Technology should support, not sideline, locally driven conservation and restoration monitoring

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Summary

The choice of how to monitor conservation and restoration is not solely technical - it shapes which outcomes are valued, whose priorities define success, where resources flow, and who benefits. The shift toward tech-based monitoring, driven by demand for scalable metrics, risks incomplete ecological understanding, sidelining Indigenous Peoples and Local Communities (IPLCs) from data ownership and decision-making. In a novel analysis of survey data from 130 reforestation organizations, we find that remote-sensing adoption has risen over time specifically among market-based organizations, which cite it nearly 50% more often than mission-based ones - a gap that appears to be widening over two decades. Adoption is outpacing the evidence that tech-based methods are cheaper or more accurate than traditional ground-based approaches. We offer targeted recommendations for researchers & research institutions, policymakers, and project developers & standards bodies to keep monitoring locally led, ecologically grounded, and economically just, and we propose auditable indicators for evaluating progress toward these goals. As conservation and restoration scale, how progress is measured shapes whether efforts deliver lasting ecological gains and benefits for IPLCs, outcomes technology alone cannot capture.

Introduction

The success of efforts to conserve and restore the world's ecosystems is increasingly measured using technology: satellites tracking vegetation cover, drones mapping structure in three dimensions, recorders listening for wildlife, and DNA extracted from soil and water. Yet which of these tools an organization adopts reflects not only what a landscape needs, but also how its work is funded. Advancing ecologically effective and socially just conservation and restoration depends on centering equity and ensuring that local land stewards lead (Sterling et al. 2017, Höhl et al. 2020). This extends to how project outcomes are monitored (Evans et al. 2018), as conservation and restoration are inherently socio-ecological endeavors (Egan and Estrada 2013).

Beyond its moral imperative, equitable approaches improve conservation and restoration outcomes and are a strong predictor of project longevity, as Indigenous Peoples and Local Communities (IPLCs) are more likely to sustain projects they benefit from and have agency over (*e.g.,* Erbaugh et al. 2020, Djenontin and Zulu 2021, Mansourian and Sgard 2021, Elias et al. 2022, Löfqvist et al. 2023b). Decisions about what is monitored, and how, shape project outcomes and how landscapes are transformed. While equitable monitoring may conceptually be most strongly linked to ground-based approaches, this does not mean rejecting technology. Rather, it means ensuring that IPLCs lead the choice of monitoring approach and are equipped to manage both ground-based and tech-based methods where appropriate.

In recent years, the focus on monitoring tree cover change – largely tracking carbon-sequestration goals set by Global North actors (Fleischman et al. 2020) – has in part driven a shift toward tech-based approaches for assessing large-scale conservation and restoration commitments (Ford et al. 2024). We use 'tech-based' broadly to encompass satellite remote sensing, drone-based LiDAR, eDNA metabarcoding, ecoacoustics, and related sensor-driven methods. Tech-based monitoring is well suited to the two metrics that dominate conservation and restoration policy discourses: tree-cover change, which it detects directly, and carbon accumulation, which it estimates from canopy structure through allometric models (Lewis et al. 2019). Tech-based monitoring often captures biodiversity only indirectly - through structural or spectral proxies or partial species detection - and cannot, on its own, measure social outcomes. The Brazil-led Tropical Forest Forever Facility, for instance, links results-based payments to satellite-monitored forest cover across up to 74 participating countries (TFFF Steering Committee 2025).

Emerging nature-finance instruments promote monitoring, reporting, and verification (MRV) that prioritizes scalability over ecological insight (TFFF Steering Committee 2025, World

Economic Forum 2025, Zu Ermgassen et al. 2025), and MRV-focused 'nature tech' firms capture a disproportionate share of conservation technology funding (Wunder et al. 2025). Disclosure frameworks such as the Taskforce on Nature-related Financial Disclosures (TNFD) increasingly mediate corporate sustainability priorities, shaping both which ecological outcomes are monitored and the methods used (TNFD 2023, World Economic Forum 2025). Consequently, conservation and restoration monitoring commonly reflects the interests of external institutions rather than local stewards, producing a system optimized for marketability and scale, instead of ecological insight and equity. To test whether the choice of monitoring is shaped by funding structure, our novel analysis of survey data from a global sample of intermediary reforestation organizations (Schubert et al. 2026) finds that market-based organizations cite remote sensing more often than mission-based ones, a gap that appears to be widening over the past two decades (Box 1).

The concern is not that technology is replacing ground-based monitoring outright – most organizations layer remote sensing on top of site visits – but that analytical capacity, data ownership, and the potential economic benefits of monitoring increasingly flow away from IPLCs. At the same time, the growing emphasis on tech-based monitoring risks sidelining ecological information that only ground-based approaches can capture – for example, when a project commissions an external firm to conduct tech-based monitoring instead of training and paying a local field team to collect the same data. The broader shift in ecology toward statistical and model-driven approaches has come at the expense of observational, locally grounded studies (McCallen et al. 2019, Anderson et al. 2021), reinforcing the perception that tech-based approaches are the standard for rigorous monitoring (Figure 1a).

Tech-based monitoring is also widely assumed to be less expensive, yet this has rarely been tested and does not always hold when it has. In many tropical contexts, ground-based approaches can be cost-competitive with, or cheaper than, tech-based alternatives, particularly where the analytical infrastructure for processing remote-sensing data is absent (Table 1). For example, a commercial LiDAR survey in Indonesia was quoted at ~US$12,100 - about a year of wages for a five-person local field team - yet delivers only point-cloud and elevation data, not biomass estimates; and monitoring bird diversity with acoustic recorders in Panama cost ~20% more than expert point counts (Tables S1, S2).

Here, we argue that technology should support, not sideline, ground-based, locally led monitoring. Building on calls to integrate local and tech-based monitoring (Danielsen et al. 2021, Tabor et al. 2025) and frameworks for why and when monitoring is justified (Helmstedt et al. 2025), we ask: how are monitoring methods shaped by funding structures, and who stands to benefit? Drawing on empirical evidence (Box 1), we describe these dynamics and diagnose how research, policy, and market incentives interact to produce self-reinforcing monitoring lock-in (Figure 1a). We then offer actionable recommendations for three stakeholder groups - researchers & research institutions, policymakers, and project developers & standards bodies - to reinvest in ground-based monitoring and better integrate tech-based and traditional tools (Figure 1), each paired with auditable indicators for evaluating progress (Table 2).

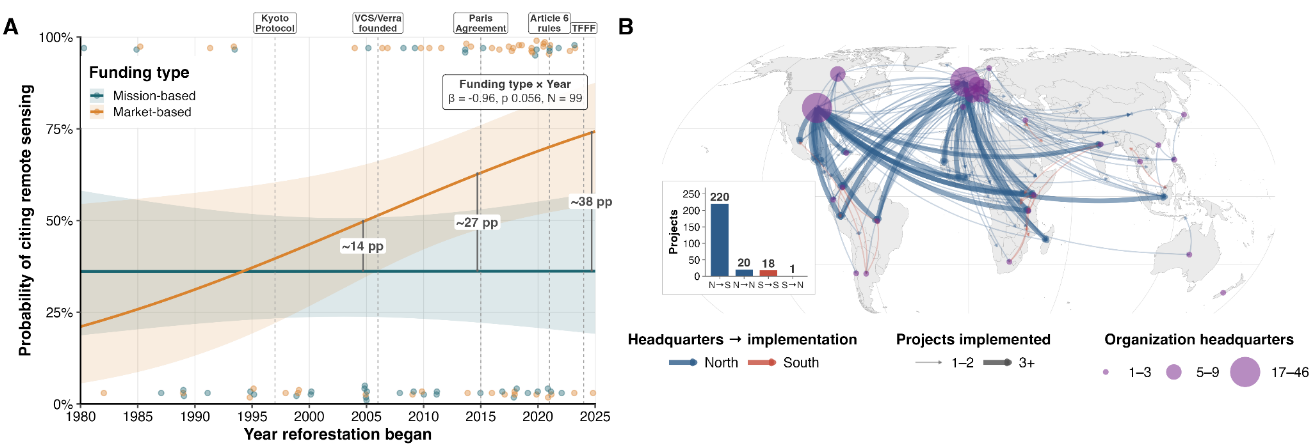
Table 1. Illustrative cost comparison of tech-based and ground-based monitoring approaches in two tropical settings. These cases show that ground-based monitoring can be cost-competitive where the analytical infrastructure for processing remote-sensing data is absent, not that it is uniformly less expensive. Costs reflect total project expenditure for each method, including personnel, equipment, and data collection. See Tables S1 and S2 for full cost breakdowns. All costs in 2025 USD (see Tables S1 and S2 for conversions). *Excludes survey-crew travel, accommodation, and per diem.

Monitoring goal	Location and scale	Tech-based method	Tech cost (USD)	Ground-based method	Field cost (USD)	Key finding
Vegetation biomass	Indonesia (130 ha)	Aerial LiDAR scan	$12,100*	Tree inventory (Trained local field technicians)	$200-$910 per month per technician	One 130-ha survey ~ up to a 5-person field team for a year (13-60 technician-months across wage ranges)
Bird diversity	Panama (64 sites)	Autonomous recording units (64 AudioMoths, 1 year)	$105,028	Point counts (local field technician + PhD student; 2 seasons)	$87,588	Acoustic monitoring cost ~20% more; mostly equipment and data storage, plus a more costly processing phase

Box 1. Market incentives shape how reforestation is monitored

Using survey data from 130 intermediary reforestation organizations (Schubert et al. 2026), we asked whether the choice of monitoring is shaped by funding structure, a question not addressed in the original study. We find that remote-sensing adoption among market-based organizations has risen over time, strengthening its link to funding structure. In a cross-sectional snapshot, organizations with market-based funding (*e.g.,* corporate sponsorship, carbon credit revenue) cite remote sensing as part of their verification approach more often than mission-based organizations (grants, government, endowments): 56% vs. 38% (N = 100). Market-based organizations showed a significant increase in remote-sensing adoption over time, whereas no significant trend emerged across the sector as a whole. This gap appears to widen from roughly 14 percentage points in 2005, when voluntary carbon markets began to scale, to approximately 38 points by 2025 (panel A).

Half of market-based organizations combine remote sensing with site visits, compared with less than a third of mission-based organizations – in both groups, fewer than 2% use remote sensing as a standalone method. The organizations driving this trend are overwhelmingly headquartered in the Global North (high-income economies per the World Bank classification) while implementation concentrates in the Global South (low- and middle-income economies), particularly East Africa and Latin America (panel B). Thus, the concern is less about direct monitoring method substitution than about where analytical capacity and economic benefits ultimately reside. As one organization noted: "We use a combination of ground-level monitoring, drone technology, and satellite imagery to track and verify the location and health of the trees we plant, relaying that information to our partners through their own unique dashboards…" These data are primarily self-reported, and the funding categorization reflects each organization's primary source, but they offer an important window into what influences the choice of monitoring in these projects.



A) Predicted probability of citing remote sensing by year reforestation began and funding type (logistic regression, N = 99). Market-based organizations show a significant increase over time (odds ratio = 2.62, 95% CI [1.14, 6.00], p = 0.023); the interaction with mission-based funding is marginal (odds ratio = 0.38, 95% CI [0.14, 1.02], p = 0.056), but a year-only model shows no significant trend (odds ratio = 1.39, p = 0.114), indicating that the gap is funding-type specific. Dashed lines mark policy milestones; shading shows 95% CIs. **B)** Headquarters-to-implementation connections, colored by the region of the headquarters: Global North (blue) or Global South (red). Line weight is proportional to the number of projects implemented in each destination country (thin: 1–2 projects; thick: 3+ projects). Purple circles denote headquarters locations, sized by the number of organizations headquartered in each country. **Inset:** total organization-implementation pairs grouped by headquarters region → implementation region. North → South flows (n = 220) dominate the other three categories by roughly an order of magnitude; South → North flows are effectively absent (n = 1, a Lebanese organization implementing in Saudi Arabia). Global North/South follow the World Bank high-income classification. In our analysis of data from Schubert et al. (2026), 70 organizations (54%) contributed direct survey responses; the remainder were characterized from public information. Logistic regression fitted with glmmTMB (binomial family, logit link). See *Supplementary Materials* for full methods.

The current monitoring imbalance and its consequences

Remote sensing and ground-based monitoring capture fundamentally different information. Satellite-based deforestation alerts can provide near-real-time detection across inaccessible terrain that ground-based methods cannot match at large scale (Hansen et al. 2013). Yet remote sensing captures biodiversity only indirectly. Structural and spectral signals such as canopy cover and greenness serve as proxies for habitat and diversity (Pettorelli et al. 2014), but these can diverge from the species composition, faunal recovery, and below-canopy processes that define restoration success (Bello et al. 2015, 2024). Nor can remote sensing detect selective harvesting, hunting of seed-dispersing animals, or livestock encroachment, changes that only ground-based monitoring can reliably detect (Fagan et al. 2026). Other emerging tech-based monitoring approaches also face important limitations. For example, eDNA methods can detect species presence but generally cannot provide reliable abundance estimates (Beng and Corlett 2020), and detections depend on species-specific DNA shedding rates and environmental persistence (Andruszkiewicz Allan et al. 2021). Acoustic monitoring is limited to vocalizing species and may miss silent or infrequently calling taxa (Bradfer-Lawrence et al. 2019). Both also depend on reference libraries that remain incomplete (Bradfer-Lawrence et al. 2025).

A common framing positions ground-based methods as unreliable, promoting technology as corrective rather than complementary (Shen et al. 2024), but these characterizations warrant scrutiny. Participatory approaches have demonstrated accuracy comparable to or exceeding remote sensing in some applications (Iheaturu et al. 2025). Monitoring systems that combine standardized protocols with the contextual knowledge of local observers can produce more equitable and actionable datasets (Kühl et al. 2020). In Panama's Darién, an Indigenous-led project trained 24 technicians who measured 30 one-hectare plots; error analyses and comparisons against Barro Colorado Island simulations confirmed their participatory protocol accurately captured plot-level aboveground biomass (Mateo-Vega et al. 2017). For many ecological metrics, ground-based methods outperform tech-based alternatives: field plots and transects yield more accurate data for fine-grained indicators such as seedling recruitment (Gong et al. 2024, Wang et al. 2024, Fleischman et al. 2025), though the relative performance of field and eDNA methods remains context-dependent (Borràs Sayas et al. 2025).

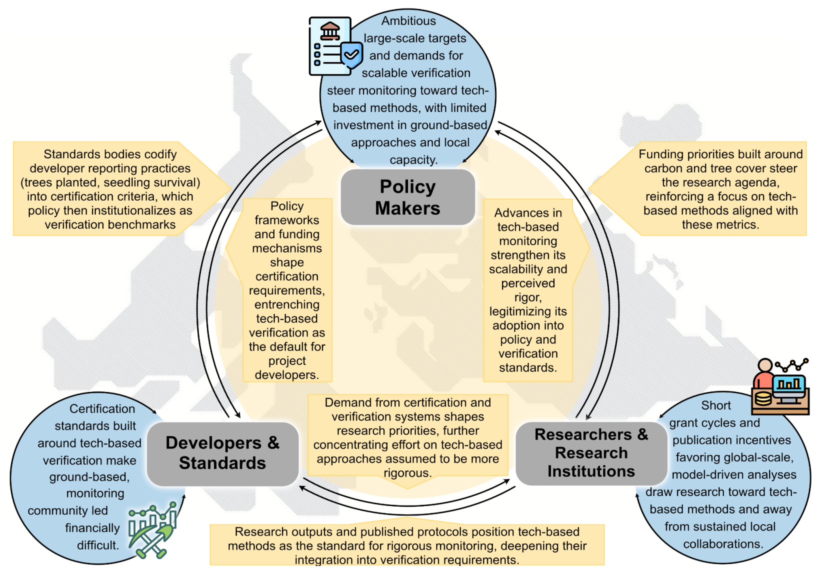
At landscape scales, ground-truth data remain essential for calibrating satellite-derived estimates (Celebrezze et al. 2024), particularly in restoration contexts where young, structurally heterogeneous stands confound allometric models calibrated on mature forests (Xu et al. 2024, Leoni et al. 2025). Data fusion frameworks that integrate field observations with remote sensing have demonstrated this complementarity in practice: in Nepal's Chitwan District, community-collected plot data calibrated satellite-derived canopy models with high accuracy (Murthy et al. 2017), and the GEO-TREES network (https://www.geo-trees.org/) coordinates permanent field plots specifically designed as foundational inputs to satellite biomass products. Despite this evidence, current verification standards and nature-finance instruments typically accept satellite-derived metrics but lack frameworks for incorporating community-collected data. Investor and funder preference for standardized, scalable metrics reinforces reliance on approaches that can be applied uniformly across geographies, regardless of whether they capture the outcomes that matter most on the ground. In this way, the choice of verification method becomes a governance decision – determining not only what is measured, but also who participates in and benefits from the monitoring process.

This governance imbalance often operates through a capacity gap. Tech-based approaches such as acoustic monitoring and drone-based LiDAR can produce large volumes of data in short periods, but resource-limited projects often lack the expertise to translate these data into ecological insights (Hahn et al. 2022). This expertise gap reflects a broader limitation: tech-based monitoring often centralizes data processing with external specialists, frequently based in the Global North or urban centers in Global South countries, rather than building local capacity (Urzedo et al. 2025). The growing use of artificial intelligence to process satellite, acoustic, and image data (Tuia et al. 2022) can deepen this dependence, concentrating analytical control in the institutions that build and run the models rather than in the communities whose landscapes they describe (Wearn et al. 2019). In practice, this analytical gap often results in data that cannot be used by people on the ground. A single drone flight or camera-trap rotation can produce gigabytes of data, but translating that volume into ecological insight requires computational resources and analytical expertise that many implementing organizations do not have in-house (Tabor et al. 2025). As a result, IPLCs are often confined to short-term data collection roles rather than leading analysis, forgoing livelihood benefits and withholding the place-based knowledge that makes monitoring data interpretable in the first place (Figure 2).

The shift toward tech-based monitoring risks transferring data collection and ownership away from local teams, marginalizing place-based ecological knowledge, and eroding employment pathways through which restoration sustains local economies (Danielsen et al. 2021, Hernandez-Montilla et al. 2026). Local employment in stewardship and monitoring can provide long-term benefits beyond landowner payments – through wages, skill development, and sustained engagement with restored landscapes (Thomas et al. 2024). Yet growing pressure to scale monitoring has concentrated authority over what is measured and who controls data in Global North institutions (Faxon and Chapman 2025). Our analysis makes this imbalance visible: 88% (114 of 130) of intermediary organizations are headquartered in the Global North while their implementation sites lie in the Global South - a skew sharper among market-based (92%) than mission-based (81%) organizations - and the flow runs overwhelmingly North to South (220 organization-implementation pairs to one; Box 1). Headquarters location is only a proxy for where data are analyzed, but it tracks where analytical capacity and the economic benefits of monitoring ultimately reside. Equitable data governance, not participation alone, determines who ultimately benefits (Reyes-García et al. 2022), and who owns and controls the data shapes whether technology advances or erodes local territorial rights (Sauls et al. 2023). Even programs designed around community participation can be undermined: in the Khasi Hills REDD+ Project in India, Indigenous communities manage their forests, but externally defined carbon accounting requirements constrain their ability to set monitoring priorities (Poffenberger 2015). Moreover, REDD+ programs have in some cases skewed landscapes toward maximum carbon accumulation to meet Global North targets, sidelining interventions better suited to local contexts (Hajjar et al. 2021, Redvers et al. 2025). Excluding IPLCs from these processes means crucial place-based knowledge is excluded (Mbizah et al. 2026), which increases the risk of project failure (Mazón et al. 2021). Conversely, when IPLCs lead restoration design and are the main beneficiaries, restored areas are protected and monitored more reliably (Sattayapanich et al. 2022), echoing Ostrom's (1990) argument that communities sustain shared resources most effectively when those who depend on them help set the rules and monitor compliance. The risk is structural: when interpreting monitoring data requires specialized capacity, the outside institutions tasked with doing so decide what counts as project success, and therefore what is funded and sustained.

Importantly, tech-based monitoring cannot measure social outcomes, making the absence of ground-based monitoring particularly problematic for evaluating whether conservation and restoration deliver equitable benefits (Holl et al. 2022). The community benefits most frequently cited by reforestation organizations – income, education and training, wellness, and food security (Schubert et al. 2024) – all require direct engagement with local people for assessment, including attention to intra-community power imbalances that shape how costs and benefits are perceived and distributed. While 98% of intermediary organizations publicly describe the benefits IPLCs would receive from tree-growing projects, only 38% reported outcomes of these metrics (Schubert et al. 2024).

(a)



(b)

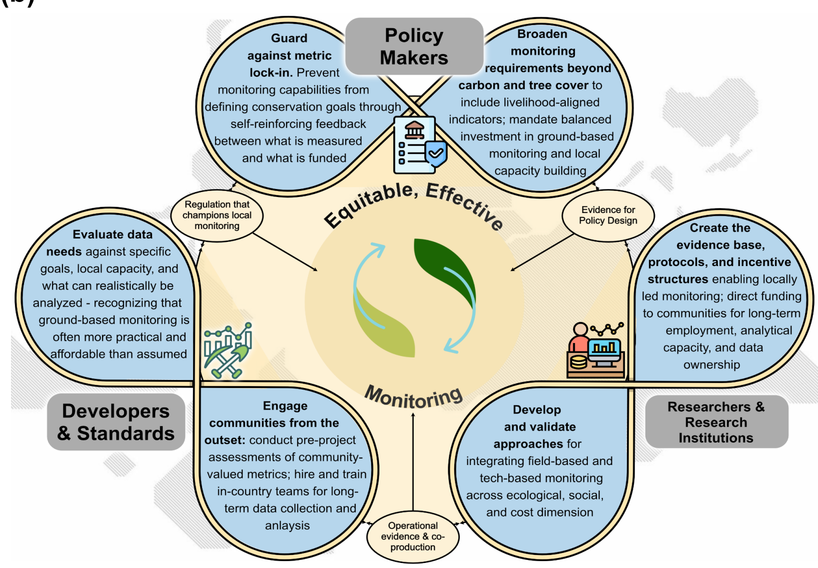


Figure 1. Market-driven funding and policy incentives risk creating an imbalanced monitoring cycle; reorienting toward equity requires interdependent action across researchers & research institutions, policymakers, and project developers & standards bodies. (a) The current cycle: market-driven funding structures and narrow verification requirements create a self-reinforcing loop that favors tech-based monitoring over locally led approaches. (b) A virtuous cycle converging on equitable, effective monitoring: technology supports rather than crowds out locally led monitoring, with the three stakeholder groups connected by interdependent pathways in which each group's actions strengthen the others. The three groups correspond to the recommendation sections of the manuscript. Progress along each pathway can be tracked using the indicators in Table 2.

A framework for rebalancing monitoring towards equitability

Breaking this growing lock-in requires more than better tools; the actors who sustain the cycle must move together. We propose a rebalancing framework (Figure 1b) in which three interdependent groups – researchers and research institutions, policymakers, and project developers and standards bodies – form a virtuous cycle, each loosening a different arm of the lock-in diagnosed above and each enabling the next. We organize the recommendations below by group, mapping each to the arm of the lock-in it targets and pairing it with an auditable indicator so that progress can be measured rather than assumed (Table 2). We then trace one policy change around the cycle to show how a single reform can catalyze change from one group to the next.

Recommendations for researchers & research institutions

Ground-based and tech-based methods capture complementary information, and integration frameworks have demonstrated their combined value. Realizing this potential at scale requires institutional change within the research community. A recent push for researchers and IPLCs to co-produce knowledge through stronger collaborations has led to emerging frameworks that aim to advance understanding of biological phenomena alongside addressing societal challenges, such as lack of local employment and capacity in monitoring (Evans et al. 2018, Longdon et al. 2024). Yet despite growing mandates for community engagement in conservation and restoration funding, the ephemeral nature of research grants – typically three to five years – often limits participation to short-term project cycles that are far too brief to properly understand the socio-ecological context of a project or to build lasting local capacity (Erbaugh et al. 2020). Publication incentives can compound the problem: high-impact journals have in recent years placed a strong focus on global-scale analyses of conservation and restoration opportunity (*e.g.,* Bastin et al. 2019, Brancalion et al. 2019, Strassburg et al. 2020, Mo et al. 2023), and scientific evaluation criteria rarely reward the sustained, place-based collaborations that community-led monitoring requires.

Recommendation 1: Build local leadership into research structures. To enable locally led monitoring, the research community should advocate for institutional changes: grant requirements that mandate and budget for community engagement in research; standardized yet adaptable monitoring protocols designed for long-term practitioner use (Lindenmayer and Likens 2010); and reformed authorship and recognition practices that give local collaborators equitable credit (Cooke et al. 2021). Equally important is ensuring that communities retain control over the data collected in their landscapes. Budgets also rarely cover the long-term data storage and management that locally held monitoring requires, so dataset ownership tends to migrate to better-resourced external partners. Training for local collaborators in data visualization and analysis is rarely included in research budgets (Danielsen et al. 2021, Reyes-García et al. 2022), and even when federal funding agencies support local collaboration in principle, institutional payment mechanisms and reporting requirements often make it difficult to direct resources to field collaborators in low-income countries. Closing these gaps requires funders and institutions to budget explicitly for long-term data storage, local analytical training, and authorship-based recognition, and to adopt payment mechanisms that can more easily direct resources to field collaborators in low-income countries.

Clear data governance agreements should be established at the outset of any project (Thung et al. 2026). Established frameworks such as the CARE Principles for Indigenous Data Governance provide a widely adopted basis for community ownership of data (Carroll et al. 2020), now operationalized for ecology and biodiversity research (Jennings et al. 2023), while Local Contexts / Traditional Knowledge Notices let communities assert provenance and permissions within existing benefit-sharing workflows (Anderson 2012). The share of datasets under such agreements is one auditable indicator of whether data ownership is staying local (Table 2). More fundamentally, wherever possible, IPLC members should help shape the research questions and choice of methods from the outset. Long-standing participatory programs illustrate what is possible: the parataxonomist model in Costa Rica's Área de Conservación Guanacaste has trained and employed hundreds of local people in monitoring over several decades, generating high-quality datasets while providing stable employment (Janzen and Hallwachs 2020). Yet when monitoring technologies generate data that hold no practical meaning for IPLCs, they risk displacing local approaches. Acoustic recorders, for instance, generate vast datasets, but the analytical tools to extract ecological meaning remain inaccessible without specialized training (Gibb et al. 2019). Investing in local analytical capacity can improve data quality through contextual interpretation while ensuring that monitoring generates sustained employment within conservation and restoration landscapes.

Recommendation 2: Develop the evidence base for how to effectively integrate tech- and ground-based methods. We encourage researchers & research institutions to develop the evidence base for integrating tech-based and traditional ground-based approaches. This evidence base should include comparative studies of how different monitoring frameworks perform across ecological, social, and financial dimensions. The uptake of such comparative studies is an auditable indicator of whether the field is building the evidence base needed to move beyond untested assumptions about cost and reliability (Table 2). Such work can build on emerging evidence that field-based methods match or outperform tech-based approaches for many ecological metrics (Danielsen et al. 2021, Gong et al. 2024, Iheaturu et al. 2025). A key barrier to broader adoption of ground-based methods is the perception that they lack consistency across sites; standardizing *in situ* monitoring protocols and public data sharing platforms could help address this limitation.

By developing data fusion frameworks that integrate field observations with remote sensing and other sensor platforms, researchers can deliver more comprehensive assessments of conservation and restoration progress while maintaining local involvement (Wang et al. 2024, Iheaturu et al. 2025). Key examples illustrate this integration in practice. In Ethiopia's Kafa Biosphere Reserve, local forest rangers submitted georeferenced disturbance reports via smartphones, which were used directly as training labels for a Landsat-based random forest classifier to detect forest degradation (DeVries et al. 2016); also see Nepal and GEO-TREES examples above).

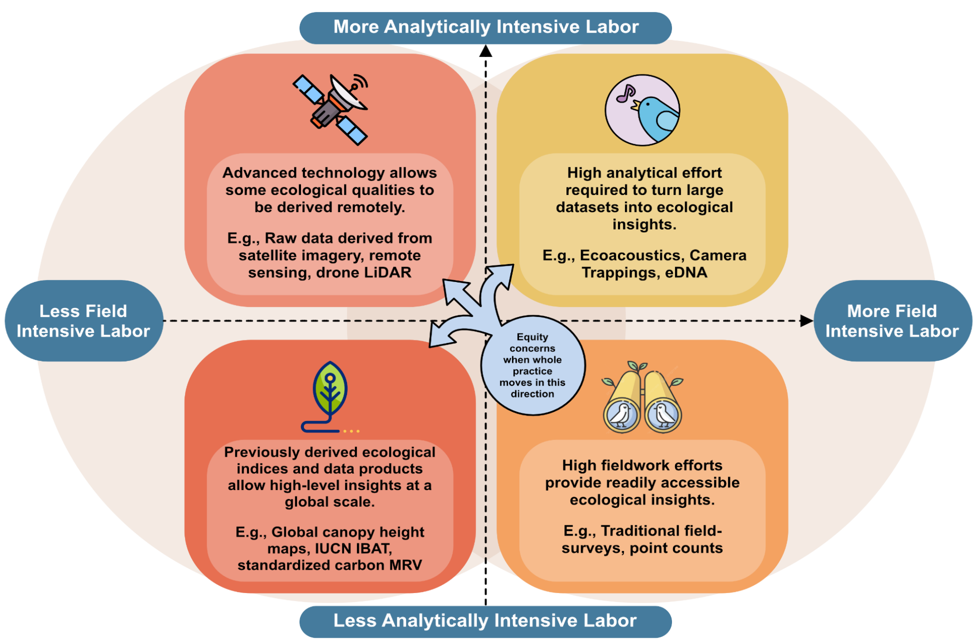


Figure 2. Conservation and restoration monitoring methods positioned along two axes: field labor intensity (horizontal) and analytical labor intensity (vertical). Shifts away from traditional field surveys (*bottom right*) in any direction can raise equity concerns: toward satellite remote sensing (*top left*), local field presence is reduced; toward ecoacoustics and camera trapping (*top right*), analytical complexity can exclude local participants; toward pre-built indices (*bottom left*), engagement with ground-level processes is abstracted away. In each case, local employment, data ownership, and participation in monitoring can erode unless the shift is designed equitably.

Recommendations for policymakers

Market-driven adoption of remote sensing, carbon-centric verification requirements, and the centralization of analytical capacity are all reinforced by policy frameworks that have traditionally underinvested in monitoring (Fagan et al. 2020), and have set ambitious targets (*e.g.,* the Bonn Challenge, https://www.bonnchallenge.org/; Trillion Trees, https://trilliontrees.org/) without clearly specifying how ecological outcomes will be tracked on the ground or how monitoring design will support IPLCs. Current policy proposals continue this trend, creating funding mechanisms that rely primarily on remote sensing without adequately weighing the tradeoffs between remotely sensed metrics and the ecological and social outcomes they omit (*e.g.,* Corson and Campbell 2023).

Without clear monitoring requirements, policy frameworks risk undermining both the ecological effectiveness and social equity of programs and, by leaving an incomplete picture of their benefits and costs, limiting the evidence needed to improve future policy. For example, programs that cap or omit monitoring spending contribute to short-lived projects (Schubert et al. 2024, West et al. 2025) and social justice risks (Parris-Piper et al. 2023). More broadly, funding is often channeled indirectly and non-transparently (Tabor et al. 2025), creating financial uncertainties for IPLCs that reduce participation incentives and limit the potential for monitoring to provide sustained employment (ILO-UNEP-IUCN 2024). Integrated monitoring and early community involvement in policy design could help prevent these outcomes (Evans et al. 2018, Höhl et al. 2020), but it requires that policy frameworks set tangible ecological targets beyond hectares restored and ensure that monitoring design supports local employment and capacity.

Recommendation 1: Measure the outcomes communities value and ensure community-engaged monitoring is required. We encourage policymakers to focus on a range of landscape restoration outcomes and recognize that prioritizing some (such as carbon drawdown) over others (such as those aligned with local livelihood objectives) risks driving social inequalities and jeopardizing ecological outcomes (Löfqvist et al. 2023b). This includes outcomes that often matter most to IPLCs – such as water quality and availability, access to agricultural and non-timber forest products, income, and livelihood diversification – outcomes that are rarely captured by remote sensing but are central to whether conservation and restoration are perceived to deliver equitable benefits (Danielsen et al. 2021). In the absence of certification requirements for community-engaged monitoring, project developers who invest in participatory approaches are financially disadvantaged against competitors that rely on tech-based systems alone (Schubert et al. 2026) – a dynamic we address further in our recommendations for project developers & standards bodies below. Regulatory frameworks must therefore establish a floor for community-engaged monitoring to prevent this race to the bottom. Nearly half of tree-growing organizations publicly report the percentage of funding reaching local projects, yet these reports rarely acknowledge the true costs of rigorous, long-term monitoring (Schubert et al. 2024). Policymakers can actively address this by promoting standards with more stringent criteria for required monitoring, especially for projects that generate offsets sold to Global North countries or private actors, where the benefits accrue far from the landscapes bearing the monitoring burden. Importantly, more stringent monitoring requirements need to be coupled with increased public funding and support for local project developers, otherwise there is a risk that more sophisticated monitoring requirements bias nature finance towards socio-economically stronger landscapes and/or projects led by actors with stronger financial means.

Currently, non-remotely-sensed metrics are often bureaucratic counts, such as the number of trees planted (Schubert et al. 2024), that are easy to collect but tell little about actual ecological outcomes or impact on communities. We argue that a minimum percentage of conservation and restoration program budgets should be allocated to traditional ground-based monitoring and local capacity building (Evans et al. 2018). Two indicators would make this auditable: the share of program budgets allocated to ground-based monitoring and local capacity, and the rate at which projects report verified – not merely described – social outcomes, currently 38% against the 98% that describe intended IPLC benefits (Table 2). Precedents exist for embedding ground-based ecological assessment within policy design. Ireland's Burren Programme (2010-2022) conditioned agri-environment payments on annual field assessments by trained advisors who scored habitat quality on each farm, demonstrating that results-based payment schemes can maintain ecological monitoring capacity at scale (Moran et al. 2021). Similarly, the Global Biodiversity Standard's regional hubs train local assessors to conduct ground-based verification, building in-country monitoring capacity (Bartholomew et al. 2026). Commodity certifications can also engage communities in biodiversity monitoring. For example, the Bird Friendly coffee certification trains coffee farmers and cooperatives to assess the biodiversity value of their farmland by conducting simple habitat surveys (e.g., canopy cover, binned tree species richness) that broadly correlate with the overall richness and diversity of birds (Bennett et al. 2022).

***R*ecommendation 2: Avoid letting what is straightforward to measure remotely define overall goals.** When monitoring capabilities define project goals, a self-reinforcing cycle often emerges; metrics that are easy to measure remotely attract funding, which entrenches those same metrics, crowding out outcomes that require ground-based assessment (Hernandez-Montilla et al. 2026). We caution policymakers against allowing this feedback loop to narrow the scope of what restoration is expected to achieve. The mechanism is concrete: because tree cover is inexpensive to measure by satellite and auditable across large areas, it is readily adopted as a verification standard and once embedded that standard entrenches the metric and the remote-sensing tooling it depends on. The complementary field- and social-monitoring capacity needed to capture other outcomes, which is costlier and harder to standardize, is then squeezed out. Capping monitoring at 5% of funds in Australia's '20 Million Trees' program (Commonwealth of Australia 2016) made labor-intensive ground monitoring unaffordable, favoring low-cost satellite imagery as the default (distinct from the costlier LiDAR and acoustic methods well-funded actors deploy). A cheap, creditable metric can scale this way; an assessment of 26 REDD+ carbon projects across six countries found that the credits they generated were systematically over-issued (West et al. 2023). Balmford et al. (2023) propose the PACT framework (Permanent Additional Carbon Tonne) for dynamically valuing impermanent nature-based carbon credits, and Swinfield et al. (2024) argue that refinements in standards, such as realizing credits ex-post project implementation, can increase the chance that credits represent real biodiversity uplift.

Despite these emerging reforms, the dominant carbon-centric metrics risk becoming further entrenched as they are institutionalized through mechanisms such as Article 6 articulated under the Paris Agreement of UNFCCC (2015), Target 19 in the Kunming-Montreal Global Biodiversity Framework UN CBD (2022), and emerging nature-finance frameworks (*e.g.,* the TFFF; TFFF Steering Committee 2025). These initiatives risk shaping research priorities and future policy at the cost of ecological and social outcomes. Some frameworks have begun to address this pattern. For example, Verra’s Sustainable Development Verified Impact Standard (SD VISta) requires projects to report and verify social and biodiversity outcomes alongside carbon (Verra 2024), although uptake remains limited (62 standalone projects as of February 2026). Policy design that integrates complementary monitoring approaches from the outset can help ensure that a narrow set of objectives does not come at the cost of positive social impact and biodiversity outcomes.

Recommendations for project developers & standards bodies

Project and certification design is often steered toward technology by the assumption that it is less expensive at scale. Our cost comparisons challenge this as field-based monitoring can be cost-competitive with tech-based alternatives in tropical contexts (Table 1), but project and certification design do not often reflect this reality. An emphasis on cost-effectiveness in monitoring can come at the expense of tailoring monitoring to track meaningful ecological and social change resulting from specific interventions – and of ensuring that the monitoring process itself supports IPLCs. This section addresses both project developers (implementing organizations and intermediary funders who often design and carry out monitoring) and the standards bodies (*e.g.,* Verra, Gold Standard) whose verification requirements shape monitoring practice.

Recommendation 1: Match the monitoring method to project goals and to local analytical capacity. In determining the appropriate mix of monitoring approaches, project developers & standards bodies should critically evaluate both what data are needed to track progress toward specific conservation or restoration goals and what local capacity exists to analyze those data. Meeting these needs credibly depends on baseline methods that are standardized yet adaptable to local contexts, and current practice falls short. Established protocols for ground-based ecological monitoring can be tailored locally (*e.g.,* Viani et al. 2020), but most cover only a narrow set of metrics, and standardization across restoration settings remains limited. The same gap undermines carbon verification, where competing baseline methods rely on divergent assumptions and can yield very different deforestation baselines for the same area (West et al. 2024). Emerging biodiversity credit markets face similar baseline and monitoring challenges (Aide 2024, Wunder et al. 2025), with corresponding integrity problems (Zu Ermgassen et al. 2019).

The cost data presented in Table 1 challenge the assumption that tech-based approaches are inherently more efficient: in contexts where analytical infrastructure for processing remote sensing data is absent, ground-based monitoring can be both cheaper and more actionable, and the costs of deploying and analyzing data from acoustic recorders can actually exceed those of traditional ground-based methods (Tables S1, S2), despite increasing promotion of automated recorders as scalable and cost-effective solutions to biodiversity monitoring. Beyond cost, accessibility matters. Cloud-dependent data analysis pipelines can be impractical in field settings with limited connectivity, creating unnecessary barriers to local data interpretation and ownership. Where possible, projects should invest in analytical tools and workflows that function offline, with intuitive interfaces, and can be maintained locally. We recognize that public institutions, especially in the Global North, play an important role in helping local project developers meet these goals through funding, technical assistance, and capacity building.

Recommendation 2: Co-design monitoring early and build local capacity to keep data and its benefits local. To increase the chance that monitoring generates long-term livelihood benefits, monitoring design should begin before project design is finalized. Pre-project assessments that map existing local monitoring practices and identify community-valued metrics can allow project developers to design monitoring that serves both accountability requirements and community needs, reducing the risk that communities face funding loss for failing to meet standards they had no role in defining. We encourage project developers, and the certification agencies whose requirements shape their options, to partner with local institutions and allocate resources to build local capacity for data collection, processing, and interpretation – including investing in local infrastructure for sample processing and analysis (*e.g.,* in-country lab capacity for eDNA; Shen et al. 2024). As established above, trained community data-collectors can produce estimates comparable to those of conventionally trained scientists, at substantially lower cost (Danielsen et al. 2021). By keeping data interpretation local, project developers can reduce dependencies on outside institutions while ensuring that monitoring knowledge remains accessible to those most affected. The auditable indicators here are the share of analysis conducted in-country and the number of standards that adopt a community-engaged-monitoring floor (Table 2).

Yet even project developers with strong capacity to execute ground-based monitoring often cannot financially justify doing so when certification standards and funders require tech-based approaches. If a nature-based credit buyer only requires remote sensing monitoring, a project developer who invests in more comprehensive ground-based methods risks being undercut by competitors who do not, creating a 'race to the bottom' that compromises ecosystem health and social justice (Löfqvist et al. 2023a). One practical step is to allocate a fixed portion of monitoring budgets to sustained local ground-truth data collection, which serves both as an independent check on remotely sensed estimates and as calibration data for local spatial models. Equitable implementation requires transparency at every stage, from who sets the monitoring agenda to how the data are shared (Sandbrook et al. 2021).

Tracing one change around the virtuous cycle

These recommendations are interdependent; tracing one change around the virtuous cycle (Figure 1b) shows how each group's action enables the next. To illustrate, consider a certification standard that adopts a floor for community-engaged monitoring and a requirement to verify social and ecological outcomes alongside carbon (enforced by audit at each crediting cycle) whether driven by regulation, by buyers conditioning their purchases on the requirement, or by the standards reform we recommend. To comply, developers must build or contract analytical capacity in-country rather than export data for processing - as the Global Biodiversity Standard's regional hubs (which train local assessors; Bartholomew et al. 2026) and Costa Rica's parataxonomist program (which turns monitoring into stable employment; Janzen and Hallwachs 2020) already do. Local teams in turn generate verified outcome data, lifting the share of projects that report, not merely describe, social outcomes above a relevant In once context benchmark of 38% (Schubert et al. 2024). Meeting the floor also pushes developers to direct budgets toward ground monitoring rather than capping it. Researchers then close the loop by merging these community records with remote sensing, as ranger reports did in training a Landsat classifier at Ethiopia's Kafa Biosphere Reserve (DeVries et al. 2016), and the verified results justify continued funding, reinforcing the standard that began the cycle.

The cycle holds only where the floor is enforced. When a buyer seeks the cheapest creditable metric, typically remote sensing alone, a developer who invests in ground-based monitoring risks being undercut, the race to the bottom noted above (Löfqvist et al. 2023a). A community-engaged-monitoring floor with an outcome-verification requirement removes that penalty: credits cannot issue without locally generated, verified outcomes, so the cheapest proxy no longer clears the bar. Ireland's Burren Programme shows this works at scale, as it released payments only against habitat quality that trained advisors scored in the field each year (Moran et al. 2021).

Table 2. Indicators for evaluating progress toward rebalanced monitoring. Each indicator maps to a stakeholder recommendation (Figure 1b) and to the arm of monitoring lock-in it is intended to loosen, with a current baseline and a working precedent. Indicator 3 is the key outcome metric; the other five are enabling conditions that make that outcome more likely.

Indicator #	What it measures	Stakeholder action tracked	Lock-in arm targeted	Baseline or anchor	Precedent – how it has worked in practice
1	[**Enabling**] Presence of data-governance / ownership agreements at project outset; share of datasets under community control	*Researchers & Research Institutions Rec. 1* – build local leadership (governance at outset)	Data ownership flowing away from IPLCs	Currently ad hoc; ownership migrates to better-resourced external partners	The CARE Principles for Indigenous Data Governance are a widely adopted framework for community ownership of data (Carroll et al. 2020), now operationalized for ecology and biodiversity research (Jennings et al. 2023); Local Contexts & Traditional Knowledge Notices let communities assert provenance and permissions (Anderson 2012)
2	[**Enabling**] Increase of cost-inclusive comparative studies of tech- vs. ground-based monitoring, with guidance on which to use in each context	*Researchers & Research Institutions Rec. 2* – develop the evidence base	Under-tested claim that field methods are unreliable or more costly	Few systematic, multi-dimensional comparisons exist	In one context, community members named 95% of trees, with diversity data comparable to that of trained botanists at one-third the cost (Zhao et al. 2016); and participatory methods have matched or exceeded remote sensing for many ecological metrics (Iheaturu et al. 2025)
3	[**Outcome**] Rate at which projects report verified (not merely described) social outcomes	*Policymakers Rec. 1* – measure the outcomes communities value	Inability of tech-based monitoring to capture social outcomes	38% report outcomes vs. 98% that describe intended IPLC benefits (Schubert et al. 2024)	Verra SD VISta requires verified social and biodiversity outcomes alongside carbon (Verra 2024), and rigorous designs can measure these outcomes at scale. For example, a counterfactual evaluation across >600 protected areas in 34 countries found higher wealth and lower poverty near reserves with tourism (Naidoo et al. 2019)
4	[**Enabling**] Proportion of certification standards and frameworks that verify community and social outcomes (not only carbon and biodiversity) and adopt a community-engaged-monitoring floor	*Policymakers Rec. 2* – avoid letting what is straightforward to measure remotely define goals	Carbon-centric, remotely measurable metrics crowd out community / social outcomes; race to the bottom	Verra SD VISta uptake is low = 62 projects (Feb 2026); most standards accept satellite-only verification	The Kunming-Montreal GBF is structured to absorb community data as ~30% of its 365 indicators can use community-based monitoring (Danielsen et al. 2024); and Equitable Earth's M002 methodology makes a livelihoods pillar and free, prior, and informed consent co-equal certification requirements (Equitable Earth 2026), though such standards mostly verify participation rather than community ownership of the data
5	[**Enabling**] Share of program budget allocated to ground-based monitoring and local capacity	*Developers & standards bodies Rec. 1* – match the method to local analytical capacity	Underinvestment in ground-based monitoring and local capacity; race to the bottom	Australia "20 Million Trees" capped monitoring at ≤5% of funds (Commonwealth of Australia 2016)	Ireland's Burren Programme conditioned results-based payments on annual field assessments scored by trained advisors, sustaining monitoring capacity at scale (Moran et al. 2021); and EU payment-by-results agri-environment schemes release payment only on a verified ecological indicator, allowing recurrent field assessment (Herzon et al. 2018)
6	[**Enabling**] Proportion of monitoring-data analysis conducted in-country / locally retained	*Developers & standards bodies Rec.* 2 – co-design early; keep data and benefits local	Centralization of analytical capacity in the Global North / urban centers	Analysis centralized with external specialists	Global Biodiversity Standard regional hubs train in-country assessors (Bartholomew et al. 2026); and Costa Rica's ACG parataxonomists produced high-quality data and stable local employment over decades (Janzen and Hallwachs 2020)

Evaluating progress toward rebalanced monitoring

Finally, a framework is only implementable if its progress can be measured. We designed the six recommendations above to be audited, and many of the instruments needed to track them already exist within conservation and restoration practice. We propose six indicators (Table 2), each tied to one stakeholder action and to the arm of the monitoring lock-in it is meant to loosen, and each anchored to a baseline or working precedent already in use - from the CARE Principles for Indigenous Data Governance to the Kunming-Montreal Global Biodiversity Framework, which by design can draw on community-based monitoring for roughly 30% of its 365 indicators (Danielsen et al. 2024). Together they can convert the virtuous cycle of Figure 1b into quantities that funders, standards bodies, and researchers can report on a common basis. The six indicators do not carry equal weight; indicator 3 – the rate at which projects report verified, not merely described, social outcomes (Schubert et al. 2024) – is the load-bearing outcome metric, while the other five track the enabling conditions for it.

These proposed indicators should be read with one important caveat. Emerging standards increasingly verify participation and consent, as with Equitable Earth's M002 methodology which makes a livelihoods pillar and free, prior, and informed consent co-equal certification requirements (Equitable Earth 2026), but community ownership and control of the monitoring data remains the harder, largely unmet bar to overcome. We therefore offer these indicators as a proposed scheme to be sharpened with community involvement and as the comparative evidence base grows, baselined at project design and re-measured at each funding or verification cycle; the immediate value is a shared, falsifiable basis for judging whether monitoring is becoming more locally led, ecologically grounded, and economically just.

Outlook

Current technologies widely promoted for landscape-scale conservation and restoration assessment may inadvertently undermine the local engagement essential for long-term project success and give an incomplete view of progress toward environmental goals. The current trajectory, toward tech-based monitoring shaped by funder- and market-driven requirements, risks sidelining communities from both data generation and the long-term social and economic benefits of conservation and restoration. It also risks reinforcing the impression that tech-based metrics alone can fully capture ecological recovery, when many dimensions of recovery require direct, locally led assessment. Monitoring that integrates technological and ground-based approaches while supporting local capacity building is not only more equitable; it is associated with greater project success and permanence. With the indicators proposed here, progress toward this goal can be tracked rather than assumed. Researchers & research institutions, policymakers, and project developers & standards bodies each have distinct roles in reorienting monitoring systems toward equity and effectiveness (Figure 1b), and these roles are deeply interdependent; progress requires change in tandem. Ultimately, the choice of monitoring approach is not solely technical; it determines who benefits from conservation and restoration, and whether interventions are effective and equitable at scale.

CRediT Authorship statement

Conceptualization: S.L., L.K.W., D.H.D. *Methodology:* L.K.W., S.C.S. *Software:* S.C.S., L.K.W. *Formal analysis:* S.C.S., L.K.W. *Resources:* S.C.S., K.D.H., C.J.P.S., R.E.B., L.K.W. *Data curation:* S.C.S., R.E.B. *Visualization:* G.D., L.K.W., S.C.S. *Writing – original draft:* L.K.W. *Writing – review & editing:* all authors. *Supervision:* L.K.W., D.H.D. *Project administration:* L.K.W., D.H.D. *Funding acquisition:* L.K.W., D.H.D.

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Data availability

All data necessary to reproduce the analyses in Box 1 are available in Schubert et al. (2026).

Declaration of interests

The authors declare no competing interests.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work, the authors used Claude (Anthropic PBC) to refine the R code for the figures presented in Box 1. The authors manually reviewed all edited code and take full responsibility for the content of the published article.

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Supplementary Material for Werden et al. 2026 - *Technology should support, not sideline, locally driven conservation and restoration monitoring*

Supplementary Methods - Analysis of monitoring methods across reforestation organizations (Box 1 figure).

The data reported in Box 1 are from a global survey of intermediary reforestation organizations conducted by Schubert et al. (2026), in which organizations reported their funding structures, monitoring and verification approaches, geographic location, and area of operation. The analyses reported in Box 1 and the main text are our own and are not presented in the original publication. The raw survey data are available from Schubert et al. (2026).

We classified each organization's primary funding structure as market-based (corporate sponsorship, carbon-credit revenue, or other earned revenue) or mission-based (grants, government funding, or endowments) and recorded whether its self-reported verification approach referenced remote sensing (satellite or drone imagery), alone or combined with ground-based site visits. Of 130 organizations surveyed, 100 reported a classifiable primary funding structure (52 market-based, 48 mission-based); across these, market-based organizations referenced remote sensing more often than mission-based organizations (55.8% [29/52] vs. 37.5% [18/48], respectively).

To test whether this association has changed over time, we modeled remote-sensing use as a function of funding structure, the year reforestation began (z-standardized), and their interaction, using logistic regression (*glmmTMB* package; binomial family, logit link; N = 99, restricted to organizations with a known start year). Remote-sensing adoption increased over time among market-based organizations (odds ratio per standard deviation of start year = 2.62, 95% CI [1.14, 6.00], $p = 0.023$); the funding-by-year interaction was marginal (OR = 0.38, 95% CI [0.14, 1.02], $p = 0.056$); funding types did not differ at the mean start year (main effect of funding structure, $p = 0.15$) and a year-only model showed no significant sector-wide trend (OR = 1.39, $p = 0.114$). Together these indicate that rising remote-sensing adoption is specific to market-based organizations. The predicted market- versus mission-based gap appeared to widen from ~14 pp in 2005 (50% vs. 36%) to ~38 pp in 2025 (74% vs. 36%; Box 1, panel A).

We also summarized the combination of remote sensing with field methods (half of market-based vs. fewer than one-third of mission-based organizations combined the two; fewer than 2% of either group used remote sensing alone) and the geographic distribution of organization headquarters versus implementation sites, classified by World Bank income group (Box 1, panel B). All analyses were conducted in R version 4.5.0 (R Development Core Team, 2025).

These data are primarily self-reported, and each organization's funding categorization reflects its primary source rather than its full funding portfolio; results should be read as indicative of sector-level patterns rather than precise estimates.

Table S1. Cost estimation of generating vegetation biomass values in Indonesia using either LiDAR scans or field labor. To compare the cost of ground-based approaches against technological approaches to monitoring in restoration, we use vegetation biomass calculations in Indonesia as an example. Indonesia is a country that hosts globally significant biodiversity hotspots and carbon reserves that are under constant pressure from deforestation and forest degradation. It is consistently identified as a priority region for ecological restoration including through carbon and biodiversity crediting schemes. This table outlines the information used to estimate prices of, and people employed in, vegetation data collection for the two methods. Estimates are based on a 2025 commercial drone LiDAR quotation obtained by the authors from an Indonesian operator to conduct flights in Indonesia, delivering point-cloud and elevation data (not biomass; Commercial UAV LiDAR quotation from an Indonesian operator, 2025; available on request from the authors). All costs reported in 2025 USD unless otherwise noted, converted at the 2025 average rate (x-rates.com). *Indicates that the number excludes flights, accommodation, and per diem for the survey crew.

Activity	Method	Price	Description
Quantifying vegetation biomass (carbon)	Aerial LiDAR	~$12,100*	Commercial drone LiDAR survey covering ~130 ha in Lampung and Sulawesi (~IDR 199.8 million = ~US$12,100). Delivers a 3D point cloud, DSM, and DTM; does not include conversion to biomass values, which requires additional processing.
	Field survey	$200 - $910 per month	*Low estimate:* provincial monthly minimum wage of ~IDR 2.2-5.4 million across provinces (~IDR 3,296,000 = US$200), as a cross-provincial average (ASEAN Briefing, 2025). *High estimate*: an entry-level technical field salary (~IDR 15,000,000 = US$910), an upper bound reflecting skilled/technical pay scales (Economic Research Institute, 2025).

Table S2. Costs of collecting and analyzing data on bird diversity in shade coffee, sun coffee, and forest sites in Chiriquí, Panama; data are from the Smithsonian Bird Friendly coffee program. Data were collected using two different methods: Point Counts (field observation of birds by sight and sound from an experienced local field technician and graduate student) and AudioMoths (Acoustic Recording Units deployed at the same sites where Point Counts were conducted). AudioMoth units (N = 64) were deployed across coffee and forest sites, spanning a ~200 km² core landscape (20 × 10 km), with sparser coverage extending across a ~20 × 70 km area. Data from Point Counts were gathered in 4 replicated 10-minute observation periods in each of 2 seasons (breeding and non-breeding seasons), while acoustic data from AudioMoths were gathered on a duty cycle of 1-minute recording every 10 minutes, 24 hours a day, for a full year. Because the acoustic detection radius of AudioMoths varies by species and vegetation, a precise per-unit sampling area cannot be defined; costs are therefore reported per recording unit. Both methods had the same costs for site selection and collection of associated habitat data. All costs reported in 2025 USD.

Activity	Method	Description	Cost per unit	Unit	No. units	Point Count Cost	Audio Moth Cost
Initial site selection (contacting landowners, obtaining permissions, establishing 64 sampling points)	Both	PhD student. Tuition and stipend	$3,000	month	2	$6,000	$6,000
	Both	Local field assistant salary	$1,500	month	2	$3,000	$3,000
	Both	Local transportation (truck rental and gas)	$2,000	month	2	$4,000	$4,000
	Both	Local housing	$285	month	2	$570	$570
Equipment	Point Counts	Binoculars	$350	unit	2	$700	
	AudioMoths	Memory cards: 3 per AudioMoth	$19	unit	192		$3,648
	AudioMoths	Batteries (lithium AA)	$0.78	unit	1152		$899
	AudioMoths	AudioMoths	$100	unit	64		$6,400
	AudioMoths	Cases for AudioMoths	$50	unit	64		$3,200
	AudioMoths	20 TB storage on computing cluster	$2,000	unit	1		$2,000

Data collection: Habitat data in a 30-m radius around each data collection point	Both	PhD student. Tuition and stipend	$3,000	month	1.5	$4,500	$4,500
	Both	Local field assistant salary	$1,500	month	1.5	$2,250	$2,250
	Both	Local transportation (truck rental and gas)	$2,000	month	1.5	$3,000	$3,000
	Both	Local housing	$285	month	1.5	$428	$428
Data collection. Bird Point Counts. (64 points, 4 repetitions per point per season, 2 seasons)	Point Counts	PhD student. Tuition and stipend	$3,000	month	4	$12,000	
	Point Counts	Local field assistant salary	$1,500	month	4	$6,000	
	Point Counts	Local transportation (truck rental and gas)	$2,000	month	4	$8,000	
	Point Counts	Local housing	$285	month	4	$1,140	
Data collection. AudioMoths (64 points; battery and memory card swapped every 60 days)	AudioMoths	Postdoc stipend and travel	$6,250	month	1		$6,250
	AudioMoths	Local field assistant salary	$1,500	month	4.5		$6,750
	AudioMoths	Local guide for field assistant	$600	month	3.5		$2,100
	AudioMoths	Local housing	$285	month	4.5		$1,283
Data Analysis	Point Counts	PhD student. Tuition and stipend	$3,000	month	12	$36,000	
	AudioMoths	Postdoc stipend	$5,417	month	9		$48,750
TOTAL						$87,588	$105,028

Supplementary references

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