), a trend also highlighted in the global 2000–2022 analysis, which reported a rapid increase in fish-focused research between 2020 and 2022 (Lawson *et al.*, 2025). Plant-based studies were also more prominent than expected, comprising 22% of the REA and 65% of questionnaire responses. This may help explain the high use of GIS and remote-sensing technologies in both datasets, suggesting that plants are frequently studied at landscape scales using satellite imagery rather than field-based methods.

# 8.2 Current benefits of technology

During interviews participants identified a wide range of current benefits associated with using technology for biodiversity monitoring. These benefits fall into three main themes:

1. Increased capacity and ability to collect and use data
2. Improved data quality
3. Resource savings

Overall, the most frequently cited benefits relate to how technology enhances data collection and enables the future use of collected data, rather than reducing costs or human labour. The limited emphasis on cost reduction is consistent with later findings that most participants believe additional funding is required for implementation. Similarly, the relatively low mention of reduced human effort may reflect a widely recognised need for training to ensure the effective adoption of new technologies.

### 8.2.1 Capacity and ability to collect and use data

This was the most widely recognised area of benefit, with three-quarters of participants citing some form of increased capacity. Key points included:

1. Ease and efficiency of data collection: 73% of participants from across community conservancies, NGOs, business, and government agencies, the groups most responsible for field data collection, stated that technology improved the ease and efficiency of data collection.
2. Better integration and reporting of data: Highlighted by almost half of participants (46%), this benefit was more commonly cited among researchers compared with community members.
3. Improved coverage, both spatial (30%) and temporal, (21%) were key.
4. Enhanced ability to use data:
    - To support better decision-making (20%)
    - Due to provision of continuous or real-time data streams (27%)
    - To apply and interpret data- These benefits were more frequently cited by government bodies, researchers, and NGOs, who are more actively using data at present.

### 8.2.2 Improved data quality

Participants across all user groups valued how technology can enhance the quality and reliability of biodiversity data. Key aspects included:

- Increased transparency and verification of measurements (32%)
- Reduction in bias (27%)
- Standardisation of monitoring methods (18%)

These benefits were most frequently mentioned by individuals in business/finance and research, suggesting these groups may prioritise data robustness for decision-making or reporting.

### 8.2.3 Resource savings

A smaller group of participants noted that technology can reduce resource requirements:

- Financial savings (11%)
- Human resource savings (7%)

These comments came mainly from groups involved in commissioning or delivering monitoring (e.g., government agencies), rather than those engaged in on-the-ground data collection such as community conservancies.

Of additional importance was the focus on technology as a complement, not a replacement: Several participants (11%) stressed that technology should support, not replace, traditional data collection methods. This reflects a desire for hybrid approaches that preserve local knowledge, cultural practices, and established workflows.

## 8.3 Future Opportunities

Participants identified a wide range of future opportunities related to both monitoring technologies and the data they generate. The percentages reported below reflect the proportion of interview participants who mentioned each opportunity. These opportunities cluster into two main areas:

1. Applications of data to real-world conservation challenges
2. Advances in data collection and integration

Overall, there is a strong emphasis on translating data into actionable conservation outcomes, alongside improved integration of multiple data sources and a shift towards continuous monitoring. Across both areas, artificial intelligence and financial mechanisms are emerging as key enabling factors. Below, we outline the major opportunities identified and the number of participants who highlighted each.

## 8.3.1 Applications of data to real-world problems

**Solving real-world conservation challenges- (45%)**

- Participants emphasised the ability of high-quality data in driving practical conservation, but only if we start applying technology and shift the focus from constant development.
- Most vocal groups: Research (100%), business/finance (100%), NGOs (100%) and government agencies (75%).

**Early-warning systems- (29%)**

- Participants highlighted the ability of technology to detect risk and ensure timely responses to ecological change.
- Most vocal groups: Government agency (75%), NGOs (80%) and business/finance (50%).

**Informing finance/investment frameworks (e.g., biodiversity credits)- (27%)**

- Participants discussed the positive impact of technology and the quality of data produced, which could feed into finance-ready metrics to support credits, disclosure, and investment decisions.
- Most vocal groups: Business/finance (100%), government agency (75%) and research (67%)

**AI for monitoring- (23%)**

- Participants highlighted the power of AI in processing big data, leading to more efficient monitoring and improved data outputs and decisions.
- Most vocal groups: Research (66%), government agency (50) and business/finance (50%).

**Linking biodiversity to socio-economic outcomes- (20%)**

- Participants emphasised the role of technology in supporting the pathway from improved biodiversity conservation to improve sustainable livelihoods.
- Most vocal groups: Business/finance (75%) and research (50%).

**Integrating traditional knowledge into decision-making- (14%)**

- Participants highlighted that, when combined, traditional knowledge and technology could be more powerful than alone, emphasising that TIK needs to hold high value in monitoring and decision making.
- Mentioned by community conservancies, government, research and NGOs.

**Technology for farmers**- **(7%)**

- Participants stated that technology could provide farm-level decision support and practical management tools.
- Most vocal groups: Business/finance (100%), government agency (75%) and research (67%)

### 8.3.2 Developments in data collection and integration

**Integration of multiple data types/sources- (50%)**

- This was the most mentioned future opportunity overall, with participants focusing on the potential for technology to improve interoperability and provide a unified evidence base.
- Most vocal groups: Research (100%), NGOs (100%), government agency (75%), business/finance (50%) and community conservancy (30%).

**Providing continuous data streams- (34%)**

- Participants highlighted that technology can provide real-time/high-frequency monitoring for faster insight and response.
- Most vocal groups: Research (100%), NGOs (80%) and government agency (75%)

**Landscape-level information- (34%)**

- Participants stated that technology can support spatially extensive monitoring and habitat-level insights.
- Most vocal groups: NGOs (100%), research (83%), government agency (75%) and business/finance (50%).

**Long-term trend data- (23%)**

- Participants stated that technology can produce long term data at wide temporal scales, to detect change and evaluate impact.
- Most vocal groups: Government agency (75%), research (68%) and NGO (60%).

**Partnerships/collaboration- (11%)**

- Highlighted by community conservancies as key if technology is to be an opportunity.

**Invasive species monitoring**- **(5%)**

- Participants stated that data from technology could provide timely data to support invasive species management.
- Mentioned by government, research, business/finance.

## 8.4 Technology: Quality, suitability, practicality, accessibility and cost

### 8.4.1 Barriers

**Technical quality and reliability**
Technical performance issues were a prominent barrier across all data sources. In the rapid evidence assessment (REA), 65% of articles reported technical challenges related to equipment quality, including in-field failures of technologies such as camera traps and poor microphone performance. Similarly, nearly a third (27%) of interview participants identified poor reliability as a key barrier to technology use, a concern shared across all user groups. Among questionnaire respondents who use monitoring data, 34% indicated that improvements in monitoring technologies would facilitate more effective data use, highlighting the downstream impacts of unreliable hardware.

**Ease of use and technological complexity**
Technology complexity emerged as a significant barrier for end users. In the questionnaire, 35% of participants reported that technologies were difficult to use, while only 22% reported that they were easy to use (with remaining responses neutral). Despite this, 56% indicated that the technologies met their needs, and only 30% reported that they did not, suggesting that users may tolerate complexity where perceived benefits exist. Interview participants reinforced this finding, with 23% identifying technological complexity as a key barrier, raised consistently across all user types.

**Access to technology**
Access to technology was widely identified as a challenge, particularly in the questionnaire and workshop data. Nearly half (47%) of questionnaire respondents reported that technology was difficult to access, with 57% selecting access as one of the most significant challenges, and only 26% stating that technology was easy to obtain. Workshop participants unanimously agreed that access was a major barrier, citing difficulties associated with procurement, high import fees, and lengthy delays, all of which constrain timely deployment. Only 11% of interview participants selected access as a key barrier, this could reflect the technologies used by these participants, the roles these participants hold, the organisations these participants worked for, or other factors

**Lack of alignment with local context**
A lack of contextual suitability further constrained effective technology use. 22% of questionnaire respondents reported that available technologies were not well suited to local environmental or socio-economic conditions. Interview participants highlighted infrastructure-related constraints as a major barrier, with 53.6% identifying inadequate network coverage or unreliable power supply as limiting technology use across user types. Workshop participants elaborated on this issue, noting that technologies are frequently developed and produced in higher-income countries, creating both access barriers and tools that are poorly adapted to local realities. Participants emphasised that such technologies often fail to align with local user needs, regulatory environments, and market conditions, limiting uptake, reducing the value of generated data, and contributing to suboptimal monitoring and conservation outcomes.

These concerns were echoed in free-text questionnaire responses, where participants cited difficulties using hardware and applications developed elsewhere that lack local contextual relevance. Workshop discussions further highlighted a perceived lack of mechanisms within East Africa to adapt or domesticate global tools for local use. Interview participants pointed to concrete consequences of this misalignment, including reduced effectiveness of technology for monitoring activities (20%), technologies that failed to improve upon existing manual methods (10.7%), and, in some cases, negative impacts on species behaviour.

**Cost and financial sustainability**
Cost emerged as a critical barrier across all sources. In the questionnaire, 65% of participants identified high upfront costs as a key challenge, while 35% cited the cost of repair and maintenance. The REA similarly identified costs related to equipment and supporting infrastructure as a barrier in 16% of articles. Workshop participants consistently reported that many technologies are currently unaffordable in practice. Interview findings aligned with this, with 43% of participants identifying cost as a key barrier and 36% highlighting the absence of sustained investment in technology and long-term monitoring as a major constraint. These cost-related barriers were consistently reported across all user groups.

Workshop participants emphasised that the value of technology lies in its sustained application rather than continual innovation. Participants noted that while many new tools are produced, relatively few are effectively implemented or maintained in the field, capturing this challenge succinctly with the statement: “It’s not innovation without implementation.”

### 8.4.2 Needs and Proposed Interventions

**Robust, practical, and easy-to-use technology**
Participants consistently emphasised the need for technology that performs reliably in local environments, is easy to use, and can operate under constrained conditions. 26% of questionnaire respondents highlighted the need for better-performing technology, while 12.5% of interview participants stressed the importance of tools that can function effectively in local environmental conditions. Workshop and interview participants further

noted that technologies must be simple, practical, and resilient, particularly in settings with limited infrastructure, intermittent power supply, and restricted connectivity. Ease of use was also identified as a major challenge by 26% of questionnaire respondents and 9% of interview participants, with overly complex systems presenting barriers to sustained adoption.

**Context-appropriate, customised, and scalable solutions**
Participants highlighted the need for technologies that are customised to specific user requirements and local contexts. 17% of questionnaire respondents reported a need for tools better aligned with their operational and monitoring needs, noting that generic solutions often fail to reflect local realities. Workshop and interview participants stressed that technologies and monitoring programmes should be co-designed with local scientists and communities from the outset, and adapted to local ecological, regulatory, and institutional contexts. At the same time, workshop participants emphasised that emerging technologies must be scalable at a global level, extending beyond higher-income countries to be applicable across diverse environments and capacities.

**Accessible tools, data infrastructure, and local support**
Accessibility emerged as a key concern across participants. Questionnaire respondents highlighted the need for access to a wider range of technological options (22%), improved data analysis tools (13%), and data storage solutions (9%). Participants noted that limitations in data infrastructure often undermine the value of collected data. Workshop and interview participants also stressed the importance of local production, adaptation, and repair of technology, or, at minimum, access to local technical support. 16% of interview participants identified local technical support as critical to successful implementation, with reliance on external parties (usually based in HICs) to carry out hardware repairs increasing costs and delaying data collection. Where local production is not possible, participants called for streamlined permitting processes and joint research permits to reduce barriers to deployment.

**Affordable, enduring technologies supported by long-term investment**
Affordability and sustainability were central themes. Nearly half of questionnaire respondents (48%) and 7% of interview participants identified the need for more affordable technologies, with workshop participants consistently prioritising affordability over technical sophistication. However, the most commonly selected intervention to better align technology with user needs was long-term monitoring funding (58%), highlighting that many challenges occur at the programme level rather than being technology-specific. Workshop participants stressed that investment should prioritise long-term monitoring, infrastructure, and sustained use, rather than short-term pilots. They further noted that technology success should be measured by enduring application and impact over time, rather than initial deployment metrics alone.

## 8.4.3 Recommendations

**Develop robust, field-ready, and context-appropriate technologies**
Technologies should be designed to be robust, durable, and fit for deployment in challenging field conditions, including harsh climates, unreliable power supply, and limited connectivity. Tools must be tested and validated under local operating conditions and comply with local regulatory requirements. Technologies that cannot function reliably in these environments should not be prioritised for deployment.

**Co-design technologies and monitoring programmes with end users**
Technologies and the monitoring programmes that use them should be co-designed with local scientists, practitioners, and communities from the outset. Solutions should be driven by local needs and use cases, rather than requiring end users to adapt their practices to the technology. Where appropriate, simplicity should be prioritised through intuitive interfaces and reduced technical and training burdens to support sustained use over time.

**Balance high-tech innovation with practical, low-tech solutions**
A balanced approach is needed between advanced technical solutions and technologies that are simple, practical, and affordable. Decision-making should prioritise fitness for purpose over technical sophistication, with greater consideration of the end user and operating environment. Open-source, low-cost, and adaptable tools should be developed alongside more complex technologies to support wider adoption and scalability.

**Decentralise technology production, maintenance, and repair**
Efforts should be made to decentralise technology production away from higher-income countries by supporting local or regional manufacturing, co-development, and adaptation of tools. Where local production is not feasible, technologies should be designed to be repairable locally, with access to spare parts, documentation, and training. Establishing local or regional technical support hubs could facilitate maintenance and repair. Where HIC based production and repair remain necessary, import and permitting processes should be streamlined to reduce costs, delays, and data gaps.

**Ensure affordability and support long-term investment**
Technologies must be affordable not only in terms of upfront costs, but also over the full lifecycle, including maintenance, replacement, data management, and supporting infrastructure. Investment should prioritise long-term monitoring and sustained deployment rather than short-term pilots. Local production, maintenance, and repair should be leveraged where possible to help reduce costs and improve financial sustainability.

**Invest in enabling local infrastructure**
For technologies to function reliably and deliver value, investment in enabling infrastructure is essential. This includes power supply, connectivity, data storage, and analysis capacity. Technology deployment should be aligned with realistic assessments of available infrastructure, and infrastructure development should be considered an integral part of monitoring and technology programmes.

# 8.5 Capacity development

## 8.5.1 Barriers

**Overview of capacity constraints**
Capacity-related challenges emerged as one of the most significant barriers to effective technology use in LMICs. In the rapid evidence assessment (REA), capacity constraints were the second most frequently cited barrier, identified in 24% of reviewed articles. These challenges cut across multiple stages of the technology lifecycle, from deployment and operation to data management and use.

Interviews further highlighted widespread skills shortages, with 62.5% of participants across community conservancies, research institutions, NGOs, government agencies, and the business and finance sector reporting gaps in local technical capacity. Key skills deficits included knowledge of how to deploy technologies within local communities, limited technical expertise to maintain and repair equipment, and insufficient capacity to analyse the data being collected. The lack of local maintenance and repair skills was frequently linked to technologies being produced and serviced in other countries (usually HICs), further exacerbating dependence on external expertise. Capacity-related barriers identified in the REA also included time and personnel constraints, as well as limited computational resources.

**Data processing and analysis constraints**
Constraints related to data processing and analysis were consistently raised. In the questionnaire, 39% of respondents reported lacking training or knowledge in how to use or interpret the data generated by technology, while 18% of interview participants highlighted insufficient technical capacity for data management and analysis. The REA similarly identified data processing challenges as a common issue, particularly the lack of specialist expertise required for tasks such as training and validating remote sensing data, and identifying species from acoustic and visual datasets. These constraints limit the ability of organisations to translate data into actionable insights.

**Data collection versus data use gaps**
While a lack of capacity was evident across both data collection and data use, workshop participants emphasised a pronounced imbalance between these two areas. Participants highlighted that training efforts are largely focused on data collection, with far less emphasis placed on data synthesis, interpretation, and application. This imbalance was attributed to data analysis often being conducted elsewhere, either at organisational headquarters or in other countries (usually HICs). Participants stressed that this separation has negative implications, including reduced local buy-in, trust, and understanding of the value of monitoring, particularly among communities involved in data generation. They further noted that when data producers are

disconnected from data use and decision-making, the likelihood of data informing conservation action is significantly diminished.

**Community participation and understanding**
Interviews with community conservancy representatives highlighted additional challenges related to community engagement and understanding of technology. Participants reported limited awareness of the purpose and value of new technologies, noting that communities are often introduced to tools as they evolve, without meaningful opportunities to contribute to their design or intended use. Instead, they described being expected to adopt technologies without adequate explanation, training, or feedback mechanisms. Participants emphasised that this lack of involvement undermines ownership and trust, and can contribute to low uptake, misuse, or eventual abandonment of technologies.

### 8.5.2 Needs and Proposed Interventions

**Expanded training across the data lifecycle**
Across all data sources, increased training emerged as the most commonly identified intervention to better align technology and data use with participant needs, cited by 48% of questionnaire respondents and 61% of interview participants. However, workshop discussions highlighted that training needs to extend beyond a narrow focus on technology operation and data collection. Participants emphasised the need for capacity building across the full data lifecycle, including data processing, interpretation, and application in decision-making. This was framed as a need to develop “data translators” and scientists, rather than only data collectors, to ensure that data generated through monitoring technologies is meaningfully used to inform management, policy, and conservation action.

**Locally and institutionally embedded capacity**
Workshop participants stressed the importance of embedding technical and analytical capacity within local institutions. Participants noted that when expertise exists internally, organisations are better able to sustain monitoring programmes independently once external funding or project support ends. This highlights the need for capacity-building approaches that prioritise local ownership and institutional resilience, rather than reliance on ongoing external expertise.

**Practical capacity and infrastructure needs**
Beyond training, participants identified practical constraints that limit effective technology use. Workshop participants stressed the need for increased staffing and improved infrastructure to support monitoring programmes, including computing resources, data management systems, and enabling infrastructure such as power and connectivity. Participants emphasised that without these foundational resources, training and technological tools alone are insufficient to address capacity gaps.

### 8.5.3 Recommendations to address capacity related challenges

**Strengthen end-to-end technical and analytical capacity**
A different approach to capacity building is required to ensure the effective use of technology and to deliver meaningful outcomes for conservation and people. Training should be designed to support the full technology and data lifecycle, from deployment and operation, through maintenance and repair, to data processing, analysis, interpretation, and decision-making, and must be responsive to the needs and priorities of practitioners and communities on the ground.

Local scientists and communities have articulated a strong desire to be involved across the full data cycle, rather than being positioned solely as data collectors. Training programmes should therefore include practical technical skills to maintain and repair equipment, alongside analytical skills that enable local actors to interpret and apply data in decision-making processes. Where technology is produced or adapted locally, this should be leveraged as an opportunity to naturally embed technical expertise and strengthen long-term capacity. Failure to integrate local actors into the full data and technology lifecycle risks undermining trust, ownership, and perceived benefits of monitoring activities. This, in turn, can reduce data uptake in decision-making and ultimately risk the sustainability and effectiveness of monitoring programmes.

**Embed capacity within local institutions**
Capacity development should prioritise embedding skills and expertise within local organisations and institutions. This reduces dependence on external funding and expertise, and supports long-term resilience and continuity of monitoring programmes beyond individual projects or funding cycles.

**Strengthen practical capacity alongside skills development**
Training alone is insufficient to address existing capacity gaps. As discussed in the technology section, there is a parallel need to strengthen practical capacity, including adequate staffing, access to appropriate infrastructure, and sufficient resources to support monitoring and data use. Long-term investment in enabling infrastructure, such as computing capacity, data management systems, and power and connectivity, is essential to ensure that skills development translates into effective and sustained technology use.

# 8.6 Data: Access, availability and ease of use

## 8.6.1 Barriers

**Access to data**
Limited access to data was a commonly reported barrier. In the questionnaire, 37% of respondents stated that data was difficult to access, with 25% of interview participants reporting similar challenges. In contrast, only 27% of questionnaire respondents indicated that data was easy to access. Nearly a third (31%) of questionnaire respondents also identified unpublished data and lack of digitisation and sharing as their primary challenge. Free-text questionnaire responses highlighted recurring access issues, including data being difficult to locate, distributed across multiple platforms, and data portals being challenging to navigate. Workshop participants echoed these concerns, noting that fragmented data systems significantly limit data discovery and use.

**Data relevance**
Data relevance was also a key constraint. Questionnaire respondents indicated that data did not meet their needs in terms of spatial coverage or resolution (27%), taxonomic coverage (25%), or temporal resolution (15%).16% of interview participants also reported that existing data were not fit for purpose or did not meet their needs, limiting their ability to use data effectively.

**Ease of use and data formats**
Challenges related to data usability were evident across sources. In the questionnaire, 19% of respondents reported that data was difficult to use, while most respondents neither agreed nor disagreed, and only 27% stated that data was easy to use. Interview participants reinforced this finding, with 23% citing data format as a key barrier, noting that outputs were often poorly structured, inconsistent, or incompatible with their analytical workflows.

**Technical and methodological constraints**
Respondents reported a range of technical barriers that limit data use. In the questionnaire, 22% cited limited or unreliable computing infrastructure as a constraint. Data storage limitations were also reported by 12% of questionnaire respondents and 10.7% of interview participants, while 9% of interview participants highlighted broader constraints related to limited technical resources.

**Trust and confidence in data quality**
Concerns about data quality and reliability were a significant barrier to data use. In the questionnaire, 20% of respondents identified uncertainty about data quality as a key challenge. This aligns with findings from the REA, where 65% of reviewed articles cited data quality issues as a primary limitation to effective data use. Participants noted that uncertainty around accuracy, validation, and methodological consistency reduces confidence in data and limits its application in decision-making.

**Data ownership and governance**
Data governance and ownership emerged as major concerns, particularly in interviews. Nearly half (43%) of interview participants expressed uncertainty about who owns, controls, and has the right to use biodiversity data. A further 25% identified poor data sharing practices and weak data management as key barriers to effective use. Workshop participants also raised equity concerns around who benefits from data, who has access, and who is excluded, noting that such uncertainties discourage data sharing and reuse.

**Cost and funding constraints**
Financial barriers further limit data use. In the questionnaire, 40% of respondents reported that the upfront costs associated with accessing and using data were a key challenge. Interview participants echoed this, with 19% reporting insufficient financial or material resources to support data management and analysis. These findings highlight that data accessibility is not only a technical issue but also a financial one.

**Limited alignment with local context**
Workshop participants emphasised that many data analysis tools are developed in other countries (usually HICs), which contributes to limited local capacity to use them, reduced understanding of their value, and ultimately low uptake. While not captured as a discrete category, free-text questionnaire responses included references from four participants to the poor performance of species-level classifiers, requiring extensive manual identification and reducing the efficiency and usefulness of data. The REA similarly highlighted the lack of comprehensive reference libraries for eDNA and genomic studies, a gap likely driven by the predominance of tools and classifiers developed for species and ecosystems outside LMIC contexts.

**Communication gaps and weak pathways to decision-making**
Interview participants highlighted communication barriers as a major limitation to data use. Over a third (37.5%) reported the absence of clear pathways linking data generation to decision-making, while the same proportion described fragmented or siloed working arrangements between organisations as a key constraint. These gaps limit the translation of data into actionable insights.

**Lack of integration and standardisation**
Finally, both interview and workshop participants, particularly from conservancies, stressed the importance of data integration and management tools. However, they highlighted incompatibility between tools and platforms as a major barrier to use. Workshop discussions further noted a lack of standardisation in data collection methods, analytical tools, and metrics across organisations. This results in outputs that are incompatible or not comparable, limiting opportunities for data synthesis and reducing the usefulness of data for decision-making at broader scales.

### 8.6.2 Needs and Proposed Interventions

**Improved access to data and analytical tools**
Respondents highlighted the need for improved access to both data and the tools required to manage and analyse it. In the questionnaire, 34% of respondents identified better access to data management and processing tools as a key need to support data use, while 30% highlighted access to currently available datasets as a priority. These findings reflect broader challenges related to fragmented data systems and difficulties locating and accessing relevant information.

**Additional and more representative data**
Respondents also identified significant gaps in the availability and scope of existing data. In the questionnaire, 50% of respondents reported that the data they required did not currently exist, citing a need to collect additional and different types of data, such as information on extent and quality. Workshop participants further emphasised the importance of long-term data collection to enable trend detection, early warning systems, and the identification of tipping points. They also highlighted that marine monitoring efforts lag behind terrestrial monitoring and require greater prioritisation.

**Data tools designed for local contexts**
Workshop participants stressed that data analysis tools should be developed in and for LMICs, rather than relying on tools produced elsewhere (most often in HICs) that often lack local relevance. Participants noted that locally appropriate tools would improve usability, build analytical capacity, and increase confidence in data outputs, ultimately supporting greater uptake and use.

**Improved data integration, standardisation, and sharing**
The need for better integration and sharing of data was a recurring theme. Workshop participants proposed the development of a national data platform to integrate datasets and improve accessibility. They suggested that tiered access models, for communities, public institutions, and private sector actors, could help address data sensitivity and security concerns. Participants also emphasised the importance of standardising data production, analytical methods, and metrics to ensure compatibility and comparability across organisations, thereby increasing the usefulness of data for decision-makers and improving outcomes.

**Clear data ownership and governance frameworks**
Stronger data governance was identified as a critical need. Workshop participants highlighted the importance of clear policies and processes to ensure that data is managed securely, accurately, and ethically. They also stressed the need for transparent and consistent data sharing policies to build trust, encourage collaboration, and enable wider use of data.

**Scaling emerging technologies for data analysis**
Workshop participants recognised the potential of emerging technologies, particularly artificial intelligence (AI), to reduce data processing times, increase spatial and temporal coverage, and extract insights from large and complex datasets. They emphasised that realising these benefits will require scaling AI tools for national-level use, supported by sustained funding and targeted training. Participants highlighted the need to develop expertise capable of interpreting and translating technical outputs into accessible and actionable information for diverse stakeholders.

**Strengthening local and regional data infrastructure**
Participants stressed the need to store and process data at national and regional levels rather than relying on external infrastructure. Workshop discussions highlighted that achieving this will require investment in local data storage, computing capacity, and supporting infrastructure to ensure data sovereignty, accessibility, and long-term sustainability.

**Improving pathways between data and decision-making**
Finally, respondents identified the need for stronger communication and coordination between data producers and decision-makers. Workshop participants called for inclusive platforms that connect data, analysts, and users, while interview participants emphasised the importance of partnerships and knowledge exchange (35.7%) and co-development approaches (20%) for successful data implementation. Participants suggested that embedding data analysts within government agencies and creating dedicated platforms linking data to decision-makers would significantly strengthen data-to-decision pathways.

## 8.6.3 Recommendations

**Establish national or regional biodiversity data platforms**
To address challenges related to fragmented, inaccessible, and hard-to-find data, national or regional biodiversity data platforms should be developed to consolidate datasets from multiple sources. A unified platform would improve data access and availability, reduce duplication, and enable users to more easily discover, integrate, and use data for decision-making.

**Invest in local data storage and processing infrastructure**
Reliance on other countries (usually HICs) for data storage and processing limits accessibility, trust, and sovereignty over data. Investment is required in national or regional data infrastructure, including local servers and processing capacity, to support secure storage, timely analysis, and sustained use of biodiversity data. Strengthening local infrastructure will increase resilience and reduce dependency on external systems.

**Standardise data formats, metadata, and analytical workflows**
Standardisation of data collection methods, metadata, processing, and analytical workflows is essential to ensure that datasets are compatible and comparable across organisations and regions. Improved standardisation will enable better data integration, increase confidence and trust in data quality, and enhance the uptake of data by decision-makers, ultimately leading to improved outcomes.

**Develop locally relevant taxonomic and ecological reference libraries**
Clear gaps exist in species-level classifiers and reference libraries for eDNA and genomic approaches. Developing country or region-specific taxonomic and ecological reference libraries is essential to improve analytical accuracy and relevance. This will require locally produced or adapted analysis tools, targeted training in data processing and analysis, and sustained support for local taxonomic expertise to ensure long-term viability and relevance.

**Prioritise closing data gaps through sustained data collection**
With 50% of questionnaire respondents reporting that the data required for decision-making does not currently exist, there is a need to prioritise data collection that addresses key gaps in ecosystem and taxonomic coverage, as well as spatial and temporal resolution. Data collection efforts should be guided by decision-making needs rather than opportunistic or short-term objectives.

**Invest in enduring, long-term monitoring systems**
Long-term monitoring should be prioritised over short-term or pilot initiatives. Sustained data collection enables the detection of trends, identification of tipping points, and development of early-warning systems, all of which are critical for evidence-based policy and conservation planning. Enduring monitoring systems also increase the long-term value and usability of collected data.

**Improve access to existing data analysis tools**
While it is not always feasible to develop bespoke tools for every country, globally produced data analysis tools remain essential. However, improved access is needed through increased support for open-access tools, funding to cover licensing costs where necessary, and targeted training to build local capacity for effective tool use. Improving access will ensure that existing tools can be meaningfully applied in local contexts.

**Establish clear national data governance frameworks**
Uncertainty around data ownership, sharing, and use continues to restrict data availability and limit its application in decision-making. National-level data governance policies are required to provide clarity on ownership, access rights, publication, and commercial use, while ensuring ethical and secure data management. Clear and transparent governance frameworks will build trust, encourage data sharing, and support wider data use.

**Strengthen communication pathways between data producers and decision-makers**
Effective use of data requires clear and sustained communication between those who generate data and those who use it. Mechanisms should be established to facilitate regular dialogue, including digital platforms that connect data producers, analysts, and decision-makers. Cross-sector collaboration should be encouraged to reduce siloed working, improve knowledge exchange, and ensure that data, tools, and lessons learned are shared and translated into action.

# 8.7 Decision making and policy

## 8.7.1 Barriers

**Poor Communication, Collaboration, and Policy Misalignment**
Challenges related to communication and collaboration between actors emerged as a significant barrier to using technology-generated data in decision-making. In the questionnaire, 21% of respondents identified difficulties related to communication and collaboration as a key challenge, while 18% highlighted challenges in coordinating with other groups or stakeholders when working with technology. Interview findings reinforced these concerns, with 37.5% of participants identifying both the absence of clear pathways or policies for applying data to decision-making and the prevalence of siloed or fragmented working arrangements as major barriers.

A clear disconnect between data collection and policy needs was evident in qualitative responses. Participants working within government and regulatory agencies highlighted limited alignment between the information generated through monitoring and the requirements of decision-makers. One data scientist noted that “there is still limited clarity around the information needs of decision-makers and policymakers,” while a project officer stated that “data collected is not made available by scientists, does not have explanation to understand the data and is not the data we need.” Workshop participants echoed these perspectives, stating that data produced through monitoring activities is often not seen, understood, or actively used by planners and decision-makers.

These communication challenges are compounded by broader governance and policy misalignment. Workshop participants described monitoring activities as being poorly integrated into regulatory and policy frameworks, with limited alignment between the expectations of those collecting data and those responsible for policy and planning. Participants further highlighted a lack of accountability for acting on monitoring findings, resulting in monitoring being treated as a compliance exercise rather than as a mechanism for learning, adaptive management, and improved outcomes. Together, weak communication, fragmented collaboration, and governance gaps significantly undermine effective data-to-decision pathways.

**Lack of standardisation and integration**
A lack of standardisation emerged as the most frequently cited challenge when respondents were asked specifically about using data to inform decision-making. Over 50% of questionnaire respondents identified the absence of standardised biodiversity data collection and reporting as a key barrier. Free-text responses suggested that this lack of standardisation leads directly to poor integration and limits the usability of data in policy contexts.

Integration challenges were further highlighted by 44% of respondents, who cited the absence of clear guidance or frameworks for integrating data as the main barrier to informing decision-making. Workshop participants expanded on these findings, explaining that organisations often use different data collection methods, tools, and analytical metrics, producing outputs that are incompatible or not comparable. This fragmentation significantly constrains the synthesis of evidence and limits the use of data at policy and planning scales.

**Funding constraints**
Insufficient funding was identified as a major barrier to the use of data in decision-making, with 44% of questionnaire respondents selecting lack of funding as their primary challenge. Participants noted that limited financial resources restrict opportunities for sustained monitoring, data analysis, synthesis, and engagement with decision-makers, thereby reducing the influence of data on policy and management decisions.

**Data quality and trust**
Concerns around data quality and trust were consistently identified as barriers to evidence-based decision-making. Nearly 20% of questionnaire respondents cited high uncertainty in data as their main challenge in using data, while 40% identified poor data quality as the key limitation to its use in decision-making. A further 12% reported that they did not trust the source of the data. Interview participants reinforced these findings, with 16% stating that available data did not support decision-making or guide action, mirrored by 9% of questionnaire respondents. These findings align with the REA, where 65% of reviewed articles identified data quality issues as a major barrier to effective use.

**Limited data sharing**
Challenges related to data sharing were frequently mentioned by both workshop participants and questionnaire respondents. Participants noted that organisations often do not collaborate on data sharing, with datasets stored across multiple, inaccessible locations and lacking formal mechanisms for exchange. These practices limit data visibility, reuse, and integration, reducing the potential for data to inform policy and decision-making.

**Complex and inaccessible data formats**
The format in which data is produced was also identified as a barrier. Workshop participants reported that data outputs are often complex and difficult to interpret, particularly for non-technical audiences. This was supported by interview findings, where 23% of participants identified data format as a key barrier to use. Several questionnaire respondents similarly selected data format issues as their primary challenge in using data to inform decision-making, highlighting the need for more accessible and decision-relevant outputs.

## 8.7.2 Needs and Proposed Interventions

**Improved access to existing data and additional data collection**
Respondents highlighted both access gaps and data shortfalls as key constraints on effective data use in decision making. In the questionnaire, 30% of respondents identified improved access to currently available data as a key need. However, many also reported that the data required to inform decisions does not yet exist, with 50% citing a need for additional data and different types of data, including improved information on extent and quality. Workshop participants reinforced this, emphasising the importance of sustained, long-term data collection to support early warning systems, detect trends, and identify tipping points that can inform proactive decision-making.

**Improved data integration and sharing mechanisms**
The need for better integration of data into decision-making processes was highlighted across respondents. Among questionnaire participants who use data for decision-making, 26% reported a need for support in integrating data into policy, planning, and management processes, while 18% of interview participants identified stronger policy support as a key requirement. Workshop participants proposed the development of a national data platform to integrate datasets and improve accessibility, suggesting that tiered access models for communities, public institutions, and private sector users could help address data sensitivity and security concerns. Participants also stressed the importance of standardising data production and use to ensure compatibility and comparability, enabling greater uptake by decision-makers and improved outcomes.

**Stronger connections between data producers and decision-makers**
Workshop participants expressed a clear need for more inclusive mechanisms that connect data producers directly with decision-makers. This was strongly supported by interview findings, where 70% of participants identified greater collaboration, through partnerships, knowledge exchange, or co-development of approaches, as a key requirement for the successful implementation of technology and data-informed decision-making. Participants emphasised that stronger relationships are essential to ensure that data outputs align with decision-making needs and are used in practice. Workshop participants also highlighted the value of embedding data analysts within government agencies and promoting co-production of knowledge and decision-support materials between communities, scientists, and policy actors. These approaches were seen as essential for building shared understanding, increasing trust, and ensuring that data is translated into actionable decisions.

**Clear governance frameworks and accountability mechanisms**
Finally, respondents highlighted the need for clearer governance and decision-making frameworks to ensure data informs action. Interview participants noted that successful implementation of monitoring technologies requires their integration into formal policy and regulatory frameworks (16%). Workshop participants further emphasised the importance of mandatory feedback loops, where decision-makers document how data is used to inform decisions. Such mechanisms were seen as necessary to move beyond data collection towards accountability for action and measurable outcomes.

## 8.7.3 Recommendations

Effective use of technology-generated data in decision-making is currently constrained by weak communication and collaboration between data producers and data users. Addressing this gap requires coordinated interventions that strengthen relationships, systems, and enabling frameworks across the data-to-decision pathway.

**Establish communication and collaboration platforms**
Dedicated platforms are needed to improve communication and coordination between researchers, communities, national and regional authorities, and policy actors. These platforms, whether digital, online, or in-person, should enable regular dialogue, knowledge exchange, and alignment on data needs, ensuring that data generated through monitoring is visible, understood, and usable by decision-makers.

**Promote interdisciplinary and embedded working models**
To strengthen collaboration and improve data usability, scientists and data analysts should be embedded within decision-making bodies, government agencies, or community governance structures. This approach can

facilitate knowledge exchange, co-production of decision-support materials, and translation of complex data into accessible formats, helping to overcome barriers related to technical complexity and limited understanding.

**Develop national data-sharing platforms for decision-making**
Decision-makers require improved access to currently available data. This should be supported through the development of national-level data platforms shared across agencies and sectors. Data presented through these platforms should be synthesised and formatted in ways that are accessible to non-scientists, enabling practical use in policy, planning, and management contexts.

**Improve data collection through coordinated planning**
Existing data gaps limit the ability of decision-makers to act effectively. Additional and targeted monitoring is therefore required; however, improved data collection must be guided by clear communication and collaboration between data producers and users. Official coordination mechanisms should ensure that monitoring priorities are aligned with decision-making needs from the outset.

**Standardise data collection, analysis, and reporting**
Standardisation of data collection methods, analytical approaches, and reporting formats is essential to produce outputs that are compatible and comparable across organisations. Greater standardisation will improve data quality, build trust in data outputs, and facilitate integration and use in decision-making processes at multiple scales.

**Ensure sustained funding for long-term data collection**
Data must be generated over sufficiently long timescales to be meaningful for decision-making. Sustained funding is required to support long-term monitoring, data management, and analysis, moving beyond short-term projects or pilots and enabling detection of trends, early warning signals, and policy-relevant insights.

**Build trust in data and data producers**
Lack of trust in data limits its use in decision-making. This may stem from issues such as inconsistent standards, limited training of data collectors or analysts, incomplete datasets, or insufficient transparency around methods. Strengthening standardisation, training, documentation, and communication around how data is collected and analysed will be essential to improving confidence and use. Further research may be needed to better understand the underlying drivers of distrust among data users.

**Strengthen governance frameworks and accountability mechanisms**
Policy and regulatory frameworks should be updated to explicitly support the use of technology and data in decision-making, removing barriers rather than inadvertently restricting use. Clear policies, procedures, and accountability mechanisms are required to mandate consideration of available data in decision-making processes, including feedback loops that document how evidence informs decisions and actions.

# 8.8 Socio-economic and community

## 8.8.1 Barriers

**Representation and inclusion**
Across the peer-reviewed literature, issues of representation remain evident. Almost a third (30%) of reviewed articles lacked a first or last author from an LMIC, indicating progress in inclusion, but also highlighting ongoing imbalances in knowledge production and leadership. Gender disparities are also apparent. In our study over two-thirds (68%) of questionnaire respondents identified as men, compared to 28% identifying as women. These patterns point to structural inequalities that may shape whose knowledge, priorities, and experiences are reflected in technology design and monitoring programmes.

**Integration of Traditional and Indigenous Knowledge (TIK)**
Levels of integration of Traditional and Indigenous Knowledge varied across respondents. In the questionnaire, 25% of participants reported that TIK was not integrated at all or only slightly integrated into biodiversity monitoring, while 43% stated that it was very or fully integrated. Only 3.6% of interview participants explicitly identified insufficient TIK integration as a barrier, suggesting variation in perceptions across contexts.

When respondents were asked about challenges to including TIK, the nature of barriers differed by identity. Among respondents identifying as Indigenous, the most commonly cited challenge was lack of access to relevant data (23%). In contrast, among non-Indigenous respondents, the most common challenge was lack of collaboration with Indigenous communities (19.5%). These findings highlight that barriers to TIK integration are as much institutional and relational as they are technical.

**Resistance to, or fear of technology**
Resistance to or fear of technology was raised by 12.5% of interview participants, primarily within community conservancy contexts. Participants suggested that unfamiliarity with technologies, limited training, and concerns over unintended consequences can create hesitation and reduce engagement with technological tools.

**Limited community involvement and perceived benefits**
Community involvement emerged as a recurring barrier to both technology use and data uptake. 20% of interview participants cited either limited understanding of the value of new technologies or lack of meaningful community involvement as key constraints. Within community conservancies, participants described a pattern of being repeatedly introduced to new technologies as tools rapidly evolve, without adequate explanation, continuity, or opportunities to influence their design or purpose.

Workshop participants reinforced these concerns, noting that technologies produced in higher-income countries are often introduced with expectations of community uptake, despite limited consultation with local communities. This lack of engagement was seen to limit relevance, ownership, and long-term use.

**Trust in technology and external actors**
Lack of trust was identified as an additional socio-economic barrier. 11% of interview participants discussed mistrust of technologies or of external organisations introducing them, a concern raised across most user groups except community conservancies. Participants suggested that mistrust can stem from limited transparency, unclear benefits, and past experiences where technologies failed to deliver promised outcomes.

**Marginalisation of community-generated data**
Workshop participants highlighted concerns that data collected by communities rarely feeds into national databases or policy processes. This disconnect was seen to contribute to misaligned incentives and limited socio-economic benefits, reducing motivation for sustained community engagement in monitoring activities.

**Data ownership and feedback gaps**
Participants also raised concerns around data ownership and feedback. Workshop discussions highlighted that local people and communities are often positioned solely as data collectors, with limited access to data outputs or insights derived from their efforts. The absence of feedback on how data is used or how it informs decisions was seen to undermine the perceived value of participation and limit the effectiveness of local conservation action.

### 8.8.2 Needs and Proposed Interventions

**Meaningful community involvement and buy-in**
Respondents consistently emphasised that addressing barriers to technology and data use requires more than technological innovation alone. Both questionnaire and interview participants highlighted the importance of involving local people and communities meaningfully in biodiversity monitoring. Workshop discussions stressed that monitoring programmes need to be co-developed with communities from the outset, with technologies designed *with* communities rather than for them.

Participants identified a need to empower community-based monitoring through formal recognition, sustained engagement, and clear feedback mechanisms that show how data contributes to decisions and outcomes. They emphasised that communities should not only participate in data collection but also shape monitoring objectives, tools, and processes. Given that socio-economic realities vary across regions and contexts, participants stressed that a one-size-fits-all approach is inappropriate, and monitoring tools must be adaptable to local needs and priorities.

**Clear and equitable data ownership arrangements**
Workshop participants highlighted the need for clarity and equity around data ownership. Communities expressed the need to retain ownership of the data they generate, with clear distinction between data ownership and data custodianship. Under this model, ownership would remain with communities or data collectors, while trusted institutions could act as custodians responsible for secure storage and management. This approach was seen as essential for ensuring access and use of data without compromising community sovereignty. Participants noted that community institutions that have been able to sustain monitoring independently demonstrate stronger ownership of both the project and the data, enhancing long-term resilience and impact.

**Integration of socio-economic, cultural, and biodiversity data**
Participants identified a need for technologies and monitoring approaches that better integrate socio-economic, cultural, and biodiversity data. Workshop participants suggested piloting multidimensional biodiversity indices that capture ecological trends alongside socio-economic data, cultural values, and ecosystem services. Such integrated approaches were seen as critical for producing evidence that is relevant to communities, decision-makers, and broader development goals, and for ensuring that monitoring reflects the full range of values associated with biodiversity.

**Integration of Traditional and Indigenous Knowledge (TIK)**
Workshop participants stressed that technologies and monitoring frameworks must be designed to integrate Traditional and Indigenous Knowledge, rather than requiring TIK systems to conform to technological structures. Participants emphasised that TIK should be recognised as a legitimate and valuable knowledge system within monitoring programmes, with technologies supporting its documentation, protection, and use in ways that are culturally appropriate and community-led.

## 8.8.3 Recommendations

**Invest in and reward community stewardship**
Conservation and biodiversity monitoring increasingly generate economic value, yet local communities who protect and manage critical ecosystems often receive limited benefits. Investment models should prioritise direct economic recognition and reward for communities undertaking stewardship and monitoring roles, rather than allowing value to accrue primarily to external or commercial actors. Valuing community contributions is essential for equity, long-term sustainability, and conservation success.

**Ensure meaningful community buy-in through co-design and participation**
Communities should be empowered, recognised, and actively involved throughout the design and implementation of monitoring technologies and data products. Rather than being treated solely as data collectors, community members should participate at every stage of the monitoring process, from defining objectives and selecting tools, to interpreting data and shaping decisions. This inclusive approach builds trust, enhances understanding of technology and data, reduces fear or resistance, and ultimately improves data quality, decision-making, and conservation outcomes.

**Establish clear pathways for community-generated data to inform action**
Clear and visible pathways are required to ensure that data produced by communities is used to inform management actions and decision-making. Without feedback on how data contributes to outcomes, communities are unlikely to see value in their contributions, undermining motivation and long-term programme viability. Mechanisms should be established to ensure community-generated data is integrated into planning, policy, and management processes, with timely feedback to data producers.

**Position technology as a complement to Traditional and Indigenous Knowledge (TIK)**
Traditional and Indigenous Knowledge should not be treated as an auxiliary component to technological monitoring. Instead, technologies should be designed and deployed as tools that complement and support TIK systems. Monitoring approaches should recognise TIK as a legitimate and valuable knowledge base, with technology enhancing documentation, transmission, and application in culturally appropriate and community-led ways.

**Integrate biodiversity, socio-economic, and cultural data**
Biodiversity data should not be treated in isolation from socio-economic and cultural information. Integrated

approaches are required to reflect the full range of values associated with ecosystems and to support decision-making that balances environmental, social, and economic objectives. Technology offers significant potential to facilitate the integration of these data types and should be leveraged to support more holistic and locally relevant monitoring frameworks.

**Establish equitable and enforceable data governance frameworks**
National-level, formalised data governance agreements are required to protect community rights and support ethical data use. These frameworks should clearly distinguish between data ownership and data custodianship, with ownership remaining with communities or data collectors and custodianship assigned to trusted institutions responsible for secure storage and management. This approach ensures accessibility and usability of data while safeguarding community sovereignty and building trust in monitoring systems.

# 8.9 Use case typology

This use case typology was developed to summarise the main barriers and needs for each user group associated with biodiversity monitoring, pulling evidence across the four evidence streams. As a summary, it captures only the overarching themes and should thus be interpreted with care.

Table 20 Summary of barriers and needs per use case.

| Use case category | Core purpose | Primary users | Barriers | Needs |
|---|---|---|---|---|
| **Data collection** | Generate primary biodiversity data | Communities, NGOs, researchers | • Cost of technology.<br>• Technology is hard to access.<br>• Technology is not location or user friendly.<br>• Data collectors are not involved in the technology design process.<br>• Technologies do not capture the data that is needed. | • Cheaper and more robust technologies.<br>• Technology better designed for local needs (power and network considerations; literacy level considerations).<br>• Local technology repair and maintenance options.<br>• Monitoring that is better connected to both local needs and decision-making needs. |
| **Data processing** | Convert data into usable information | Researchers, NGOs | • Cost of data processing tools.<br>• Lack of locally relevant resources (e.g. AI classifiers, DNA libraries).<br>• Computing infrastructure and data storage capacity.<br>• Lack of training for data processing.<br>• Fragmented, inaccessible, or incomplete datasets.<br>• Lack of standardisation in data collection processes.<br>• Dependence on external institutions for analysis. | • Investment in computing infrastructure.<br>• Locally relevant classifiers, reference libraries, and analytical software.<br>• Standardised data and metadata formats.<br>• Training in data management, analysis and interpretation.<br>• Improved communication with data collectors and decision makers. |
| **Decision making** | Use biodiversity data to inform decisions and actions | NGOs, policy makers, private sector | • Data needed is not available, hard to | • Clear data governance frameworks defining |

| | | | | |
|---|---|---|---|---|
| | | | access or expensive.<br>• Lack of standardisation and integration of different data sources.<br>• Lack of policy frameworks guiding data use.<br>• Lack training or knowledge to interpret data.<br>• Unclear data ownership.<br>• Weak coordination between data producers and users. | ownership, access, and ethical use..<br>• Standardisation and transparency across the data lifecycle.<br>• Improved communication with data collectors and processors.<br>• Frameworks to embed expertise within decision-making bodies. |
| **Local communities** | Live alongside biodiversity, may rely on biodiversity related resources. | Local communities, Indigenous Peoples | • Local communities are not involved in data production or decision making.<br>• Technologies designed without input.<br>• Technologies do not capture information needed.<br>• Challenges related to data sovereignty and governance. | • Co-designed technologies and involvement in biodiversity monitoring programmes.<br>• Training delivered in local languages.<br>• Clear benefit-sharing and ownership agreements.<br>• Monitoring systems that respect and integrate TIK.<br>• Accessible data outputs. |

# Annexe 1 REA searches

| Location | Location type | Search string | N. returns |
|---|---|---|---|
| WoS | Academic publication database | ("biodiversity monitoring" OR "ecological monitoring" OR "species monitoring" OR habitat assess*) AND (technolog* OR tool* OR device* OR sensor* OR "mobile phone" OR smartphone OR app OR "remote sensing" OR "geographic information system" OR GIS OR satellite OR drone* OR "unmanned aerial vehicle" OR UAV* OR camera* OR acoustic* OR "citizen science" OR eDNA OR biologger* OR telemetry OR "artificial intelligence" OR AI) AND (barrier* OR challenge* OR constraint* OR obstacle* OR limitation* OR solution* OR opportunit*) AND (Angola OR Benin OR "Burkina Faso" OR Burundi OR "Central African Republic" OR Chad OR Comoros OR "Democratic Republic of the Congo" OR Djibouti OR Eritrea OR Ethiopia OR Gambia OR Guinea OR "Guinea-Bissau" OR Lesotho OR Liberia OR Madagascar OR Malawi OR Mali OR Mauritania OR Mozambique OR Niger OR Rwanda OR "Saint Helena" OR "Sao Tome and Principe" OR Senegal OR "Sierra Leone") | 101 |
| WoS | Academic publication database | ("biodiversity monitoring" OR "ecological monitoring" OR "species monitoring" OR habitat assess*) AND (technolog* OR tool* OR device* OR sensor* OR "mobile phone" OR smartphone OR app OR "remote sensing" OR "geographic information system" OR GIS OR satellite OR drone* OR "unmanned aerial vehicle" OR UAV* OR camera* OR acoustic* OR "citizen science" OR eDNA OR biologger* OR telemetry OR "artificial intelligence" OR AI) AND (barrier* OR challenge* OR constraint* OR | 378 |

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|---|---|---|---|
| | | obstacle* OR limitation* OR solution* OR opportunit*) AND (Somalia OR "South Sudan" OR Sudan OR Tanzania OR Togo OR Uganda OR Zambia OR Algeria OR "Cabo Verde" OR Cameroon OR Congo OR "Côte d'Ivoire" OR Egypt OR Eswatini OR Ghana OR Kenya OR Morocco OR Nigeria OR Tunisia OR Zimbabwe OR Botswana OR "Equatorial Guinea" OR Gabon OR Libya OR Mauritius OR Namibia OR "South Africa" OR Africa) | |
| WoS | Academic publication database | ("biodiversity monitoring" OR "ecological monitoring" OR "species monitoring" OR habitat assess*) AND (technolog* OR tool* OR device* OR sensor* OR "mobile phone" OR smartphone OR app OR "remote sensing" OR "geographic information system" OR GIS OR satellite OR drone* OR "unmanned aerial vehicle" OR UAV* OR camera* OR acoustic* OR "citizen science" OR eDNA OR biologger* OR telemetry OR "artificial intelligence" OR AI) AND (barrier* OR challenge* OR constraint* OR obstacle* OR limitation* OR solution* OR opportunit*) AND (Afghanistan OR Bangladesh OR Cambodia OR "Lao People's Democratic Republic" OR Myanmar OR Nepal OR "Timor-Leste" OR Yemen OR "Democratic People's Republic of Korea" OR "Syrian Arab Republic" OR Bhutan OR India OR Iran OR Jordan OR Kyrgyzstan OR Lebanon OR Mongolia OR Pakistan OR Philippines OR "Sri Lanka" OR Tajikistan OR Uzbekistan OR "Viet Nam" OR Armenia OR Azerbaijan OR "China" OR Indonesia OR Iraq OR Kazakhstan OR Malaysia OR Maldives OR Thailand OR Turkmenistan OR "West Bank and Gaza Strip" OR Asia) | 986 |

| | | | |
|---|---|---|---|
| WoS | Academic publication database | ("biodiversity monitoring" OR "ecological monitoring" OR "species monitoring" OR habitat assess*) AND (technolog* OR tool* OR device* OR sensor* OR "mobile phone" OR smartphone OR app OR "remote sensing" OR "geographic information system" OR GIS OR satellite OR drone* OR "unmanned aerial vehicle" OR UAV* OR camera* OR acoustic* OR "citizen science" OR eDNA OR biologger* OR telemetry OR "artificial intelligence" OR AI) AND (barrier* OR challenge* OR constraint* OR obstacle* OR limitation* OR solution* OR opportunit*) AND (Haiti OR Bolivia OR Honduras OR Nicaragua OR Argentina OR Belize OR Brazil OR Colombia OR "Costa Rica" OR Cuba OR Dominica OR "Dominican Republic" OR Ecuador OR "El Salvador" OR Grenada OR Guatemala OR Guyana OR Jamaica OR Mexico OR Montserrat OR Panama OR Paraguay OR Peru OR "Saint Lucia" OR "Saint Vincent and the Grenadines" OR Suriname OR Venezuela OR "Latin America") | 449 |
| WoS | Academic publication database | ("biodiversity monitoring" OR "ecological monitoring" OR "species monitoring" OR habitat assess*) AND (technolog* OR tool* OR device* OR sensor* OR "mobile phone" OR smartphone OR app OR "remote sensing" OR "geographic information system" OR GIS OR satellite OR drone* OR "unmanned aerial vehicle" OR UAV* OR camera* OR acoustic* OR "citizen science" OR eDNA OR biologger* OR telemetry OR "artificial intelligence" OR AI) AND (barrier* OR challenge* OR constraint* OR obstacle* OR limitation* OR solution* OR opportunit*) AND (Kiribati OR "Solomon Islands" OR Tuvalu OR Micronesia OR "Papua New Guinea" OR Samoa OR Vanuatu OR Fiji OR "Marshall Islands" OR Nauru OR Palau OR Tonga OR Oceania) | 35 |

| | | | |
|---|---|---|---|
| WoS | Academic publication database | ("biodiversity monitoring" OR "ecological monitoring" OR "species monitoring" OR habitat assess*) AND (technolog* OR tool* OR device* OR sensor* OR "mobile phone" OR smartphone OR app OR "remote sensing" OR "geographic information system" OR GIS OR satellite OR drone* OR "unmanned aerial vehicle" OR UAV* OR camera* OR acoustic* OR "citizen science" OR eDNA OR biologger* OR telemetry OR "artificial intelligence" OR AI) AND (barrier* OR challenge* OR constraint* OR obstacle* OR limitation* OR solution* OR opportunit*) AND (Ukraine OR Albania OR Belarus OR "Bosnia and Herzegovina" OR Georgia OR Kosovo OR Moldova OR Montenegro OR "North Macedonia" OR Serbia OR Turkey) | 158 |
| Scopus | Academic publication database | (TITLE-ABS-KEY("biodiversity monitoring" OR "ecological monitoring" OR "species monitoring" OR "habitat assess*")) AND (TITLE-ABS-KEY(technolog* OR tool* OR device* OR sensor* OR "mobile phone" OR smartphone OR app OR "remote sensing" OR "geographic information system" OR GIS OR satellite OR drone* OR "unmanned aerial vehicle" OR UAV* OR camera* OR acoustic* OR "citizen science" OR eDNA OR biologger* OR telemetry OR "artificial intelligence" OR AI)) AND (TITLE-ABS-KEY(barrier* OR challenge* OR constraint* OR obstacle* OR limitation* OR solution* OR opportunit*)) AND (TITLE-ABS-KEY(angola OR benin OR "burkina faso" OR burundi OR "central african republic" OR chad OR comoros OR "democratic republic of the congo" OR djibouti OR eritrea OR ethiopia OR gambia OR guinea OR "guinea-bissau" OR lesotho OR liberia OR madagascar OR malawi OR mali OR mauritania OR mozambique OR niger OR rwanda OR "saint helena" OR "sao tome and principe" OR | 13 |

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|---|---|---|---|
| | | senegal OR "sierra leone")) AND PUBYEAR > 2009 AND PUBYEAR < 2026 | |
| Scopus | Academic publication database | (TITLE-ABS-KEY("biodiversity monitoring" OR "ecological monitoring" OR "species monitoring" OR "habitat assess*")) AND (TITLE-ABS-KEY(technolog* OR tool* OR device* OR sensor* OR "mobile phone" OR smartphone OR app OR "remote sensing" OR "geographic information system" OR GIS OR satellite OR drone* OR "unmanned aerial vehicle" OR UAV* OR camera* OR acoustic* OR "citizen science" OR eDNA OR biologger* OR telemetry OR "artificial intelligence" OR AI)) AND (TITLE-ABS-KEY(barrier* OR challenge* OR constraint* OR obstacle* OR limitation* OR solution* OR opportunit*)) AND (TITLE-ABS-KEY(Somalia OR "South Sudan" OR Sudan OR Tanzania OR Togo OR Uganda OR Zambia OR Algeria OR "Cabo Verde" OR Cameroon OR Congo OR "Côte d'Ivoire" OR Egypt OR Eswatini OR Ghana OR Kenya OR Morocco OR Nigeria OR Tunisia OR Zimbabwe OR Botswana OR "Equatorial Guinea" OR Gabon OR Libya OR Mauritius OR Namibia OR "South Africa" OR Africa)) AND PUBYEAR > 2009 AND PUBYEAR < 2026 | 49 |

| | | | |
|---|---|---|---|
| Scopus | Academic publication database | (TITLE-ABS-KEY("biodiversity monitoring" OR "ecological monitoring" OR "species monitoring" OR "habitat assess*")) AND (TITLE-ABS-KEY(technolog* OR tool* OR device* OR sensor* OR "mobile phone" OR smartphone OR app OR "remote sensing" OR "geographic information system" OR GIS OR satellite OR drone* OR "unmanned aerial vehicle" OR UAV* OR camera* OR acoustic* OR "citizen science" OR eDNA OR biologger* OR telemetry OR "artificial intelligence" OR AI)) AND (TITLE-ABS-KEY(barrier* OR challenge* OR constraint* OR obstacle* OR limitation* OR solution* OR opportunit*)) AND (TITLE-ABS-KEY(Afghanistan OR Bangladesh OR Cambodia OR "Lao People's Democratic Republic" OR Myanmar OR Nepal OR "Timor-Leste" OR Yemen OR "Democratic People's Republic of Korea" OR "Syrian Arab Republic" OR Bhutan OR India OR Iran OR Jordan OR Kyrgyzstan OR Lebanon OR Mongolia OR Pakistan OR Philippines OR "Sri Lanka" OR Tajikistan OR Uzbekistan OR "Viet Nam" OR Armenia OR Azerbaijan OR "China" OR Indonesia OR Iraq OR Kazakhstan OR Malaysia OR Maldives OR Thailand OR Turkmenistan OR "West Bank and Gaza Strip" OR Asia)) AND PUBYEAR > 2009 AND PUBYEAR < 2026 | 163 |
| Scopus | Academic publication database | (TITLE-ABS-KEY("biodiversity monitoring" OR "ecological monitoring" OR "species monitoring" OR "habitat assess*")) AND (TITLE-ABS-KEY(technolog* OR tool* OR device* OR sensor* OR "mobile phone" OR smartphone OR app OR "remote sensing" OR "geographic information system" OR GIS OR satellite OR drone* OR "unmanned aerial vehicle" OR UAV* OR camera* OR acoustic* OR "citizen science" OR eDNA OR biologger* OR telemetry OR "artificial intelligence" OR AI)) AND (TITLE-ABS-KEY(barrier* OR | 28 |

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|---|---|---|---|
| | | challenge* OR constraint* OR obstacle* OR limitation* OR solution* OR opportunit*)) AND (TITLE-ABS-KEY(Haiti OR Bolivia OR Honduras OR Nicaragua OR Argentina OR Belize OR Brazil OR Colombia OR "Costa Rica" OR Cuba OR Dominica OR "Dominican Republic" OR Ecuador OR "El Salvador" OR Grenada OR Guatemala OR Guyana OR Jamaica OR Mexico OR Montserrat OR Panama OR Paraguay OR Peru OR "Saint Lucia" OR "Saint Vincent and the Grenadines" OR Suriname OR Venezuela OR "Latin America")) AND PUBYEAR > 2009 AND PUBYEAR < 2026 | |
| Scopus | Academic publication database | (TITLE-ABS-KEY("biodiversity monitoring" OR "ecological monitoring" OR "species monitoring" OR "habitat assess*")) AND (TITLE-ABS-KEY(technolog* OR tool* OR device* OR sensor* OR "mobile phone" OR smartphone OR app OR "remote sensing" OR "geographic information system" OR GIS OR satellite OR drone* OR "unmanned aerial vehicle" OR UAV* OR camera* OR acoustic* OR "citizen science" OR eDNA OR biologger* OR telemetry OR "artificial intelligence" OR AI)) AND (TITLE-ABS-KEY(barrier* OR challenge* OR constraint* OR obstacle* OR limitation* OR solution* OR opportunit*)) AND (TITLE-ABS-KEY(Kiribati OR "Solomon Islands" OR Tuvalu OR Micronesia OR "Papua New Guinea" OR Samoa OR Vanuatu OR Fiji OR "Marshall Islands" OR Nauru OR Palau OR Tonga OR Oceania)) AND PUBYEAR > 2009 AND PUBYEAR < 2026 | 3 |
| Scopus | Academic publication database | (TITLE-ABS-KEY("biodiversity monitoring" OR "ecological monitoring" OR "species monitoring" OR "habitat assess*")) AND (TITLE-ABS-KEY(technolog* OR tool* OR device* OR sensor* OR "mobile phone" OR smartphone OR app OR "remote sensing" OR "geographic information system" OR GIS OR | 8 |

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|---|---|---|---|
| | | satellite OR drone* OR "unmanned aerial vehicle" OR UAV* OR camera* OR acoustic* OR "citizen science" OR eDNA OR biologger* OR telemetry OR "artificial intelligence" OR AI)) AND (TITLE-ABS-KEY(barrier* OR challenge* OR constraint* OR obstacle* OR limitation* OR solution* OR opportunit*)) AND (TITLE-ABS-KEY(Ukraine OR Albania OR Belarus OR "Bosnia and Herzegovina" OR Georgia OR Kosovo OR Moldova OR Montenegro OR "North Macedonia" OR Serbia OR Turkey)) AND PUBYEAR > 2009 AND PUBYEAR < 2026 | |
| DevTracker | FCDO programme database | biodiversity monitoring | 39 |
| UNEP-WCMC | Search page for UNEP-WCMC resources | biodiversity monitoring [filter = peer-reviewed paper or report] | 42 |
| Fauna & Flora | Search page for research | filter = Document theme: Technology | 14 |
| WCS | Search page for research publications | Topic = Technology; year from 2010 to 2025 | 111 |

# Annexe 2 Copy of the questionnaire

**Title of Project:** *Innovate 4 Nature*

**Introduction**

We would like to invite you to take part in a research study. Joining the study is voluntary and your decision. The next two pages will explain why the research is being done and what taking part would involve. Please ask questions if anything is not clear or you would like more information. Please feel free to talk to others about the study if you wish. Take time to decide whether to take part. This questionnaire will be open until **8th December 2025**, please submit your response before then if you wish to take part.

**What is the purpose of the study?**

This research is being run by the UK Centre for Ecology & Hydrology (UKCEH) and funded by Defra. Defra is the UK government's Department for Environment, Food and Rural Affairs. Defra is responsible for improving and protecting the environment and aims to grow a green economy and sustain thriving rural communities. Defra also supports the UK's food, farming and fishing industries.

This study is called Innovate 4 Nature. We want to learn more about using technology and data to help monitor biodiversity in low- and middle-income countries. **Monitoring biodiversity** means **regularly checking and keeping track of the different types of animals, plants, and other living things in a certain area**. This could include counting numbers and species of insects on a farm, or tracking changes of forest cover from satellite imagery.

We'd like to hear from people who do any of the following:

- Live near, rely on, or work with nature or natural resources
- Have Indigenous or community land rights
- Work in biodiversity conservation or research
- Use environmental data for business, policy, or funding decisions

What you tell us will help guide future funding and programme development to help make biodiversity monitoring technology easier to use and more useful.

**Why have I been asked/offered the opportunity to take part?**

We're asking people from different backgrounds and roles to share their views and experiences.

You don't need to use any technology now, we still want to hear from you. We want to know how better tools or data might help you in your work or community.

**What will I have to do to take part?**

This questionnaire involves answering a series of questions about your opinions and experiences with biodiversity and the environment, monitoring, technology, and data. Some of the questions need yes/no answers, some ask you to rate how much you agree or disagree with a statement, others ask for more information. All questions are optional. This questionnaire is currently in English, if you need it in a different language then please contact us: laubra@ceh.ac.uk. **The questionnaire should take 20-30 minutes to complete.**

**What are the possible risks and disadvantages?**

We do not believe there are any risks or disadvantages to taking part. You do not need to give your name and contact information. If you do these will only be used to contact you in regard to this questionnaire. Only the project team will be able to access the answers you give in this questionnaire. We will not use your name in any reports or publications.

**What are the possible benefits?**

You may not directly benefit, but the information we get from the study will help our knowledge and understanding of how to improve monitoring of ecosystems and biodiversity in lower- and middle-income countries. We hope that this could lead to more effective conservation strategies, better-informed policy decisions and stronger support for local communities in biodiversity-rich areas. The results of the questionnaire will be shared in early 2026, you can sign up to the mailing list at the end of this form.

**What if something goes wrong?**
If you have a concern, please speak to the research team. The main point of contact is Laura Braunholtz (laubra@ceh.ac.uk).
If you're still not happy and wish to complain formally, you can do this by contacting the UK Research Ethics Committee ukcehresearchethics@ceh.ac.uk or the project PI Jenna Lawson (jenlaw@ceh.ac.uk).
If you have a safeguarding concern to report you can contact the dedicated safeguarding email address safeguarding@ceh.ac.uk.
**Can I change my mind about taking part?**
You can stop taking part at any time. Your answers will not be recorded until you click 'submit' at the end of the questionnaire.
You will have the option to enter a personal identifier at the start of the questionnaire. This could be a word that is meaningful and memorable to you. You will need to keep this for your own records, and supply this to have your answers deleted. If you want to delete your answers after you submit them, you need to contact Laura Braunholtz (laubra@ceh.ac.uk), we will delete the anonymised data associated with your individual personal identifier.
If you choose not to enter a personal identifier as part of the questionnaire, your questionnaire responses will not be linked to any personal information, and it will not be possible to identify your data or delete it once it has been submitted. If your answers have already been used in the analysis, we won't be able to remove them.
**What will happen to the information/data collected?**
Your data will be handled securely and confidentially. If you choose to supply them, your personal details, meaning your name and contact information, will be stored securely in a password protected folder separately to the other study information. Your answers to the questionnaire will be stored securely following UK General Data Protection Regulation (UK GDPR) and only the research team can access your full data. This data will be securely stored by UKCEH for 2 years from the end of the study and then securely deleted (in March 2028).
Your responses to the interview questions will be anonymous, meaning no personally identifiable information will be included in any publications, reports, or shared data. If your answers could be
linked back to you because very few people share your background or job, we won't publish that information.
The data will be analysed by the research team at UKCEH to identify key themes, opportunities, and challenges in the use of biodiversity monitoring technologies and data. The results will be shared as a report with Defra and may be published in peer-reviewed articles.
**Who is organising and funding this study?**
Defra is funding this research project. UKCEH is the overall project lead for the research, and we have full responsibility for the project including the collection, storage and analysis of your data, and will act as the Data Controller for the study. This means that we are responsible for looking after your information and using it properly.
**Who has reviewed this study?**
An independent group of people, called a Research Ethics Committee, checked the study. They made sure it protects your rights and interests. This study has been reviewed and approved by UK Centre for Ecology & Hydrology Human Research Ethics Committee (UKCEH-HREC).
**Further information and contact details**
Thank you for reading this. If you agree to take part in the research, please tick the box below.
If you would like any further information, please contact Laura Braunholtz who can answer any questions you may have about the study.
Contact details:
Dr Laura Braunholtz
laubra@ceh.ac.uk

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1. Please confirm the following two statements:*

☐ I confirm that I have read and understood the information about the Innovate 4 Nature research project.

☐ I agree to take part in this research project.

* indicates the question requires a response.

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2. Which of the following statements best describes you? *

☐ I am involved in collecting biodiversity data [*Go to Section 1*]

☐ I am involved in the use of biodiversity data (*including in research, decision making, funding*) [*Go to Section 2*]

☐ I don’t collect or use biodiversity data, but I am (or I represent) a community member interested in information about my local environment [*Go to Section 5*]

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**Section 1: Technologies for biodiversity monitoring**
**Part 1: Background on biodiversity monitoring**
3. What type of biodiversity data are you collecting? *Select all that are appropriate.**
*We are using categories as set out in Essential Biodiversity Variables (EBVs) https://geobon.org/ebvs/what-are-ebvs/*
☐ Species traits (e.g. body mass, migration patterns, flowering dates)
☐ Species populations (e.g. species distributions, species abundances)
☐ Genetic composition (e.g. genetic diversity, genetic markers)
☐Community composition (e.g. community abundance, species richness)
☐ Ecosystem structure (e.g. tree density, woodland area, 3D mapping of habitats)
☐ Ecosystem functioning (e.g. pollination rates, soil nutrient levels, plant biomass)
☐ Other, please specify: Click or tap here to enter text.
4. What is the taxonomic focus of the biodiversity data you collect? *Select all that are appropriate.**
☐ Amphibians and reptiles
☐ Bacteria and Archaea
☐ Bats
☐ Birds
☐ Fish
☐ Freshwater invertebrates
☐ Fungi and protists
☐ Land mammals
☐ Marine invertebrates
☐ Marine mammals
☐ Plants
☐ Terrestrial invertebrates
☐ No taxonomic focus
5. What is the habitat focus of the biodiversity data you collect? *Select all that are appropriate.**
☐ Forest
☐ Savanna
☐ Shrubland
☐ Grassland
☐ Wetlands
☐ Rocky areas (e.g., inland cliffs, mountain peaks)
☐ Caves & subterranean habitats
☐ Desert
☐ Polar
☐ Marine
☐ Human-modified (including agriculture and urban areas)
☐ No habitat focus
6. Please add any additional details about your study focus:
Click or tap here to enter text.
7. At what scale do you monitor biodiversity? *Select all that are appropriate.**
☐ Multinational
☐ National
☐ Sub-national
☐ Study site
☐ Other, please specify: Click or tap here to enter text.
8. In which country or countries do you monitor biodiversity? *Enter up to **3** countries:**
Click or tap here to enter text.

9. What types of technology are you using to collect biodiversity data? *Select up to **3** you use the most.**
☐ Camera traps
☐ Acoustic devices
☐ Biologgers/tracking devices
☐ UAVs/drones
☐ eDNA/genomics
☐ Mobile applications (incl. on smart phones, tablets, e.g. citizen science apps)
☐ Machine learning/AI (e.g. for identification of species from images or sounds)
☐ Protected area management systems (e.g. SMART, EarthRanger)
☐ GIS/remote sensing (satellite, multispectral, and thermal imagery; LiDAR)
☐ Other, please specify: Click or tap here to enter text.
☐ I'm not using technology
10. How confident are you with the biodiversity monitoring technology you use?*
☐ Novice *I follow rules or guidance to use technology*
☐ Beginner *I can perform basic tasks with technology independently, but still rely on guidance*
☐ Average *I can confidently carry out tasks with technology*
☐ Advanced *I can adapt the technology for different contexts and anticipate challenges*
☐ Expert *I use technology intuitively, I can innovate new solutions, I guide others in best practices*
☐ Not applicable - *I don't use technology*
**Part 2: Current status of biodiversity monitoring technologies**
11. How easy is it for you to **access** the technology you use most often for biodiversity monitoring? *By ease of access we include finding and purchasing or borrowing the technology you need**
☐ Very easy
☐ Easy
☐ Neither easy nor difficult
☐ Difficult
☐ Very difficult
☐ I don't know
12. How easy is it for you to **use** the technology you use most often for biodiversity monitoring? *By ease of use we include deploying and maintaining the technology in the field**
☐ Very easy
☐ Easy
☐ Neither easy nor difficult
☐ Difficult
☐ Very difficult
☐ I don't know
13. To what extent do you agree with the statement "The biodiversity monitoring technology that is available to me meets my needs"? *By meeting your needs we include the extent to which the technology allows you to collect the data or to complete the tasks you need to**
☐ Strongly agree
☐ Agree
☐ Neither agree nor disagree
☐ Disagree
☐ Strongly disagree
☐ I don't know
14. What barriers do you currently face when **accessing and using**, or attempting to use, biodiversity monitoring technology*? Please **select the 3 greatest** challenges you face.**
☐ Lack of access to technology (devices or components not available to purchase in-country or not available to import)
☐ Upfront cost of technology or software
☐ Cost of maintenance/repair of technology
☐ Available technology is not suitable for local environment

☐ Available technology performance is not good enough (e.g. quality, robustness)
☐ Lack of training or technical knowledge
☐ Language barriers (interface or guides not in your language)
☐ Lack of time to stay up to date with tools/approaches
☐ Limited storage capacity for volume of data
☐ Limited or unreliable computing infrastructure (e.g. unstable power supply, slow internet, outdated computing hardware)
☐ Ethical concerns about surveillance and monitoring
☐ Difficulty coordinating with other groups or stakeholders
☐ Technology does not support or integrate Traditional and Indigenous knowledge
☐ Other, please specify: Click or tap here to enter text.
15. Could you give more information about the barriers you currently face in accessing and/or using biodiversity monitoring technology:
Click or tap here to enter text.
**Part 3: Opportunities in biodiversity monitoring technologies**
16. What interventions or improvements would help you adopt biodiversity monitoring technology or advance their use? *Please select the **3** most important to you.**
☐ Greater access to a range of technology options
☐ More affordable technology or components
☐ Technology that is easier to use
☐ Technology that performs better (e.g. higher quality, more robust)
☐ Technology that is more customised to my requirements
☐ More training or technical support
☐ Access to standardised methods
☐ Improved information sharing or collaboration platforms
☐ Support for long-term monitoring (e.g., funding, staff)
☐ Improved access to data storage
☐ Improved computing infrastructure
☐ Improved access to data analysis tools or experts
☐ Information or tools in your language
☐ More support for or integration with Traditional and Indigenous knowledge
☐ Stronger partnerships with researchers or institutions
☐ Other, please specify: Click or tap here to enter text.
17. In your opinion, where do you see the biggest opportunities to use new or improved technologies for biodiversity monitoring in the future?:
Click or tap here to enter text.
18. In your opinion, how could biodiversity data be better used to address local/global issues?:
Click or tap here to enter text.
19. Please use this space to give any more details on your views of the current state and future of biodiversity monitoring technology and data:
Click or tap here to enter text.
20. Do you also work with the biodiversity data you collect with technology?*
☐ No, I only work with technology [*Go to Section 3*]
☐ Yes, I also work with the data [*Go to Section 2, Part 2*]

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**Section 2: Biodiversity monitoring data**
**Part 1: Background on biodiversity monitoring**
21. What type of biodiversity data do you work with? *Select all that are appropriate.**
*We are using categories as set out in Essential Biodiversity Variables (EBVs) https://geobon.org/ebvs/what-are-ebvs/*
☐ Species traits (e.g. body mass, migration patterns, flowering dates)
☐ Species populations (e.g. species distributions, species abundances)
☐ Genetic composition (e.g. genetic diversity, genetic markers)

☐Community composition (e.g. community abundance, species richness)
☐ Ecosystem structure (e.g. tree density, woodland area, 3D mapping of habitats)
☐ Ecosystem functioning (e.g. pollination rates, soil nutrient levels, plant biomass)
☐ Other, please specify: Click or tap here to enter text.
22. Does the biodiversity data you work with have a taxonomic focus? *Select all that are appropriate.**
☐ Amphibians and reptiles
☐ Bacteria and Archaea
☐ Bats
☐ Birds
☐ Fish
☐ Freshwater invertebrates
☐ Fungi and protists
☐ Land mammals
☐ Marine invertebrates
☐ Marine mammals
☐ Plants
☐ Terrestrial invertebrates
☐ No taxonomic focus
23. Does the biodiversity data you work with have a habitat focus? *Select all that are appropriate.**
☐ Forest
☐ Savanna
☐ Shrubland
☐ Grassland
☐ Wetlands
☐ Rocky areas (e.g., inland cliffs, mountain peaks)
☐ Caves & subterranean habitats
☐ Desert
☐ Polar
☐ Marine
☐ Human-modified (including agriculture and urban areas)
☐ No habitat focus
24. Please add any details about your study focus:
Click or tap here to enter text.
25. What scale is the biodiversity data you use collected at? *Select all that are appropriate.**
☐] Multinational
☐ National
☐ Sub-national
☐ Study site
☐ Other, please specify: Click or tap here to enter text.
26. Which country or countries is the biodiversity data you use collected in? *Enter up to **3** countries:**
Click or tap here to enter text.
27. Where do you get the biodiversity data you use? *Select all that are appropriate.**
☐ Internally (e.g. collected by others within your organisation)
☐ Externally through private sources (e.g. collaborations or contracts with other organisations)
☐ Externally through public sources/repositories (e.g. GBIF, OBIS, BOLD)
28. What technology is used to collect the biodiversity data you use? *Select up to **3** if different technologies are used.**
☐ Camera traps
☐ Acoustic devices
☐ Biologgers/tracking devices
☐ UAVs/drones
☐ eDNA/genomics

☐ Mobile applications (incl. on smart phones, tablets, e.g. citizen science apps)
☐ GIS/remote sensing (satellite, multispectral, and thermal imagery; LiDAR)
☐ Other, please specify: Click or tap here to enter text.
☐ I don't know
☐ No technology used
29. What tools are you currently using for data management, processing and analysis? *Select all that are appropriate.**
☐ Biodiversity data specific tools (e.g. movebank, camelot)
☐ Citizen science platforms (e.g. Zooniverse, SciStarter)
☐ Protected area management systems (e.g. SMART, EarthRanger)
☐ Spatial data tools (e.g. ArcGIS, QGIS, Google Earth Engine)
☐ Programming language tools (e.g. R, Python, MATLAB)
☐ Machine learning/AI (e.g. image or sound classification tools)
☐ Other, please specify: Click or tap here to enter text.
☐ I don't know
☐ No tools used
30. How confident are you with the biodiversity data you use?*
☐ Novice *I follow rules or guidance to use data but have little understanding of its meaning or context*
☐ Beginner *I can perform basic tasks with data independently, but still rely on guidance to interpret or apply the data*
☐ Average *I can confidently carry out tasks with data and can judge which information is relevant to the situation*
☐ Advanced *I can confidently interpret data in context, draw meaningful conclusions, and apply insights to real-world challenges*
☐ Expert *I use data intuitively and strategically, often guiding others and shaping how data is used in my organization*

**Part 2: Current status of biodiversity monitoring data**

31. How easy is it for you to **access** the biodiversity data you use most often for your work? *By ease of access we include whether the data you need exists, is findable, and is retrieved or obtained without barriers**
☐ Very easy
☐ Easy
☐ Neither easy nor difficult
☐ Difficult
☐ Very difficult
☐ I don't know
32. How easy is it for you to **use** the biodiversity data you use most often for your work? *By ease of use we include whether you have the technical skills and availability of resources to work with the data**
☐ Very easy
☐ Easy
☐ Neither easy nor difficult
☐ Difficult
☐ Very difficult
☐ I don't know
33. To what extent do you agree with the statement "The biodiversity data that is available to me meet my needs?" *By meeting your needs we include the extent to which the data allows you to complete the tasks you need to e.g. inform decision making, answering research questions**
☐ Strongly agree
☐ Agree
☐ Neither agree nor disagree
☐ Disagree
☐ Strongly disagree
☐ I don't know

34. What barriers do you currently face when **accessing and using** biodiversity data? *Please select the **3** greatest challenges you face.**
☐ Upfront cost of obtaining or retrieving data
☐ Data I need is not available (e.g. data is not published or digitised)
☐ Data is difficult to access (e.g. data is hard to find, data is located across multiple sources, data portals are difficult to use)
☐ Spatial scale and/or resolution of data doesn't meet my needs
☐ Temporal scale and/or resolution of data doesn't meet my needs
☐ Taxonomic coverage doesn't meet my needs
☐ Too much uncertainty in the data
☐ Poor metadata/documentation for data
☐ Format of data does not meet my needs
☐ Limited storage capacity for volume of data
☐ Limited or unreliable computing infrastructure (e.g. unstable power supply, slow internet, outdated hardware)
☐ Limited technical resources to access or use the data (e.g. lack of software/tools)
☐ Language barriers (tools and data portals not in our language)
☐ Lack of time to stay up to date with tools/approaches
☐ Lack of training or technical knowledge
☐ Ethical concerns about data (e.g. data justice or privacy concerns)
☐ Difficulty coordinating with other groups or stakeholders
☐ Data does not support or integrate Traditional and Indigenous knowledge
☐ Other, please specify: Click or tap here to enter text.
35. Could you give more information about the barriers you currently face in accessing and/or using biodiversity data:
Click or tap here to enter text.
36. Do you/your organisation use biodiversity data to inform decisions/actions?*
☐ Yes [*Go to Section 2, Part 3*]
☐ No [*Go to Section 2, Part 4*]
☐ I don't know [*Go to Section 2, Part 4*]
**Part 3: Decisions and actions with biodiversity data**
37. What do you/your organisation use biodiversity data to inform? *Select all that are appropriate.**
☐ Establishing baselines
☐ Targeting interventions or actions
☐ Measuring progress or change
☐ Biodiversity inventories
☐ Environmental impact assessments
☐ Developing/enforcing environmental regulations (incl. guiding law enforcement)
☐ Land/sea-use planning
☐ Protected area designation
☐ Natural capital/ecosystem services assessments
☐ Education/outreach
☐ Other, please specify: Click or tap here to enter text.
38. What challenges do you face in using current biodiversity data to the inform decisions/actions mentioned above? *Please select the **3** greatest challenges you face.**
☐ Lack of clear guidance or frameworks for data integration
☐ Lack of standardisation in biodiversity data (e.g. collection methods, reported metrics)
☐ Data quality is not high enough
☐ Insufficient capacity or expertise in data analysis
☐ Mismatch between monitoring outputs and decision timelines
☐ The data available doesn't help guide decisions or actions
☐ Limited or unreliable computing infrastructure (e.g. unstable power supply, slow internet, outdated hardware)
☐ Lack of trust in data sources

☐ Lack of funding
☐ Ethical concerns about data (e.g. data justice or privacy concerns)
☐ Difficulty communicating/collaborating with other groups or stakeholders
☐ Other, please specify: Click or tap here to enter text.
39. Could you give more information about the barriers you/your organisation currently face in using biodiversity data to inform decisions/actions:
Click or tap here to enter text.

**Part 4: Opportunities in biodiversity monitoring data**

40. What interventions or improvements would help biodiversity data to better meet your needs? *Please select the **3** most important to you.**
☐ Additional data (i.e., the quantity of data currently available is insufficient)
☐ Greater access to the currently available data
☐ Different types/extents/quality of data being available
☐ Improved access to data storage
☐ Improved access to data management tools or software
☐ Improved access to analytical tools or software
☐ Improved computing infrastructure
☐ More training or technical support
☐ Guidance on integrating data into policy or planning
☐ Improvements in biodiversity monitoring technology (e.g. greater abilities of technology, greater robustness or quality of technologies)
☐ Wider availability of biodiversity monitoring technology
☐ Other, please specify: Click or tap here to enter text.
41. In your opinion, where could new or improved technologies have the biggest impact on collecting or improving biodiversity data?
Click or tap here to enter text.
42. In your opinion, how could biodiversity data be better used to address local/global issues?
Click or tap here to enter text.
43. Please use this space to give any more details on your views of the current state and future of biodiversity monitoring technology and data.
Click or tap here to enter text.
*Please now go to Section 3.*

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**Section 3: Traditional and Indigenous knowledge**

The next questions are about Traditional and Indigenous knowledge in relation to biodiversity monitoring data. Indigenous communities often observe environmental changes long before they are detected by scientific instruments, providing early warnings and complementary insights. Integrating Traditional and Indigenous knowledge respects the rights, roles, and stewardship of Indigenous Peoples in managing their lands, aligning with global commitments to equity and co-production of knowledge (e.g. Kunming-Montreal Global Biodiversity Framework Target 21).
44. To what extent do you consider Traditional and Indigenous knowledge to be integrated into the biodiversity monitoring you are involved in?*
☐ Fully integrated
☐ Very integrated
☐ Moderately integrated
☐ Slightly integrated
☐ Not at all integrated
☐ I don't know
45. In your opinion, what are the main challenges in including Traditional and Indigenous knowledge into biodiversity monitoring? *Please select the **3** greatest challenges.**
☐ Lack of access to Traditional and Indigenous knowledge or data
☐ Unclear guidance / lack of guidance on how to include
☐ Concerns or uncertainties over permissions, data ownership, or ethics
☐ Concerns about misuse of knowledge

☐ Lack of collaboration with Indigenous communities
☐ Lack of institutional support
☐ Lack of policy frameworks
☐ Other, please specify: Click or tap here to enter text.
46. Could you give more information about your thoughts on the challenges and opportunities for including Traditional and Indigenous knowledge into biodiversity monitoring?
Click or tap here to enter text.
47. Do you have any examples of successful combination of Traditional and Indigenous knowledge and biodiversity monitoring technology?
Click or tap here to enter text.
*Please now go to Section 4.*

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**Section 4: Developing biodiversity monitoring technology**
48. Do you think the demand for biodiversity monitoring technology is growing in your region?
☐ Yes
☐ No
☐ I don't know
☐ Other, please specify: Click or tap here to enter text.
49. Approximately how much has your organisation spent/invested in biodiversity monitoring technology over the past 5 years? *Please give the currency.*
Click or tap here to enter text.

| 50. We are interested in new technology or technology applied to new areas of biodiversity monitoring. How would you rate the readiness/deployment level of each technology for your specific biodiversity monitoring? * Not known | No technology/ method developed | Technology / method concept in progress (invention stage) *e.g. building and testing of components* | Technology and method in development and validation stage *e.g. prototype testing and demonstration in lab and field settings* | Technology and method in pilot production and demonstration stage *e.g. successfully demonstrated in 1-2 projects, not yet scaled* | Technology and method fully developed and available for use across multiple projects/locations *e.g. technology proven to work under multiple operating conditions* | Not applicable *e.g. this technology would not work for my specific biodiversity monitoring* |
|---|---|---|---|---|---|---|
| Camera traps | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |
| Acoustic devices | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |
| Biologgers/tracking devices | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |
| UAVS/drones | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |
| eDNA/genomics | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Mobile applications | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |
| Machine learning/ AI | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |
| GIS/remote sensing | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |

*Please now go to Section 6.*

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**Section 5: Understand local environment**

**Part 1: Background on biodiversity monitoring**

51. Are you answering these questions for yourself or on behalf of a local community?*

☐ I am answering for myself
☐ I am answering on behalf of a local community
☐ I am answering as both an individual and a community representative
☐ Other, please specify: Click or tap here to enter text.

52. Do you or your community rely on the environment around you for making decisions or earning a living? If yes, can you give some examples?
Click or tap here to enter text.

53. Do you or your community currently monitor the nature or the environment around you? *By monitor we include observe and check the progress or quality**

☐ Yes
☐ No
☐ I don’t know
☐ We used to, but not anymore
☐ Not currently, but plan to or would like to

54. Do you use what you learn from monitoring to make decisions about your local area, your work or your life? *For example: changing how land is used, making plans for the future, deciding how to spend your money.**

☐ Yes
☐ Sometimes
☐ No
☐ I don’t know

55. Have you/your community used any technology to help monitor nature or the environment?*

☐ Camera traps - *automatic cameras that take pictures or videos of animals when they pass by*
☐ Sound recorders (acoustic devices) - *small devices that record animal sounds*
☐ Animal trackers (biologgers/tracking devices) - *collars or small tags placed on animals to follow their movements*
☐ Drones (UAVs) – *cameras attached to small flying vehicles*
☐ DNA from the environment (eDNA/genomics) - c*ollecting water, soil, or air to find traces of animals or plants by testing their DNA*
☐ Mobile phone tools (applications on phones or tablets) - *phone apps to report animal sightings, forest fires, or illegal activities*
☐ Smart computers (AI or machine learning) - *computer programs that help identify animals in photos or sounds*
☐ Park and reserve management tools (protected area systems like SMART or EarthRanger) - *phone or computer tools that help protect wildlife and track patrols, animals, and threats*
☐ Maps from satellites (GIS or remote sensing) - *using satellite images or drones to see land changes, forest loss, or wildlife habitats from above.*
☐ Other, please specify: Click or tap here to enter text.
☐ No technology used
☐ I don’t know

**Part 2: Current status of biodiversity monitoring**

56. Do you feel you or others in your community have the skills and knowledge needed to monitor nature or the environment?*
☐ Yes
☐ Somewhat
☐ No
☐ I don’t know
57. What are problems you or your community have had (or could have) when using technology for monitoring nature or the environment? *Select **3** biggest problems.**
☐ Technology is too difficult to get
☐ Technology is too expensive
☐ Technology is too difficult to use
☐ Not enough time
☐ Technology doesn’t work for our monitoring
☐ Difficult to access computers, internet or electricity
☐ Difficult to get long-term support e.g. from government or NGOs
☐ No trust in the technology
☐ Understanding the results is difficult
☐ No trust in how the results will be used
☐ No benefits to using technology
☐ Other, please specify: Click or tap here to enter text.
58. Could you give more information about the difficulty you/your community have when monitoring nature or the environment?
Click or tap here to enter text.

**Part 3: Opportunities in biodiversity monitoring**

59. What support would help your community take part in monitoring nature or the environment? *Select the **3** most important.**
☐ Access to tools or equipment (e.g. GPS, smartphones, field guides)
☐ Training in how to take part
☐ Support for combining Traditional knowledge with scientific methods
☐ Partnerships with researchers or organisations
☐ Funding
☐ Information or tools in our language
☐ Clear agreements on how information will be used and shared
☐ Recognition of community contribution
☐ Other, please specify: Click or tap here to enter text.
60. How could information about nature or the environment around you support you/your community’s goals or decision making? *Select the **3** most important.**
☐ Help protect important plants or animals
☐ Support sustainable use of natural resources
☐ Help to make land or resource management decisions
☐ Provide information for negotiations or advocacy
☐ Contribute to environmental education
☐ Strengthen community voice in conservation projects or government planning
☐ Bring jobs or income
☐ Understand environmental changes or threats (e.g. climate change, pollution)
☐ Other, please specify: Click or tap here to enter text.
☐ I don’t know
☐ I don’t think biodiversity monitoring can help me/my community
61. Do you have anything else to say about monitoring nature or the environment around you?
Click or tap here to enter text.
*Please now go to Section 6.*

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**Section 6: Demographic information**

**Why we ask these questions:** We want to understand how different people experience barriers and opportunities with biodiversity monitoring. This includes people from different backgrounds and groups. Your answers help us see if some groups face more challenges than others.
We will not use this information to identify you.

62. What age group are you in?*
☐ 18–24
☐ 25–34
☐ 35–44
☐ 45–54
☐ 55–64
☐ 65+
☐ Prefer not to say

63. What is your gender?*
☐ Man
☐ Woman
☐ Other
☐ Prefer not to say

64. Do you have difficulty seeing, even if wearing glasses?*
☐ No difficulty
☐ Some difficulty
☐ A lot of difficulty
☐ Cannot do at all
☐ Prefer not to say

65. Do you have difficulty hearing, even if using a hearing aid(s)?*
☐ No difficulty
☐ Some difficulty
☐ A lot of difficulty
☐ Cannot do at all
☐ Prefer not to say

66. Do you have difficulty walking or climbing steps?*
☐ No difficulty
☐ Some difficulty
☐ A lot of difficulty
☐ Cannot do at all
☐ Prefer not to say

67. Do you have difficulty remembering or concentrating?*
☐ No difficulty
☐ Some difficulty
☐ A lot of difficulty
☐ Cannot do at all
☐ Prefer not to say

68. Do you have difficulty with self-care, such as washing all over or dressing?*
☐ No difficulty
☐ Some difficulty
☐ A lot of difficulty
☐ Cannot do at all
☐ Prefer not to say

69. Using your usual language, do you have difficulty communicating by speaking, for example understanding or being understood?*
☐ No difficulty
☐ Some difficulty
☐ A lot of difficulty

☐ Cannot do at all
☐ Prefer not to say
70. Do you identify as an Indigenous person?*
☐ Yes
☐ No
☐ I don’t know
☐ Prefer not to say
71. What country do you live in?*
Click or tap here to enter text.
72. Is the area you live urban or rural?*
☐ Rural
☐ Urban
☐ I don’t know
☐ Prefer not to say
73. What type of organisation do you currently work for?*
☐ University or research institute
☐ Non-governmental organisation or charity
☐ Government or regulatory agency
☐ Nature or climate finance
☐ Technology development
☐ I don’t work for an organisation
☐ Other, please specify: Click or tap here to enter text.
☐ Prefer not to say
74. What is your primary role in the organisation you work for?*
☐ Academic researcher
☐ Project coordinator or leader
☐ Project officer or technician
☐ Policy maker/advisor
☐ Finance/risk analyst
☐ Software developer/engineer
☐ Hardware developer/engineer
☐ Data scientist
☐ Other, please specify: Click or tap here to enter text.
☐ Prefer not to say

**End of questionnaire**

75. To create a personal identifier, please enter a word below that is meaningful and memorable to you. Please also keep this for your own records. You will need this if you want us to delete your answers in the future.
Click or tap here to enter text.

Thank you for completing this questionnaire, your time is appreciated**. Please submit your form by emailing it to: Laura Braunholtz (laubra@ceh.ac.uk).**

If you would like any further information, please contact Laura Braunholtz (laubra@ceh.ac.uk).

**To receive updates about the project including the results of this questionnaire, please click this link and submit your email address: https://forms.office.com/e/ampSML6mCJ**

# Annexe 3 Interview topic guide

Innovate 4 Nature Interview Topic Guide
Please tailor these questions to the participant you are interviewing – e.g. don't ask irrelevant questions but allow more time for those that are relevant.
**Introduction (5 mins)**

- Introduce the project
- Go through the information for participant's sheet (including data privacy and anonymity aspects)
- Explain outline of interview
- Give time for questions
- Get signature for consent form

**Background and Role (5–10 mins)**

1. Can you tell me about your current role/job?
   *(Prompt: What kind of decisions or work are you involved in? Does the local environment affect your decision making?)*
2. In your view, what are the main biodiversity challenges in your area/country?
   *(Prompt: Are species or habitats being lost? Are there data gaps?)*

**Current Use of Technology (5-10 mins)**

3. What does biodiversity monitoring technology mean to you? What types of technologies are you aware of?
4. Are you or your organisation/community currently using any technologies to monitor biodiversity?
   *(Prompt: camera traps, drones, mobile apps, satellite data, acoustic sensors, eDNA, etc.)*
5. How are these technologies being used?
   *(Prompt: For what purposes – data collection, reporting, community engagement, early warning, etc.; what are the focal taxa or ecosystem?; what type of biodiversity data)*
6. How effective have these tools been in your experience?
   *(Prompt: In terms of ease of use, cost, usefulness, reliability)*

**Barriers (10–15 mins)**
IF WORKING WITH TECHNOLOGY

7. What challenges or barriers have you or others faced when using biodiversity monitoring technologies?
   *(Prompt: Infrastructure, internet, electricity, skills, funding, language barriers, cultural fit, alignment with working needs/existing ways of working)*

IF WORKING WITH DATA

8. What are the challenges that limit the use or sharing of biodiversity data?

*(Prompt: Is it shared openly? Do people use the data to make decisions? Are there institutional or policy barriers? Infrastructure barriers?)*

**Opportunities and Needs (10–15 mins)**

9. In an ideal world, what information about the environment or biodiversity would help you in your role/job in regard to decision making or actions?
10. Are you aware of any emerging biodiversity challenges or opportunities in your area or sector that may increase the need for biodiversity data collection?
*(Prompt: For instance, new threats to species or ecosystems, climate-related pressures, or opportunities for improved conservation planning and decision-making.)*
11. Could technology help you in this? What kinds of technologies or approaches?
*(Prompt: What could technology help you do better or differently? What tools would you need?)*
12. What types of support or investment would help you or your community/organisation make better use of monitoring technologies?
*(Prompt: Training, funding, partnerships, guidance, translation/localisation)*
13. How could local communities be better engaged in biodiversity monitoring using technology? Specifically, how could Indigenous or traditional knowledge be supported?
*(Prompt: Incentives, co-design, culturally relevant tools)*
14. Do you think demand for technology is growing in your region/sector? *Only ask where relevant*
15. How much has your organisation spent/invested in biodiversity monitoring technology over the past 5 years ? *Only ask where relevant*

**15. Is there anything that we haven't talked about that you would like to say?**

**Demographic information (<5 mins)**

Needed for gender and social inclusion analyses – don't include anything that would make them identifiable

- Age group:

☐ 18–24
☐ 25–34
☐ 35–44
☐ 45–54
☐ 55–64
☐ 65+
☐ Prefer not to say

- Gender: [ ] Man [ ] Woman [ ] Other [ ] Prefer not to say

- Questions about difficulties doing certain activities:
    - Do you have difficulty seeing, even if wearing glasses?

  1. No difficulty 2. Some difficulty 3. A lot of difficulty 4. Cannot do at al
    - Do you have difficulty hearing, even if using a hearing aid(s)?

  1. No difficulty 2. Some difficulty 3. A lot of difficulty 4. Cannot do at all
    - Do you have difficulty walking or climbing steps?

  1. No difficulty 2. Some difficulty 3. A lot of difficulty 4. Cannot do at all
    - Do you have difficulty remembering or concentrating?

  1. No difficulty 2. Some difficulty 3. A lot of difficulty 4. Cannot do at all
    - Do you have difficulty with self-care, such as washing all over or dressing?

  1. No difficulty 2. Some difficulty 3. A lot of difficulty 4. Cannot do at all
    - Using your usual language, do you have difficulty communicating verbally, for example understanding or being understood?

1. No difficulty 2. Some difficulty 3. A lot of difficulty 4. Cannot do at all

- Nationality: Are you Kenyan or Non-Kenyan?
- Do you identify as an Indigenous person?: ______
- Is the area you live urban or rural?
  - Rural
  - Urban
- What type of organisation do you currently work for?

☐ University or research institute
☐ Non-governmental organisation or charity
☐ Community group
☐ Government or regulatory agency
☐ Nature or climate finance
☐ Technology development
☐ I don't work for an organisation
☐ Other, please specify: Click or tap here to enter text.
☐ Prefer not to say

- What is your primary role: _____________________

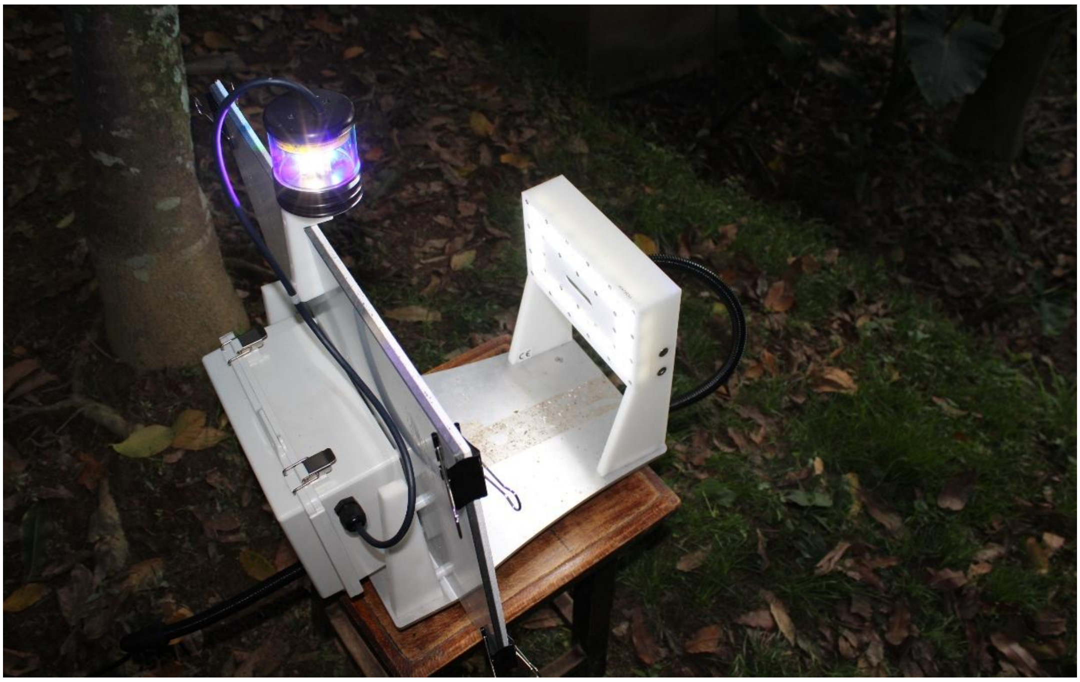
☐ Academic researcher
☐ Project coordinator or leader
☐ Project officer or technician
☐ Policy maker
☐ Finance/risk analyst
☐ Software developer/engineer
☐ Hardware developer/engineer
☐ Data scientist
☐ Fisher
☐ Farmer
☐ Pastoralist
☐ Forester
☐ Other, please specify: Click or tap here to enter text.
☐ Prefer not to say

**End of interview**
Give thanks for participation. Let them know about planned timelines. Can take contact details if they want to be informed about the outcomes/information about the workshop.
Give time for questions. Give contact details of Laura – laubra@ceh.ac.uk for any follow up

# Annexe 4 Workshop programme

## Technology for Biodiversity Monitoring in Africa

*An **Innovate 4 Nature** workshop to advance the effective use of technology in biodiversity monitoring to strengthen conservation outcomes, support evidence-based decision-making and investment into nature.*



## Workshop Programme

**12th — 13th February 2026**
*14th Tech Demo (optional)*

**KCB Leadership Centre**
*Off Karen-Ngong Rd, Nairobi, Kenya*

## About this workshop

The **Technology for Biodiversity Monitoring workshop** aims to advance the effective use of technology in biodiversity monitoring to strengthen conservation outcomes, support evidence-based decision-making and investment into nature.

By bringing together researchers, practitioners, technologists, policymakers, and community stakeholders, we seek to identify key barriers to technology and data accessibility, usability, and impact, and to collaboratively explore practical solutions. Through the sharing of case studies and successful applications of technological tools, the workshop will highlight opportunities for scaling innovations and enhancing their contribution to biodiversity conservation across East Africa.

The workshop is part of the **Innovate 4 Nature**—a study led by the UK Centre for Ecology & Hydrology (UKCEH) and funded by the UK Department for Environment, Food and Rural Affairs (Defra)—which is exploring how technology and data can improve biodiversity monitoring in low and middle-income countries.

The **Tropical Biology Association** and **UKCEH** are partnering to host this workshop for East Africans working in biodiversity conservation, natural resources, and environmental data use.

## Organising committee

- Mr. Anthony Kuria, *Tropical Biology Association, Kenya*
- Dr Rosie Trevelyan, *Tropical Biology Association, UK*
- Dr Jenna Lawson, UK *Centre for Ecology & Hydrology*
- Dr Laura Braunholtz, UK *Centre for Ecology & Hydrology*

## With co-facilitation and support from

- **Tropical Biology Association**
  - Dr Caroline Ng'weno
  - Dr Geoffrey Mwangi Wambugu
  - Mr. Gregory Maina
- **UKCEH Consultants**
  - Eric Ole Reson
  - Zachary Mikwa

TROPICAL BIOLOGY ASSOCIATION    UK Government    Centre for Ecology & Hydrology NATURAL ENVIRONMENT RESEARCH COUNCIL

# Thursday 12 February 2026 Technology for monitoring

| | |
|---|---|
| 08:30 | **Registration**<br>Pick workshop materials. First opportunity for networking and interacting with other delegates. |

| **Workshop scene setting**<br>**Chair:** Mr. Anthony Kuria, Tropical Biology Association | |
|---|---|
| 9:00 | **About the workshop, expectations** |
| | Dr Rosie Trevelyan, Tropical Biology Association |
| 9:15 | **Talk: Technology for biodiversity monitoring** |
| | Dr Jenna Lawson, Centre for Ecology & Hydrology |
| 9:45 | **Talk: Systemic barriers and the policy dimension on use of technology in Africa** |
| | Dr Ann Njoki Kingiri, African Centre for Science and Technology |
| 10:15 | **Technology & data in biodiversity monitoring in Kenya** |
| | Mrs. Lucy Waruingi, Africa Conservation Centre, Kenya |
| 10:25 | **Q&A & delegates reactions** |
| 10:35 | **Coffee/tea break** |

| **Exploring current use of Technology in biodiversity monitoring**<br>**Chair**: Dr. Rosie Trevelyan, Tropical Biology Association | |
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| | **Case studies** |
| 11:05 | **Using camera traps for biodiversity conservation in the Serengeti** |
| | Dr Stanslaus Mwampeta, Grumeti Fund, Tanzania |
| 11:10 | **Improving coral reef health monitoring at Kisite-Mpunguti Marine Park and Reserve** |
| | Mr. Francis Okalo, IUCN, Kenya |
| 11:15 | **Revealing hidden freshwater biodiversity in East Africa using eDNA** |
| | Dr Asilatu Hamisi Shechonge, Tanzania Fisheries research Institute |
| 11:20 | **Monitoring Forest Threats and High Conservation Value Species in a Dryland REDD+ Corridor** |
| | Dr Geoffrey Mwangi Wambugu, Wildlife Works Sanctuary, Kenya |
| 11:25 | **Q&A on the case studies** |
| | |
| | **World Cafes** |
| 11:35 | **Discussion I: From data to impact: pathway strengths and weak points** |
| | • Where does the “data-to-impact” chain most often fail?<br>• How can technology help fix these weak points—and where does it create new ones? What technologies are working well here?<br>• What’s missing? What minimum systems, skills, and partnerships are needed to ensure data leads to action? Where should technology be used but currently isn’t? Why is the tech not being used?<br>• What is “ideal” data and technology in real-world decisions? What decision would it support? |
| 13:00 | **Lunch break-cum-interaction session** |

| Barriers to technology in biodiversity monitoring<br>**Chair**: Dr Geoffrey Mwangi Wambugu, Wildlife Works Sanctuary | |
|---|---|
| **14:00** | Feedback from Discussion 1 |
| | **Case studies** |
| **14:30** | **Results from the CEH survey on barriers & opportunities** *(ask if they will have preliminary results?)* |
| | Zachary Mikwa / Eric Ole Reson, CEH Consultants |
| | **Working groups** |
| **15:15** | **Discussion II: Barriers to technology in biodiversity monitoring** |
| | • What challenges make it difficult to adopt or scale up biodiversity monitoring technologies? What re the needs |
| **17:00** | **End of the day** |

## Friday 13 February 2026 Informing decisions from data

| Barriers to technology in biodiversity monitoring<br>**Chair**: Dr Geoffrey Mwangi Wambugu, Wildlife Works Sanctuary | |
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| | |
| **8:30** | **Recap: feedback on discussion 2 (day 1)** |
| | |
| **8:50** | **Developing technology for monitoring in Africa** |
| | Dr Jake Wall, EarthRanger |

| Informing management and decisions/policy<br>**Chair:** Mr. Anthony Kuria, Tropical Biology Association | |
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| | **Case studies** |
| **9:10** | **Using the Freshwater Biodiversity Data Portal to inform decision-making in Uganda** |
| | Dr Mark Olokotum, National Fisheries Resources Research Institute, Uganda |
| **9:15** | **Integrating technology into Government decision-making: The KWS experience** |
| | Mr. Victor Ian Mika Matsanza, Kenya Wildlife Service |
| **9:20** | **Applying technology in Community Conservancies: Lessons from wildlife, vegetation, and marine monitoring** |
| | Mr. Athuman Komora Garisse, Northern Rangelands Trust, Kenya |
| **9:30** | **From data silos to decision intelligence: Turning data into action** |
| | Mrs. Kariuki Truphena, Laikipia Conservancies Association, Kenya |
| **9:35** | **Monitoring wildlife habitats: Lessons from Burunge Wildlife Management Area** |
| | Lazaro Johana Mangewa, Sokoine University of Agriculture |
| **9:40** | **Q&A on the case studies** |
| | |
| **9:55** | **Role of capacity building in enhancing conservation outcomes** |
| | TBA |
| **10:10** | **Coffee/tea break** |

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| **Chair: Dr Caroline Ng'weno** | |
| **10:40** | **From data to impact:** how biodiversity data informs national planning & development & existing gaps |
| | Dr Joseph Mukeka, Wildlife Research & Training Institute, Kenya |
| | **Panel Discussion** |
| **11:20** | **Discussion III: Problem: use of technology & biodiversity data in decision-making**<br><br>**Possible Panellists**<br>○ Truphena Kariuki (Laikipia Conservancies Association), Data management, Kenya<br>○ Mark Olokotum (National Fisheries Resources Research Institute), eDNA/data management, Uganda<br>○ Christine J. W. Mwangi (UNDP) or Dorothy Maseke (FSD), finance, Kenya<br>○ Joseph Mukeka (WRTI), data/policy/practice, Kenya<br>○ Stanslaus Mwampeta (M), Practice, Grumeti, Tanzania |
| | **Q&A session** |
| **13:00** | **Lunch break-cum-interaction session** |

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| **Vision for the future**<br>**Chair**: Dr. Rosie Trevelyan, Tropical Biology Association | |
| | **Working session** |
| **14:00** | **Discussion IV: Reflection and way forward: co-designing the next steps** |
| | Delegates reflect on everything + draw a vision for the future guided by the following ideas<br>• Capacity: Inclusive training approaches and equitable access to technology for biodiversity monitoring<br>• Data hubs: Creating/strengthening national/regional systems for data management, sharing, and access<br>• Partnerships: Catalysing collaboration among individuals and institutions<br>• Funding: attracting support for technology and data |
| **16:00** | **Plenary session – workshop wrap up** |
| | Dr Rosie Trevelyan |

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| **Chair: Mr. Anthony Kuria, Tropical Biology Association** | |
| | **Workshop closure** |
| **16:30** | **Comment from CEH** |
| | Dr Jenna Lawson |
| | **Vote of thanks & debrief on next day** |
| | Anthony Kuria |
| | **Invitation to cocktail** |
| | *Delegates depart at their own pleasure* |

# Annexe 5 GEDSI Analysis from GEDSI Action Plan

# GEDSI Action Plan

| GEDSI integration requirement | Programme Baseline: *(SRO to define assess current status and insert here. If the programme is under design / not yet started, baseline is likely to be 'unaware')* GEDSI unaware (below HMG minimum standard) | Programme Ambition: *(SRO to define programme ambition and insert here)* GEDSI empowering | Actions Planned *(SRO to complete)* | Updates *(SRO to complete)* |
|---|---|---|---|---|
| **Analysis / Design** | Lack of gender equality, disability and social inclusion analysis means that interventions may fail to acknowledge the impacts of gender and broader exclusion. This may lead to interventions that exacerbate existing inequalities and barriers, or create new ones, or fail to deliver on UK commitments for GEDSI responsive programming. | Gender equality, disability and social inclusion analysis (see Annex 3) is conducted to assess the potential effects of interventions on women and men and marginalised groups relevant to the programme context. Findings are used to design interventions that address practical barriers and support opportunities for increased equality in access to assets, resources, capabilities and opportunities, such as inclusive and accessible jobs, markets, services, skills, knowledge and decision-making. | The Innovate 4 Nature project has conducted a preliminary desk-based gender analysis, see previous section of this document. This analysis highlights key gender and social disparities that have informed the project's design, with the aim of addressing barriers and creating opportunities for disadvantaged groups. In addition to considerations of gender, we aimed to ensure the voices of Indigenous people and communities were represented. We employed a consultant to specifically focus on conducting interviews with local community members from a diverse range of communities across Kenya. Due to the project's short timeline, the initial analysis was limited to secondary data sources. However, | |

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| | | | as the project progresses, all data collected will be disaggregated by gender. This will enhance understanding of GEDSI dynamics in the context of biodiversity monitoring technologies in low- and middle-income countries, and will help shape more inclusive and effective future interventions. | |
| **Procurement / calls for proposals** | Procurement processes and calls for proposals for grants fail to include any GEDSI scoring criteria. | Procurement processes and calls for proposals for grants include GEDSI considerations in invitation to tender/bid documents. Suppliers and bids are assessed and scored on GEDSI criteria. Relevant criteria include a strong organisational commitment, policies, culture, resources and incentives to ensure GEDSI responsive implementation; dedicated expert staff working on GEDSI and ability to draw on relevant expertise and resources; innovative approaches to ensure locally led delivery. For procurements, the Social Value can be applied to GEDSI criteria relevant to the programme context, allocating 10% of the contract value. | | |

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| **Engagement and participation of women and girls and marginalised groups** | Inadequate consultation with women and girls and marginalised groups (including people living in poverty, Indigenous People, people with disabilities and Local Communities) that are affected by the programme directly or indirectly. | Regular and meaningful participation throughout the programme of women and girls (as relevant) and marginalised groups, including people with disabilities, informs programme design, implementation, MEL, risk management and safeguarding measures. | Women and persons with disabilities are actively engaged throughout the Innovate for Nature project, contributing to its planning, design, and implementation. Their involvement, alongside a diverse project team representing multiple countries and backgrounds, reflects a deliberate effort to embed GEDSI principles across all stages of the project. Inclusion and accessibility are central to participation strategies. While for some aspects of the evidence gathering (e.g. the global questionnaire) participant diversity is partially constrained by the recruitment strategy, which relies on volunteers from organisations approached, and the project's short timeframe, proactive steps are being taken to encourage the involvement of women and other underrepresented groups in other aspects of the project. We have specifically contacted women and members of Indigenous communities to participate in our interviews. Additionally, the project is being implemented across a range of countries and regions within the low- to middle-income bracket | |

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| | | | which aims to provide a broad range of experience informing the self-report data collected. Active engagement of women, girls, and minority groups in project activities will be encouraged through the inclusive and sensitive design of project materials, such as questionnaires and interview guides. These materials are carefully developed to avoid gendered language and to ensure accessibility for individuals with varying levels of education and English literacy. The project materials are being developed in consultation with a multidisciplinary team, including social scientists and members trained in the field of Gender and Environment. The team brings experience in gender mainstreaming approaches, ensuring that the tools are designed to be inclusive, context-sensitive, and aligned with GEDSI principles. Workshops will offer multiple modes of participation,These approaches are designed to foster empowerment and ensure that all participants, especially those from traditionally underrepresented groups, can contribute meaningfully and comfortably | |

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| | | | Survey and interview data will be disaggregated by key GEDSI demographics, allowing the project to systematically track and assess the participation of women, girls, and other marginalized groups throughout its implementation. | |
| **Implementation** | No GEDSI action plan / strategy in place. The programme workplan, management information and contractual Key Performance Indicators (KPIs) fail to consider GEDSI. | GEDSI analysis has informed programme design and implementation to mitigate the risk of doing harm and support the programme's ambition to be GEDSI empowering. The programme's delivery on GEDSI should be reviewed regularly, including during Annual Reviews. Developing and implementing a programme GEDSI strategy or action plan is recommended to support continuous improvement. The programme workplan, management information and contractual Key Performance Indicators (KPIs) includes GEDSI integration targets to ensure monitoring and accountability of the programme's ambition to be GEDSI empowering. | *See Results Framework in Appendix 1.0* Given the short duration of the Innovate for Nature project, a single review will be conducted to assess the implementation of GEDSI principles. However, GEDSI considerations have been embedded from the outset, informing both programme design and delivery to mitigate risks of exclusion or harm and to actively promote empowerment of women, persons with disabilities, and other marginalised groups. The annual review will evaluate the efforts to incorporate GEDSI throughout the projects assessing against the project framework GEDSI considerations and targets as well as the Defra GEDSI Empowering requirements detailed in this table and further detailed in Appendix 2.0. To support continuous improvement, lessons learned throughout the project will be documented and shared, particularly | · |

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| | | | to inform future phases or related initiatives that may focus more directly on implementing targeted interventions. | |
| **Team capacity and organisational commitment** | Lack of expertise / resourcing dedicated to GEDSI in the programme delivery team.<br>Delivery / implementing partner(s) lack a strong organisational commitment / policies / culture / incentives / resources to effectively integrate GEDSI and meet HMG safeguarding standards. . | The programme delivery team includes dedicated GEDSI experts as a core part of the delivery team, and ability to draw on additional expertise and resources as needed.<br>Delivery / implementing partner(s) Implementing partner widely recognised for excellent track record and strong organisational commitment, policies, culture and incentives to adhere to HMG safeguarding standards and ensure GEDSI responsive implementation.<br>Adequate budget is committed to achieving the programme's ambition of GEDSI transformative. | The project is being delivered by a multidisciplinary team, including social scientists and those with training in Gender and Environment. This team brings strong experience in gender mainstreaming and questionnaire design, ensuring that tools such as questionnaires and workshop formats are inclusive and aligned with GEDSI principles. The project's gender expert has led gender mainstreaming efforts in large-scale international programmes and completed specialised UN training, contributing valuable expertise to the design and delivery of GEDSI-responsive activities. The project team also consists of UKCEH International Office representation and there is ongoing consultation with in-country partners to ensure that local and regional social norms, disparities, and accepted terminology are appropriately reflected in all project materials and engagement strategies.<br><br>UKCEH is committed to inclusive practices. | |

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| | | | Its Strategy 2025 outlines a clear principles excellence and a people-centred approach. UKCEH fosters a working culture that supports equality, diversity, and inclusion. The organisation invests in developing current experts, recruiting diverse talent, and training future environmental scientists in partnership with UK and international universities. UKCEH's Equality, Equity, Diversity and Inclusion (EEDI) statement highlights a strong commitment to inclusive values and practices, outlining clear actions to promote fairness, respect, and representation across its workforce and operations. UKCEH has a strong approach to safeguarding and has recently updated policies and procedures to bring them in line with latest advice.<br><br>Project partner; The Tropical Biology Association (TBA) has a strong commitment to ethical approaches and inclusivity, with clear priorities around empowerment and support for early-career scientists. TBA's culture reflects values that form a solid foundation for more formal safeguarding training and frameworks | |

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| | | | associated with this project.<br><br>Project team members responsible for conducting questionnaires, interviews, workshops, and other relevant activities will undergo safeguarding training to ensure the safety and wellbeing of all participants. | |
| **Monitoring, Evaluation and Learning** | Programme MEL plan fails to consider or integrate GEDSI considerations throughout MEL activities. This may include: a lack of disaggregated data and GEDSI specific outputs, outcomes and impacts; a failure to consider GEDSI impacts in evaluations; a lack of GEDSI focused learning activities. | Programme MEL plan considers and mainstreams GEDSI considerations throughout MEL activities. Results framework includes data disaggregated by protected characteristics including by sex, age and disability. Qualitative as well as quantitative methods are applied to understand how programme interventions effect men and women, and marginalised groups differently.<br><br>The results framework has GEDSI specific indicators at each level. Driving greater gender equality, disability and social inclusion in support of climate/biodiversity goals is the principal programme objective. Programme evaluation appraises where programmes could | Data collected through questionnaires and interviews will be disaggregated by gender, age, ethnicity, disability status, and education level. This disaggregation will support the evaluation of GEDSI-related indicators within the project's results framework. Additionally, this will also support work to achieve the project's objectives, enabling a nuanced understanding of how different social groups experience barriers and opportunities in accessing and using biodiversity monitoring technologies. By taking an intersectional approach, the analysis will explore how overlapping demographics, such as being a young woman with a disability or an older person from an ethnic minority, shape engagement with biodiversity | |

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| | | improve GEDSI impacts and considers unintended consequences.<br><br>GEDSI focused leaning activities are used to continually adapt and improve programme implementation. Results shared with internal and external stakeholders.<br><br>Adaptive management approaches are used when needed. | monitoring technology.<br><br>GEDSI specific KPIs outlined in the results framework (Appendix 1.0) will be assessed during the analysis portion of the project implementation.<br><br>Due to the short duration of the project, opportunities for adaptive management will be limited; however, still applied as the incorporation of GEDSI considerations and the implementation of the GEDSI action plan will be continually monitored throughout the different stages of the project with view to responding from lesson's learned and committing to deliver targets set in the results framework. To support continuous improvement, lessons learned during the project will be documented and shared to inform future phases and related initiatives, particularly those focused on targeted interventions. | |
| **Communication** | Lack of GEDSI sensitivity in programme communications with target populations / general public / programme stakeholders and risk of GEDSI discriminatory language. | Programme partners have guidelines in place to promote contextually appropriate, GEDSI sensitive communications throughout programme implementation. Consistent use of inclusive language that challenges | The language used throughout the questionnaires and interviews has been reviewed by the project's GEDSI and Social Science team members to ensure it is inclusive and free from GEDSI-related bias. Demographic questions have been designed in | |

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| | | stereotypes, invisibility, and subordination of marginalised groups. | alignment with the UK International Climate Finance Guidance Note for Delivery Partners: Integration of Gender Equality, Disability and Social Inclusion. For gender reporting in the questionnaire and interviews, gender-related language has been intentionally minimised in line with safeguarding advice and to ensure cultural sensitivity across countries with differing norms, legislation, and attitudes toward gender identity and expression. To maintain inclusivity and respect participant autonomy, self-report options such as 'other' and 'prefer not to say' will be included. | |
| **Identification of safeguarding risks** | Lack of gender equality, disability and social inclusion analysis may result in safeguarding risks not being identified or adequately mitigated against. | Gender equality, disability and social inclusion analysis and enhanced due diligence supports identification of GEDSI / Safeguarding risks and mitigation actions which are monitored via the risk management process. | Safeguarding risks in the Innovation 4 Nature project include cultural and gender norms that may restrict women's participation or expose them to harassment, and heightened dangers for LGBTQ+ individuals in countries where their identities are criminalized or stigmatized. Power imbalances between facilitators and participants, combined with sensitive discussions on gender and inclusion, can lead to coercion or | |

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| | | | backlash. These challenges highlight the need for proactive measures such as culturally informed facilitation, strict data protection, and staff training to ensure participant safety.<br><br>See 'Safeguarding Risks' section above, for more detail. | |
| **Mitigation of safeguarding risks** | Safeguarding policies and procedures not well established and/or project stakeholders not aware of available channels to raise concerns. | Delivery partners have robust safeguarding measures in place, assessed through due diligence. Safeguarding policies and procedures are well established and effectively managed by all project partners. All project stakeholders are made aware of channels to raise any concerns. | Delivery partners (TBA, independent consultants) received safeguarding training as recommended by Defra, and were included in briefings on UKCEH reporting procedures. | |

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