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Review article

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The role of conservation bioacoustics in achieving global biodiversity goals

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Sections

Abstract

Conservation bioacoustics – the science of recording and analysing animal sounds for biodiversity conservation purposes – has become an important part of the conservation toolkit, spurred by the ever-growing need to monitor species on a rapidly changing planet. Innovations in recording hardware, artificial intelligence and ecological understanding of animal sounds and soundscapes have helped to drive forward bioacoustic research. In this Review, we explore the main ways conservation science uses bioacoustics and ecoacoustics, with particular focus on the Kunming–Montreal Global Biodiversity Framework, which requires robust, scalable biodiversity methodologies to achieve its 2030 targets. We review the main considerations for evaluating the evidentiary strength of acoustic data in conservation science, both in the field and during analysis. This Review empowers conservation scientists and practitioners with the knowledge to determine whether conservation bioacoustics is the right approach for a particular need, what kind of results it is going to yield and with what uncertainty. As conservation efforts globalize, involving diverse partners, larger investments and claims of impact, evidence on biodiversity impacts needs to be externally verifiable and comparable across ecosystems and regions. Understanding when and how bioacoustics can provide that evidence is key for a responsible uptake by conservation.

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Introduction

Conservation bioacoustics, camera traps, environmental DNA (eDNA) and remote sensing have transformed biodiversity assessments[1]. Passive acoustic monitoring (PAM) has emerged as particularly powerful owing to its ability to operate continuously, even in conventionally challenging conditions such as at night, underground or in deep water. Bioacoustics is applicable to any taxon that produces detectable sound, including birds, frogs, bats, marine mammals, fishes and many terrestrial and aquatic invertebrates. Acoustic data, often recorded as entire soundscapes, can be standardized, archived and reanalysed[2], enabling inference on species presence, activity, fitness, behaviour, abundance, phenology, community structure and many threats to biodiversity[2].

Throughout this Review, we use the term conservation bioacoustics to refer to the application of sound-based methods to conservation science and practice. This term aims to encompass a range of methods traditionally falling under both ecoacoustics, as well as techniques such as recognition of individual animals based on their sound, which traditionally might fall under bioacoustics[3–5]. For brevity, we sometimes refer to conservation bioacoustics simply as bioacoustics, recognizing, however, that the disciplinary boundaries between bioacoustics and ecoacoustics continue to evolve across disciplines, applications and research communities. Conservation bioacoustics encompasses a heterogeneous set of data types, analytical approaches and inferential claims, ranging from direct evidence of species presence to indirect proxies of biodiversity change. Interpreting sound as conservation evidence requires understanding the full pathway from sound production and propagation to detection, classification and aggregation into metrics that inform decisions.

As conservation efforts globalize, involving more diverse actors, larger investments and claims of impact, evidence on biodiversity outcomes needs to be externally verifiable and comparable across landscapes and regions. For example, the Kunming–Montreal Global Biodiversity Framework (hereafter, Kunming–Montreal GBF), adopted in 2022, sets the global agenda for biodiversity conservation, establishing 4 long-term goals and 23 targets for 2030[6]. The long-term goals, to be achieved by 2050, include protecting and restoring all ecosystems, using biodiversity sustainably and fairly, and investing and collaborating to increase biodiversity finance. Its official monitoring framework includes broad and sometimes vague indicators such as 'species trends and population status' or 'ecosystem structure and function' (ref. 6), terms that are quantifiable for individual species or structural habitat features but more difficult to apply in practice when it comes to ecosystem function or 'biodiversity' overall. The GBF explicitly recognizes the need for better technology for global biodiversity reporting[7]. In parallel, natural climate solutions or nature-based climate solutions (NCS), which are actions to protect, sustainably manage, and restore ecosystems to address climate change, emphasize human well-being and biodiversity as important co-benefits of climate actions[8,9]. Within the European Union, nature-based solutions (a more general term encompassing climate and other solutions) are mandated to 'benefit biodiversity', whereas, globally, NCS must cause 'no net harm to biodiversity'[10,11]. Finally, biodiversity credits require standardized measurements of biodiversity that are evidenceable (that is, able to generate independent, externally verifiable evidence of the biodiversity impact[12]).

These efforts, therefore, need reliable, scalable and transparent methods for biodiversity monitoring, and bioacoustics is one such method that many conservation organizations and other actors in the conservation and climate sector have adopted. However, succinct guidance is missing on what questions bioacoustics can (and cannot) answer, how to decide when bioacoustics is the best approach, what specific bioacoustic method to use, and the expected strengths and uncertainties of the results.

In this Review, we explore where, in the conservation landscape, bioacoustics has been used, what results have been achieved and the key considerations for integrating bioacoustics into biodiversity monitoring. We first describe the main uses of bioacoustics along the conservation science continuum from understanding threats and setting goals to implementing solutions and evaluating their effectiveness. We review the types of results and metrics that are commonly extracted from bioacoustic data for conservation, along with their evidentiary strength, such as the degree to which data reliably support or refute a scientific or conservation claim, given how the data were generated, processed and interpreted. Several reviews have already been published on various topics within bioacoustics and ecoacoustics, including those on terrestrial[13,14], freshwater[15,16] and marine systems[17]; we point to these throughout and in Box 1. The focus of this Review is on the realized and potential uses of bioacoustics in achieving global conservation targets, such as the Kunming–Montreal GBF, and the evidentiary strength of the diverse bioacoustic data types.

Application of bioacoustics in conservation

Conservation research can be conceptualized as first identifying problems and diagnosing their causes, setting goals to solve them, designing and implementing solutions and finally testing and evaluating their effectiveness[18]. Many comprehensive biodiversity agendas, such as the Kunming–Montreal GBF, can be mapped onto this conservation conceptual framework. Here, we illustrate the typical and increasing uses of bioacoustics in each stage of this framework (Fig. 1).

Identifying problems and diagnosing their causes

Identifying conservation problems and understanding their causes are the first steps in the conservation science conceptual framework[18]. Autonomous recording units (ARUs, marine (MARUs) or terrestrial) can serve as long-term observatories[19–21], generating soundscape recordings that can be analysed to detect threats with prominent acoustic signatures, increases in or emergence of ecologically problematic species (for example, those labelled as invasive), or declines in sensitive species or overall vocalizing biodiversity through monitoring soundscapes over time. Measuring animal populations and communities at different sites using PAM can also be used to understand the drivers of their decline. Finally, identifying a truly new conservation problem by detecting previously unsuspected changes in soundscapes is a promising but as yet rare use of bioacoustics that will be increasingly enabled by long-term acoustic monitoring networks or observatories[20–23].

Sound-based systems are used to detect potentially illegal human activities, such as gunshots from poaching or hunting[24,25], blast fishing[26], illegal boat activities within marine protected areas[27,28], or chainsaw sounds associated with logging[29,30]. Detecting threats through sound monitoring has two major advantages. First, threats (and organisms' responses to them) can be measured at the same spatial and temporal scales and using the same instruments, thereby increasing the feasibility of causal inference, which is rarely done in biodiversity conservation studies[31–33]. Second, near-real-time detection allows for rapid, and in principle more effective, responses. Gunshot monitoring on land and illegal vessel presence on water can help to distribute patrols dynamically in space and time[24,34]. For example,

Box 1 | Essential literature for conservation bioacoustics workflow

Conservation question or need

Bioacoustic project design (Box figure) varies substantially depending on the conservation question or need. This Review provides an overview of the various conservation questions in which bioacoustics has already been used, from identifying and diagnosing the cause of a new conservation problem, to prioritization and goal setting, to implementing the solution and evaluating its effectiveness (Fig. 1).

Ethical and practical suitability of bioacoustics

Whether bioacoustics is practical depends on the surveyed organisms[150], their environment, the monitoring necessity[240], permissions[40,241] and goals[242], and on whether resulting metrics will be suitable to achieve the goals[132].

Sampling design and deployment

What sensors to deploy, where, for how long and with what settings are key decisions to ensure the suitability of the resulting dataset for answering the conservation questions. Important factors to consider include species-specific detection ranges, acoustic independence among sensors or optimal spacing for arrays, the phenology and vocalizing frequency of the surveyed organisms[141,215,226,243–245].

Acoustic data collection and management

Standardized metadata collection, including environmental data, is essential for transparency and use as covariates in ecological statistical models[246–248]. Data storage and permanent archiving solutions are important part of the project design[247,249,250] because data-sharing platforms typically used alongside peer-reviewed publications do not accept the amount of raw soundscape data generated by even modest-sized bioacoustic projects.

Manual annotations and acoustic analysis

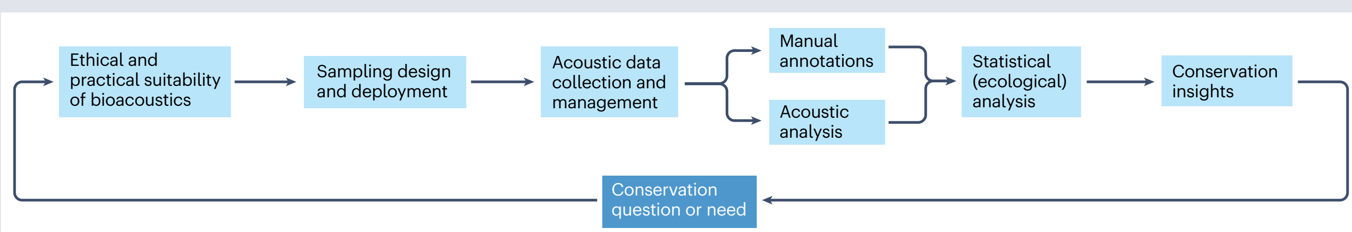
Different software is available at every stage of the analysis (such as Raven Pro and Kaleidoscope) as well as open-source R packages (such as seewave[251], warbleR[252], ohun[253] and opensoundscape[254]). Reporting which tools are used at each stage is essential for reproducibility. Almost all conservation bioacoustic projects require some manual annotations or expert listening, yet few specify annotation standards or explain how species inclusion was determined[255,256]. When training detection or classification models, a clear division into training, testing and validation datasets is important[255–258]. The latter enables quantifying false positive and negative rates for the taxa of interest, which should be reported along with models, training data and code[258]. Other machine learning options include using embeddings and self-supervised clustering[181]. If acoustic indices are used, it is important to consider the influence of any thresholds or values (via sensitivity analyses[259]), the rationale for an index choice and the interpretation of the index[226].

Statistical (ecological) analysis

Acoustic analysis outputs are frequently more dimensional and richer than traditional expert surveys, and appropriate statistical ecological models are still evolving to support this[135,173,206,260]. Analytical methods that can deal with these rich datasets include generalized additive mixed models and hierarchical modelling approaches such as occupancy models.

Conservation insights

For conservation decision-making, model outputs and acoustic metrics must be intuitive and easily interpretable and must clearly convey associated uncertainty. The relative complexity of bioacoustic projects often warrants a multidisciplinary team, with expertise in conservation, ecology, statistics, signal propagation, machine learning, ethics and social science.



acoustic arrays in Sabah, Malaysia, allowed for near-real-time detection of blast-fishing events to be located with 60 m accuracy and geographically mapped on a computer within 10 s (ref. 34). In most terrestrial cases, such real-time or near-real-time systems are still at a proof-of-concept stage, such as gunshot monitoring projects in Canada, Gabon and Vietnam[35–37]. Time lag between data collection, analysis and conservation action remains common, especially in tropical regions with limited data connectivity, but lightweight on-board convolutional neural networks (CNNs) are beginning to solve this problem[38]. Meanwhile, even lagged analyses of gun hunting rates can help to achieve Target 5 of the Kunming–Montreal GBF (Ensure sustainable, safe and legal harvesting and trade of wild species; Fig. 1) by enabling communities implementing self-governance of hunting to establish sustainable off-take[39].

The use of bioacoustics by scientists and conservation practitioners for surveillance of illegal activities raises complex ethical concerns[40] (Box 2). At the very least, the implementation of such systems requires rigorous risk analysis of potential data misuse (such as by oppressive governments) and robust data distribution security; careful free, prior, informed consent from resident human populations; and thorough consideration of who bears the risk when action is taken. For instance, when real-time poaching alerts are issued, forest rangers need to be adequately equipped, trained and supported to confront armed poachers safely. Further ethical dilemmas concern hunting management in general and are not specific to bioacoustics[41]. PAM, through the increased effectiveness of hunting monitoring, could exacerbate existing controversies, particularly conflicts between conservation managers and subsistence hunters.

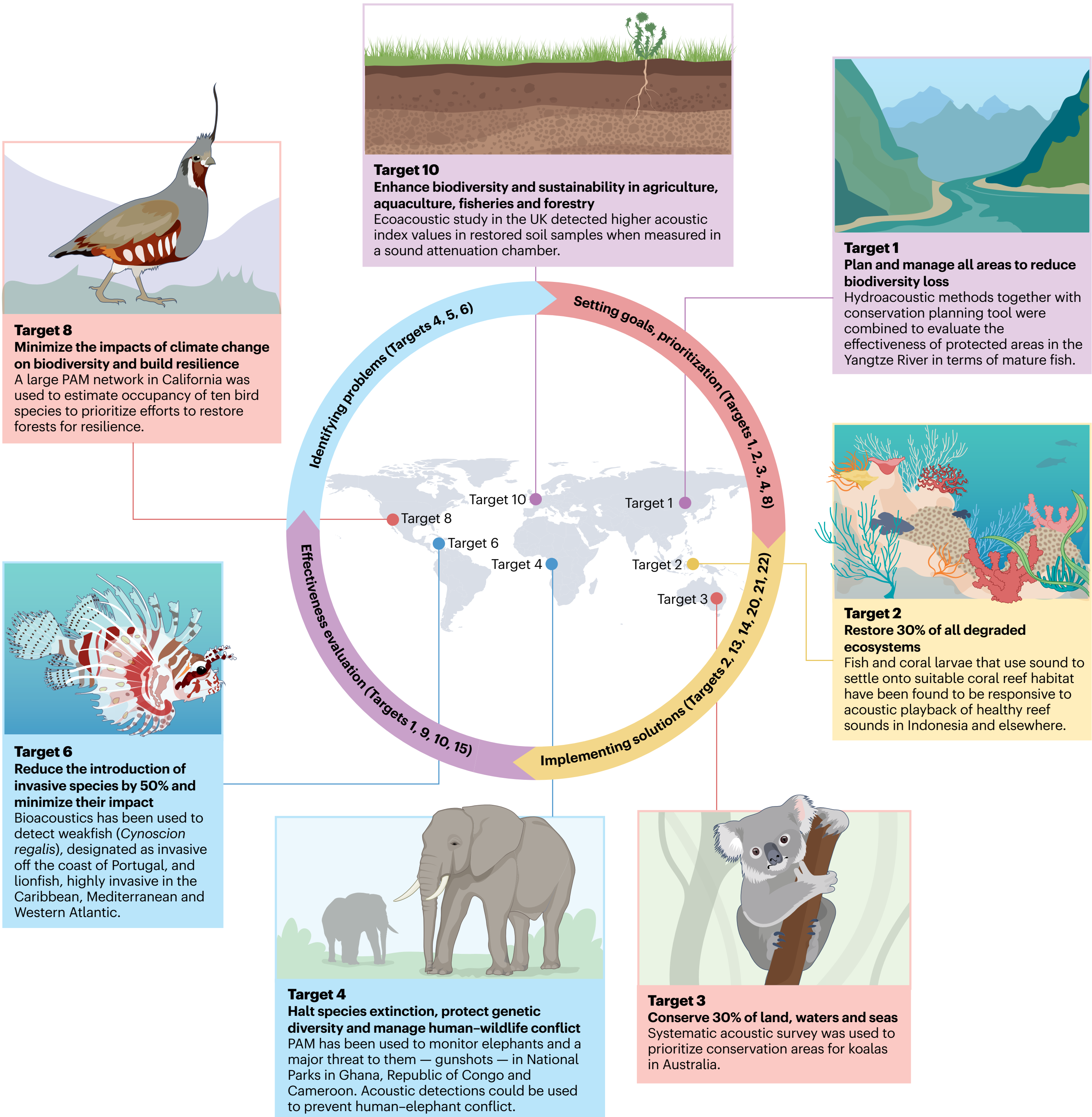


Fig. 1 | The role of bioacoustics in conservation. Example applications of bioacoustics at different stages of the conservation science cycle, from identifying problems, setting goals, prioritizing, designing and implementing solutions to evaluating their effectiveness[18], along with relevant Kunming–Montreal Global Biodiversity Framework 2030 targets. Examples included for Target 1 (ref. 236), Target 2 (refs. 93,237), Target 3 (ref. 68), Target 4 (refs. 56,238,239), Target 6 (ref. 43), Target 8 (ref. 69) and Target 10 (ref. 118). PAM, passive acoustic monitoring.

Box 2 | Ethical considerations in bioacoustics

Ethical implications relevant to bioacoustics have been examined in a handful of publications, as well as in broader studies of conservation surveillance technology (CST), parachute science, artificial intelligence (AI) and data sovereignty, neocolonialism in science and conservation, and environmental criminology. Here, we illustrate three selected concepts with practical implications.

Preventing harm to people

The main danger to people from bioacoustic recordings stems from potential identification of humans from incidental voice recordings and the misuse of such information by bad actors in what has been termed surveillance creep[40]. Because bioacoustic studies are not typically subjected to rigorous institutional reviews, assessing potential risks and planning research accordingly is generally the sole responsibility of researchers. The proportionality (the likely benefits of acoustic monitoring) and necessity (the alternatives to PAM) of bioacoustic monitoring should be carefully reviewed, with not proceeding with CST considered as a legitimate outcome[40]. The willingness to not proceed with PAM is particularly relevant when considering research with Indigenous communities[261,262]. In many countries, research permits stipulate that collected data enter the public domain, and requesting exceptions might be warranted[263].

Preventing harm to animals

Passive acoustic monitoring has a major ethical advantage over field methods that require capturing or collection of specimens, in that it does not cause direct physical harm to the surveyed animals. However, the potential for both direct and indirect harm needs to be considered. For example, direct harm can occur through neophobia or behavioural disturbance in response to the physical presence of recording equipment, which has been documented in birds and in narwhals interacting with acoustic moorings in the Arctic[264]. Publishing bioacoustic data on threatened species can further endanger them if misused by wildlife trade through data-driven poaching[241,265]. Poachers capturing songbirds could use georeferenced song recordings to locate source populations and attract individual birds through playback[266]. Some citizen science sound databases restrict public access to certain species' songs in response to this threat. A less direct threat can entail an increase in public visitation and disturbance of a rare species after publishing georeferenced occurrences of those species[263].

Whom conservation bioacoustics empowers and disempowers

Bioacoustics exemplifies the tension between potentially transforming conservation by giving voice to non-human species and fostering deeper listening practices[138] and falling prey to the economic interests of large multinational companies (Big Tech)[263]. A project in Ghana developed justice-oriented design listening with a community participating in a bioacoustics experiment design[242]. This new participatory approach suggested that "listening to the forest […] involves more than measuring and monitoring biodiversity. Instead, it requires tuning in to a multiplicity of forest livelihoods and worlds." Similarly, researchers combined bioacoustics and ethnography methods in Indonesia, including community sound walks and ARU listening sessions, to centre community knowledge and biocultural values in acoustic monitoring[267]. Simultaneously, large investments by Big Tech companies in bioacoustic algorithm development might be motivated by true philanthropic interests to help to conserve nature, as well as opportunities for technology companies to commodify and experiment with sound data with minimal legal oversight, appropriating nature and volunteer-science and citizen-science work for monetary gain[138,263]. Bioacoustics and other CSTs are also particularly prone to parachute science practices, whereby external institutions deploy sensors in other regions, collect vast datasets and publish findings without meaningful involvement of local communities or in-country researchers and without providing lasting benefits to those regions[268–270]. With intentional consideration[271], bioacoustics could avoid such extractive models.

PAM has also been used to detect the arrival and spread of invasive species such as cane toads (*Rhinella marina*) in Australia[42], weakfish (*Cynoscion regalis*) in the Tagus Estuary in Portugal[43], American bullfrogs (*Lithobates catesbeianus*) in Spain[44] or invasive birds, mammals and frogs in Puerto Rico[45]. In the western USA, PAM guided the killing of 76 barred owls (*Strix varia*) from Sierra Nevada, resulting in increased occupancy of spotted owls (*Strix occidentalis*)[46]. In the same context, real-time PAM was also used to detect and kill three barred owls[47]. In agriculture and forests, ARUs have long been used to detect pest outbreaks, such as grain weevils, termites and wood-boring beetles, including using sound-based models that can identify species and even estimate infestation density in real time[48,49]. In beekeeping, PAM has been used to detect European bee-eaters (*Merops apiaster*) and quantify their impact on honeybees[50]. ARUs combined with automated signal recognition have helped to detect illicit cattle ranching in the Brazilian Pantanal[51].

Such early detection methods can, for example, help to achieve Target 6 of the Kunming–Montreal GBF by improving the management of invasive or locally harmful species (Fig. 1). However, increasingly efficient sound-based detection does not necessarily equate with ethical and societal readiness for the elimination or population management of problem species. Understanding and reconciling varied perspectives towards species labelled as invasive, such as discovering the purpose for a new species, takes time[52]. The cultural implications of managing invasive species are not distinct to bioacoustics and have been reviewed elsewhere[53], but powerful sound-analysis tools, such as species detection models driven by artificial intelligence (AI), could precipitate action at a broader scale. Both the examples from hunting and invasive species detection illustrate that, as automated analysis makes detection increasingly efficient, conservation practitioners might also need to invest more in ethical and societal preparedness, so that management action does not outpace consent or acceptability.

Once a conservation problem has been identified, effective intervention depends on diagnosing its underlying causes. PAM is used to measure spatial variation or temporal trends in populations or occupancies of sensitive species, or in overall vocalizing biodiversity across environmental and anthropogenic pressure gradients, to identify the drivers of these patterns. Sometimes, the same acoustic system can record both a declining biological signal and the stressor responsible. Simultaneous recordings of humpback whale (*Megaptera novaeangliae*) song and vessel noise in Japan directly attributed reduced acoustic behaviour (with fitness implications) to shipping disturbance[54,55]. In the Republic of Congo, an acoustic grid monitoring simultaneously poaching events and African forest elephant (*Loxodonta cyclotis*) vocalizations revealed that higher gunshot activity was associated with elephant nocturnalization[56]. In other cases, using bioacoustics with complementary environmental data can help to diagnose a driver of a problem: the Great Barrier Reef soundscapes became markedly quieter following coral bleaching events, implicating climate-driven habitat degradation as the driver of community change[57]. Likewise, recordings at natural CO_2 vents demonstrated that ocean acidification suppresses reef soundscapes through declines in snapping shrimp activity[58]. Bioacoustics is particularly suitable for understanding drivers of biodiversity declines, as it can yield sufficient sample size to measure responses along threat gradients and account for numerous confounding variables.

Setting goals and prioritization

A fundamental tenet of conservation science is the prioritization of areas to conserve and manage to improve the likelihood of species survival[59]. Under the Kunming–Montreal GBF, many Targets set ambitious goals, such as Target 2 (Restore 30% of all degraded areas) or Target 3 (Conserve 30% of land, waters and seas)[6]. Prioritization schemes have been devised to identify where such targets can be met[60]. At global scales, prioritization maps have known issues, including a lack of grounding in local contexts[61]. Although few, if any, terrestrial or marine bioacoustic studies compare vocalizing biodiversity across a global, continental or ocean-basin scale to support such prioritization, bioacoustic surveys could help to ground global maps in local ecological realities.

The conservation of intact forests illustrates this issue. A component indicator of Target 1 of the Kunming–Montreal GBF (Plan and manage all areas to reduce biodiversity loss) is the priority retention of intact and wilderness areas. A commonly used metric of intactness is the spatial layer of 'Intact Forest Landscapes'[62] based on remotely sensed criteria such as no forest loss, minimum size and the absence of visible human infrastructure. Bioacoustic biodiversity monitoring within intact forests could be critical in two ways. First, even forests that appear intact from space might be undergoing disturbance, both physical (such as overhunting or selective logging) and acoustic (for example, aircraft noise[63]), and bioacoustics can complement remote sensing in monitoring such pressures[64]. Second, to qualify as Intact Forest Landscapes, an intact area must span at least 500 km^2 and be 10 km wide[62]. However, smaller intact areas can still host important biodiversity assemblages[65]. For example, in Gabon, a selective logging concession contained a never-logged area that a local community identified as their ancestral forest and an important biodiversity area. This approximately 11,000 ha area exhibited a more saturated soundscape during key vocalization periods and differed from forests in national parks that had been logged decades earlier. Whereas such finding does not prove, for example, a higher species richness, a distinct soundscape structure is suggestive of a distinct vocalizing community, warranting further investigation, at species and community levels[37]. Recognizing such areas as intact forests could help communities to achieve their conservation goals and enable countries to meet Target 1 of the Kunming–Montreal GBF. An important question remains on how the intactness of faunal communities can be defined from a bioacoustic perspective, complementing measures of structural intactness.

Bioacoustics is well suited for local and regional prioritization and decision-making, such as determining appropriate conservation actions for existing protected areas[66,67], or landscape-scale prioritization for specific taxonomic groups, such as koalas (*Phascolarctos cinereus*) in southern Australia[68]. Bioacoustics has been extensively used to guide forest management in North America. For example, in California, occupancy of ten bird species was predicted across a mountain range to prioritize forest restoration efforts[69]. PAM has been widely used to guide forest management practices for anurans[70], bats[71–73] and birds[74,75]. Bioacoustic measurement of activity and diversity throughout the year have guided the location of wind farms to reduce bat and bird mortalities[76–78].

In the marine realm, PAM combined with other data sources has been used to inform and evaluate the effectiveness of coastal management and spatial planning. For example, acoustically derived whale or reef fish spatial use and underwater noise have informed the planning of shipping routes and offshore infrastructure[79–83]. National and international policies often require offshore industries to provide or support acoustic monitoring as baseline evidence, noise exposure compliance and impact assessments[84–89]. In summary, bioacoustic data help to translate broad conservation targets into spatial priorities that reflect local ecological conditions, management needs and community contexts across terrestrial and marine systems.

Designing and implementing solutions

Bioacoustics has several uses in implementing conservation solutions, including in restoration, human–wildlife conflict and adaptive management. Broadcasting intact soundscapes or sounds of specific species has been proposed to attract species to a restoration area, potentially accelerating restoration, relevant to Kunming–Montreal GBF Target 2 (Fig. 1). Acoustic attraction of specific species has resulted in real-world success, including luring frogs to suitable breeding sites through mating call playback[90] and re-establishing seabird colonies through vocalization playbacks[91], although broadcasting soundscapes to restore entire terrestrial ecosystems remains largely theoretical[90,92]. Acoustic enrichment has repeatedly contributed to experimental coral reef restoration[93,94]. Nevertheless, the success of any acoustic restoration hinges on first restoring the habitat and addressing the original threats, such as coral bleaching and ocean acidification[90].

Broadcasting sounds has been used commercially and experimentally to deter animals in human–wildlife conflict, relevant to Kunming–Montreal GBF Target 4. Ultrasonic rodent deterrents have been widely used in houses since the 1990s[95]. Sound-based deterrents are also common tools for discouraging birds and bats from agricultural fields, wind turbines and airports, with demonstrated effectiveness in conserving protected species, such as the black-necked crane (*Grus nigricollis*) in China[96] or Mexican free-tailed (*Tadarida brasiliensis*) and hoary (*Lasiurus cinereus*) bats at wind turbines in southern Texas, USA[97].

Experimental acoustic deterrent applications have also been explored in the marine realm. In the Baltic Sea, acoustic deterrent devices have successfully prevented grey and ringed seals (*Halichoerus grypus* and *Pusa hispida*) from crossing into fisheries[98]. Acoustic playback has been explored as a tool to actively manage the invasive lionfish (*Pterois volitans*), although without significant results[99,100]. Aquatic acoustic deterrents overall remain exploratory, especially as such sound risks hearing damage and disturbance of non-target species, and long-term success has been limited. Lower-intensity pingers, however, have proven more effective in reducing small odontocete bycatch in fishing gear[101].

Various sounds, including bee buzzing, warning calls and human noises, have been tested in human–elephant conflict, with limited success[102] (the most promising results at present record a 65% flight response in male Asian elephants (*Elephas maximus*) in response to elephant matriarchal group vocalizations[103]). However, the potential habituation or return of the elephants once the sound is gone remains to be determined. Human–wildlife conflict is projected to increase with time[104], owing to both the recovery of wildlife populations through successful biodiversity conservation and the shrinking of available habitat driven by climate and land use change. Acoustic deterrents could, therefore, provide a valuable tool for managing interactions with many hearing-sensitive species.

Finally, real-time ocean acoustic data are used to support adaptive management. Real-time baleen whale monitoring along shipping routes has prevented ship strikes, for example, which are a primary threat to baleen whales[105,106]. Marine mammal real-time detection is also used in the vicinity of industrial activities to mitigate noise exposure levels. For example, acoustic monitoring is the recommended method for seismic airgun-towing vessels and is used during pile driving for offshore wind installation, which creates intense underwater noise[107]. Overall, although the majority of bioacoustic applications in conservation rely on passive sound recordings, the analysis of which can happen in real time or be delayed, active bioacoustics interventions through sound broadcasting can directly elicit behavioural changes in animals.

Evaluating effectiveness

A common application of bioacoustics in conservation is evaluating the effectiveness of various interventions. For example, dynamic occupancy models of acoustic detections have been used to assess the success of translocation of the endangered hihi (*Notiomystis cincta*) in New Zealand[108]. Under the Kunming–Montreal GBF, PAM is directly relevant to Targets 1–5, 8–10 and 12, as all of them rely on understanding whether interventions are effective. Target 2, for example, calls for restoring 30% of degraded ecosystems. The most common metrics of success rely on the quantity of habitat restored, such as tree or coral cover in forest and reef restoration[109]. However, habitat metrics do not necessarily reflect the return of biodiversity or ecosystem functioning[110,111].

PAM and other technologies are increasingly used to assess biodiversity restoration outcomes more directly[109]. In Ecuador, Costa Rica and India, researchers have compared acoustic diversity, acoustic space use and complexity before and after restoration[112–116]. In Indonesia, restored coral reefs had soundscapes more similar to healthy reefs[117], and a transplanted seagrass meadow in Italy had higher sound pressure levels than an unrestored seabed[117]. Higher acoustic index values were detected in restored soil samples from the UK when measured in a sound attenuation chamber but not in situ[118]. In the USA, PAM has been used to monitor responses of bird indicator species to forest restoration projects[119,120] and to assess sensitive species responses to forest management, severe wildfires and droughts[121]. Another potential avenue worth deeper study is monitoring species that are acoustically detectable and known to have an important ecological role in times of environmental stress. For example, certain damselfish that live within branches of corals are known to be soniferous (for example, *Dascyllus flavicaudus*[122–124]), and the presence of such species can have measurable impacts on the tissues of their coral hosts, influencing their thermal tolerance, bleaching susceptibility and recovery[125,126].

Biodiversity credits and sustainability certification schemes (relevant to the Kunming–Montreal GBF Targets 5, 9 and 10) also need to demonstrate biodiversity conservation success on a case-by-case basis and over time[110]. For example, the Forest Stewardship Council (FSC) certification for sustainable forest management can be renewed after a major audit every 5 years. Auditors make limited visits to each concession and lack the capacity to thoroughly assess biodiversity changes or threats, such as poaching. PAM has been proposed and tested as part of the solution, yielding varied results that point to both the potential and future research needs for bioacoustics to be incorporated into audits[127]. In Peru, the soundscape at FSC-certified sites had higher values of the 'Acoustic Space Occupied' metric, based on all sound-emitting species, compared with non-FSC sites. Because no differences were found in bird species richness or composition, this change in soundscapes was probably due to non-avian species[127]. In Gabon, one study found that FSC-certified logging produced soundscapes more similar to those of national parks than conventional logging[37], whereas another study, based on a separate dataset and considering only the dawn and dusk chorus, found no difference in the soundscapes of FSC-certified and non-certified concessions[128]. In Indonesia, an FSC-certified concession had slightly higher soundscape saturation during dawn and dusk than a conventional concession[129].

These heterogeneous results, which echo non-bioacoustic studies on improved forest management[130], might reflect differences in the underlying biodiversity or management practices, underscoring the need for biodiversity monitoring on a case-by-case basis (such as during audits). Differences could also stem from variations in recording and analytical methods, emphasizing the importance of reporting recording parameters, open-access code and data for greater interoperability and sensitivity analyses[131–133]. Although acoustic monitoring is not yet a formal part of any sustainability certification[134], such incorporation could be enabled in the future through developing optimal deployment strategies, user-friendly analyses accessible to non-specialists and quantitative biodiversity goals of certification schemes.

Evidentiary strength of conservation bioacoustics

As acoustic data are increasingly used in conservation, their evidentiary strength, both alone and relative to other biodiversity data, is scrutinized[135]. In this section, we first highlight the benefits of conservation bioacoustic methods relative to other approaches and then consider in detail the main types of bioacoustic evidence used in conservation, in terms of their strengths, uncertainties and opportunities for ecological and conservation insights.

Comparison of bioacoustics with other methods

Methods to generate biodiversity evidence can be divided into those relying on a person in the field making visual and auditory observation (for example, line transects or point counts on land or underwater), those using specimen collection or animal capture and those that involve sensors, including camera traps, remote sensing and eDNA[136]. PAM, like other sensor-based methods, has a key evidentiary advantage over purely expert in-person surveys: without harming organisms (but see Box 2), it produces re-examinable evidence, which is less susceptible to manipulation, errors and biases. Although the risk of manipulation should be minimal in scientific studies without a conflict of interest, it becomes unacceptable under evidence frameworks such as the SAGED (scalable, accessible, granular, evidenceable and directly measured) criteria for biodiversity credits[12]. Whereas expert-in-the-field surveys might result in a closer connection with local communities, or incidental knowledge gain through unstructured observations[137], such benefits could be obtained independently through focused, intentional work with communities, regardless of using sensors[138]. On balance, PAM and other sensor-based methods offer a stronger evidentiary foundation for formal biodiversity accounting at scale than in-person surveys.

Performance of PAM relative to other sensor-based methods depends on ecological and logistic context and study goals. For example, in Australian agricultural landscapes, PAM detected the most species and had the lowest cost per detection compared with camera traps, eDNA and in-person surveys[139], although a survey with a purely mammalian focus found that PAM detected the fewest species compared with camera traps and in-person surveys[140]. Bioacoustics generally has a higher chance of detecting a soniferous species per device and survey time than terrestrial camera traps or underwater cameras, owing to a larger detection space, although this varies between species, environmental conditions and sensors[141]. As PAM can record continuous soundscapes, establishing species absence is easier compared with camera traps. In Tanzania, chimpanzee (*Pan troglodytes*) absence could be confirmed with 95% certainty using occupancy modelling with 10 days of acoustic data compared with 50 days of camera trapping[142].

The most effective biodiversity monitoring often requires multiple methods. For example, PAM can detect more cetacean groups at greater distances than visual surveys, but visual surveys provide more accurate identifications; combining the two methods can reduce biases[143]. New combinations of 360-degree cameras and hydrophone triangulation have enabled efficient attribution of sounds to specific coral reef fish species through audio-visual confirmation[144]. Similarly, combining PAM with camera traps has allowed the identification of individual leopards (*Panthera pardus*) in Tanzania based on distinct roar patterns[145].

No single method outperforms others across all contexts, and combining methods often yields the strongest evidence[1,135]. However, expanding the range of taxa and ecological processes observed through multiple technologies might also expose conservation trade-offs that would be unseen when relying on a single method, potentially complicating conservation decision-making. The complementarity, redundancy and cost-effectiveness of different combinations of biodiversity monitoring techniques constitute an active area of research.

Types of acoustic evidence and their evidentiary strength

Interpreting sound as evidence requires an understanding of how sound originates (sound source), how it travels (sound propagation) and how it is perceived, recorded and interpreted by humans, non-humans or machines[146–148]. Here, we review the most common types of evidence generated by bioacoustics (see ref. 132 for a larger list also relevant for ecology) and examine the factors that influence their strength. As with any biodiversity monitoring method, acoustic evidence can be used in a range of study designs, from observational surveys to experimental approaches. Here, we focus on the evidentiary strength of the acoustic outputs rather than on general study design (see Box 1 for main considerations), as study design is reviewed elsewhere[130,149]. Bioacoustics has a broad spectrum of applications in conservation, and different decisions and decision-makers have different tolerance for uncertainty. Our goal is not to provide an exhaustive decision key but to illustrate considerations for how acoustic data can support conservation actions.

Evidence for species presence and absence. The simplest and perhaps most common form of evidence from acoustic monitoring entails detecting a species' sound to infer its presence or absence[132,150–154]. The benefits of PAM for this purpose are transformative and evident from the broad application of the technology. Here, we examine multiple factors along the pathway from an organism emitting a sound to a conclusion about the species' presence or absence, which could influence the strength of the evidence (Fig. 2). Such factors include the acoustic behaviour of individual species (such as mimicry or the production of previously undocumented sounds), the vulnerability of the evidence to manipulation (for example, by changing the location of ARUs or MARUs) and achieving certainty that a recorded sound truly originated from the target species (Fig. 2).

Carefully curated sound libraries are rare but essential for achieving the highest certainty in sound source identification, at least for taxa not commonly targeted by citizen scientists[155–157]. The largest sound libraries and repositories, such as the Macaulay Library, the Animal Sound Archive, eBird, National Oceanic and Atmospheric Administration (NOAA) passive acoustic data or Xeno-canto (Supplementary Table 1), rely on volunteer contributions, which offer excellent coverage for some taxonomic groups. For example, Xeno-canto contains recordings of 10,544 out of 11,086 bird species and is now open to all taxa. Although these databases could be prone to several evidentiary issues, such as accidental species misidentification, many have self-correcting mechanisms (such as local reviewers in eBird). Other sound libraries only include peer-reviewed sound labels from publications, including a narrower range of sound types. Methods development for appropriate use of bioacoustic citizen science data is ongoing, and many issues have already been successfully addressed (for example, through data integration[158–163]).

The complexity of understanding the strength and uncertainty of evidence increases when a sound or terabytes of soundscapes are processed with a machine learning model. Machine learning methods are now perhaps the most common approach to analysing acoustic data across many taxonomic groups (Supplementary Table 1) and have revolutionized conservation bioacoustics (Box 3). Advances in AI, especially deep learning approaches such as CNNs, have greatly improved automated detection and identification of vocal species and are increasingly applied at conservation-relevant scales (Box 3 and Supplementary Table 1). Although traditionally limited by the need for large, labelled datasets, specialist technical expertise and substantial computational resources, these barriers are rapidly diminishing with open-access acoustic libraries, cloud-based processing, user-friendly interfaces and widely used algorithms such as BirdNET and Google Perch[164,165] (Supplementary Table 1).

Given the contributions of CNNs are immense, associated uncertainty is important to review. When machine learning models detect and classify a sound as a particular class (in this case, species), the models frequently make false-positive (predicting a sound class that is not present) and false-negative (failing to recognize the presence of a sound that is present) errors. Without further consideration (for example, estimation of false-positive and false-negative rates), such a model provides, at best, weak and, at worst, misleading evidence for species presence. A high false-positive rate might be acceptable if all model-derived detections are manually reviewed[166]. Guidelines have been developed on how to establish species-specific thresholds that help to translate machine learning outputs into probabilities of true positives[167–170]. A high false-negative rate is harder to address, as correcting it would require manually reviewing much of or all the data, defeating the purpose of automated classification. False negatives are particularly challenging for rare or infrequently vocalizing species or those without strong or known diel or seasonal patterns in vocalizations. Occupancy models offer a useful framework for addressing this challenge, as they explicitly account for false negatives[151,171,172].

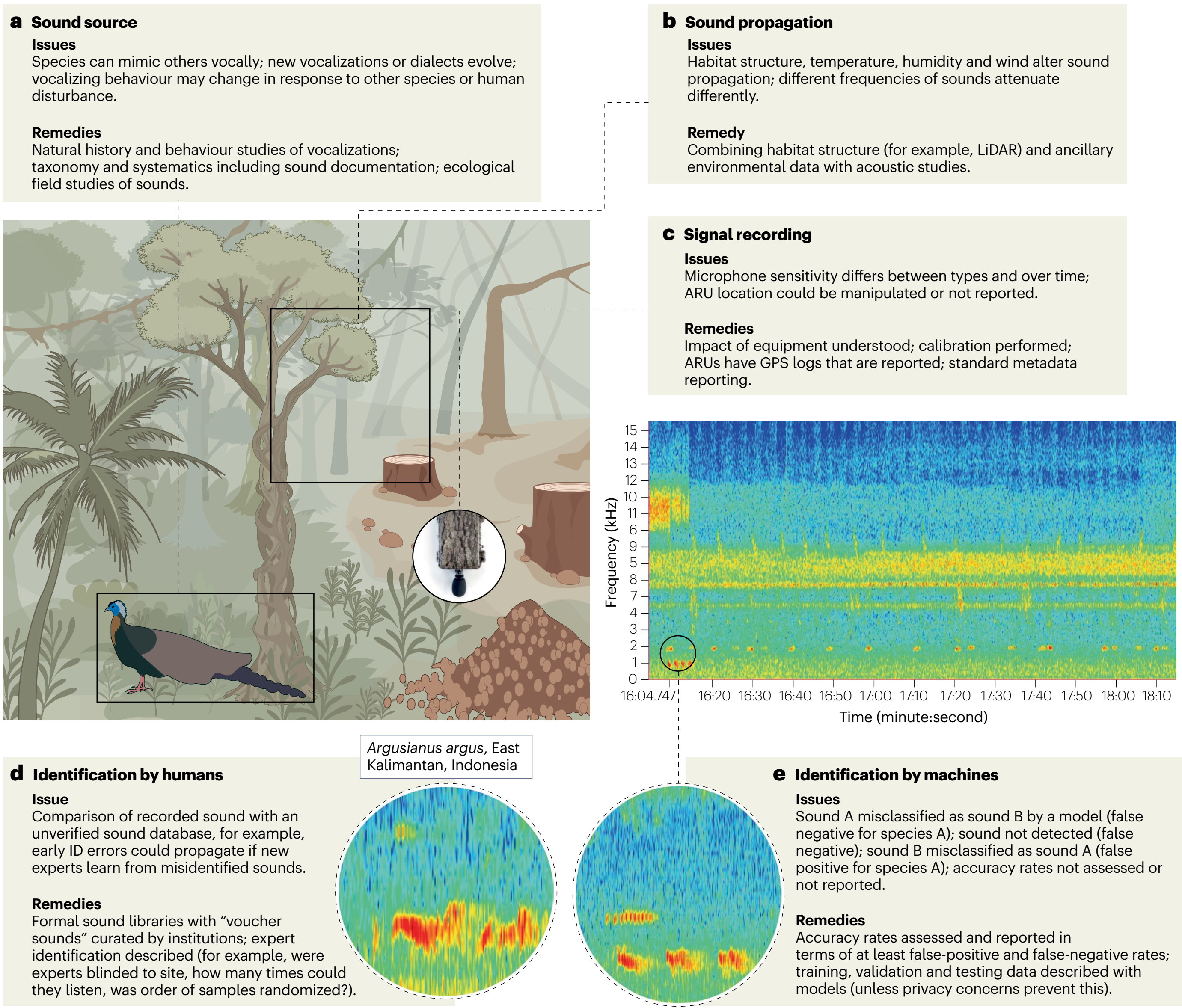


Fig. 2 | Factors influencing evidentiary strength of bioacoustic data. a, Sound source variance, such as mimicry. **b**, Factors affecting sound propagation, such as the physical environment. **c**, Inconsistencies in signal recording. **d**, Human error in identification (ID) of sounds. **e**, Machine error in identification of sounds. ARU, autonomous recording unit; GPS, Global Positioning System; LiDAR, light detection and ranging.

Finally, interpretation depends on both the sampling design and the purpose of the survey[173]. For example, a single detection of a species might not be sufficient to classify a site as occupied, but it could be enough to expand the species' area of occurrence[173,174].

Overall, in terms of evidence on species presence and absence, PAM has benefitted immensely from developments in machine learning, and as uptake increases, researchers are answering important questions on how to correctly navigate uncertainties in model outputs.

Evidence for abundance and population density. Abundance and population density are key metrics of interest to many conservation programmes, especially when measured over time, as their insights are crucial in evaluating the need for and success of species-focused interventions, such as species translocation, disease eradication or anti-poaching interventions[175,176]. Several analytical methods have been developed to estimate relative abundance or approximate population densities from bioacoustic data[177–180]. The central challenge in estimating abundance or density from soundscapes is distinguishing whether occurrences of one sound type are produced by one or more individuals, which is needed to convert counts of sounds into counts of individuals. Here, we outline five main approaches for abundance estimation[181]: using detection–nondetection data, distance estimates, counts or rates of species detections, and identification of individuals through estimating their geographic position or using sound features distinct to each individual.

Box 3 | Species detection and classification from soundscapes

Early automated species detection systems relied on deterministic approaches to isolate and classify target sounds based on pre-defined acoustic features. These methods typically detected energy bursts in the time domain within specified frequency ranges and filtered the detected sounds based on features such as duration[253] or pulse repetition patterns[272,273]. Before the advent of deep learning, template matching via cross-correlation combined with statistical classification methods, such as random forests, was among the most effective approaches for detecting wildlife sounds[247,274–278].

Automated acoustic species identification changed markedly with the deep learning revolution of the 2000s and 2010s, especially with the development of convolutional neural network (CNN) architectures and the release of the TensorFlow platform for machine learning model development[279]. With many well-trained CNNs developed for image classification, CNNs can be applied to wildlife sound classification by converting short audio clips into spectrograms, which decompose the audio signal into its constituent frequencies at successive time windows. Spectrograms are then used to train, validate and test models. In the context of PAM, CNNs are commonly used for multilabel classification, in which a short clip of an entire soundscape is assigned one or more labels, often representing different species.

Several large CNNs are now freely available to classify vocalizations from most bird species worldwide[164,280] and subsets of other taxonomic groups, such as whale sounds (Supplementary Table 1). Application of foundation models to new or low-data domains is a current focus, using techniques such as transfer learning, few-shot classification and zero-shot classification, as well as multimodal models[281]. The use of soundscapes for the detection and classification of sounds that are more fine-grained than the level of species remains an active area of research, including the detection of functional sounds[282] and the recognition of individual animals from their vocalizations[208].

Key challenges for users of existing and new CNNs are the need for substantial labelled training data, which might not exist for many taxa (but see few-shot learning approaches[283]); manually establishing and validating model accuracy, such as through false-positive and false-negative rates[168]; and ensuring reproducibility through transparent sharing of models, training data and code. An additional challenge is the durability of CNNs: deep learning frameworks and associated development libraries (such as TensorFlow and PyTorch) evolve rapidly, which may affect year-to-year consistency in analyses, particularly for multi-year time series, raising questions about how best to support stable, long-term workflows.

The detection–nondetection data used in occupancy modelling can also be used to estimate abundance. The Royle–Nichols model[182], for instance, links local detection probability to the number of individuals present at a site. By analysing how often a species is detected across repeated surveys, it infers not only whether the species occurs there but also approximately how many individuals are probably responsible for those detections. Time-to-detection models[183], also based on detection–nondetection data, use a measure of how quickly a species is first detected as a proxy for its abundance. The Royle–Nichols and time-to-detection models estimated similar abundances to those estimated by in-person survey for two forest bird species[120]. However, similarly to the in-person surveys that use them, these models are sensitive to violations of their core assumption that the detection rate is constant[184]. Interestingly, emerging evidence shows that there might be seasonal trends in false-positive rates of bird detection algorithms, suggesting that future work will be needed to carefully disentangle changes in abundance from the effects of soundscape phenology on the detectability of species[185].

Distance sampling is used during in-person surveys to estimate abundance by accounting for missed detections. This estimation is achieved by relating the probability of detection to the distance of the organism from the surveyor[186]. In PAM, distance to vocalizing individuals is estimated from sound pressure level received at the sensor[187,188]. Distance estimation is challenging because received sound level might reflect distance poorly, for example, because of environmental heterogeneity[189] or directionality of animals' sounds[190].

Approaches based on vocalization rates, including vocal activity rates (VAR or related indices that quantify the number of calls recorded per unit time) and cue rates (the rate at which an individual animal produces sounds), assume density-dependent calling behaviour, such that more individuals equal more calls[179]. These approaches are promising but face two main challenges. First, validating the relationship between VAR and abundances can require time-consuming, species-specific calibration. Although some assessments show strong correlations with traditional abundance estimates for several species (such as the European bee-eater (*Merops apiaster*), Dupont's lark (*Chersophilus duponti*) or a suite of Hawaiian bird species[50,191–193]), other assessments reveal that traditional, expert-led surveys probably underestimate species abundance, such as in European nightjars (*Caprimulgus europaeus*) in the UK, which complicates calibration[194]. Sampling requirements also vary widely: VAR stabilized only after 75 days of sampling in seabirds[195], compared with reasonable stabilization after 9 days in Dupont's lark[196], a terrestrial species. Second, calling behaviour might vary with density in different ways. For example, individuals defending territories might vocalize more frequently at higher population densities, whereas those attracting mates might vocalize more frequently at lower densities[197]. Unpaired animals could vocalize more frequently than paired ones[198], and rates can vary in response to noise[199]. Estimating VAR through automated detection must correct for false positives and negatives[179,200].

Identifying individuals by their spatial positions via acoustic localization is another approach to estimating density or abundance. Such localization usually requires deploying an array of synchronized ARUs or a single multichannel recorder, estimating position or direction of arrival using the time difference of arrival of the sound to each microphone, and postprocessing to estimate abundance[201]. These approaches have been widely used in birds and bats and also in orangutans[202], elephants[203], wolves[204] and marine mammals[205]. The number and position of acoustic recorders in an array and the precision of the localization influence uncertainty[206].

A final approach identifies individuals based on distinctive characteristics of their sound. Many species are confirmed to have acoustic individuality, but this individuality has been used for abundance estimation in wild populations for only a few species[207,208]. Gathering ground truth data for testing individual identification is time-intensive, meaning few benchmark datasets exist. Further, to successfully estimate abundance, models must distinguish individuals for which no prior ground truth data exist, a task accomplished by few models[209,210].

A major advantage of PAM is the possibility of using repeated data collection, which enables the estimation of occupancy, abundance or density trends. For example, a dynamic occupancy model framework generated estimates of colonization and extinction rates across successive survey periods[14,211]. In California, large-scale PAM paired with dynamic occupancy models was used to characterize spotted owl occupancy trends and responses to high-severity fire[212]. Long-term mobile acoustic monitoring programmes have similarly documented multi-year population declines in North American bat species affected by white-nose syndrome[213,214]. Long-term acoustic monitoring of baleen whales has tracked changes in seasonal presence, distribution shifts and acoustic activity trends over years to decades, often representing the only continuous population trend data available for these species[215].

Evidence on species diversity and community composition. Many conservation decisions are based on diversity or community composition metrics, or on some other measure of overall biodiversity. Acoustic data can inform these decisions in both ground-up (through identifying as many species as possible) and top-down (through evaluating the overall soundscape structure, viewed as an emergent property of the underlying faunal community) directions.

Once all biological sounds are identified to a species level, calculating diversity metrics involves similar evidence considerations as for other methods, including questions about sample coverage, sampling design and the statistical uncertainty of estimates[216]. However, in practice, it is unlikely for all species potentially present in a soundscape to be confidently identified or modelled with high precision. Even studies focusing solely on birds, possibly the best-studied animal group in bioacoustics, rarely commit to identifying all species[23,114,217]. Currently and in the near future (by the Kunming–Montreal GBF deadline of 2030), the feasibility of using machine learning models to directly estimate the total diversity of vocalizing species of broad taxonomic groups (such as anurans, bats, birds and fish) is relatively low in hyperdiverse ecosystems or those with many rare, rarely vocalizing or poorly known species[218–220]. Understanding the conditions under which different species detection models (Box 2 and Supplementary Table 1) work best is essential, including whether machine learning-derived partial diversity metrics correlate with diversity metrics derived from soundscape segments fully annotated by experts[114,218] and to what extent species-specific precision thresholds can be generalized[168–170]. Separately, whether vocalizing species diversity correlates with overall diversity within (or even across) major taxonomic groups is unknown beyond birds and marine mammals, among which approximately 99% of species vocalize[221].

Acoustic indices are commonly used to describe the structure of the soundscape and, in many cases, have been implicitly or explicitly used as proxies for various biodiversity metrics[222–225]. The evidentiary strength of acoustic indices is currently debated. On the one hand, some scientists argue that acoustic indices should be abandoned as biodiversity proxies, mainly because they have been found to not generalize well in terms of correlation with species richness. Furthermore, many acoustic indices lack an intuitive ecological interpretation, and because they are typically calculated on a soundscape as a whole, they are influenced by non-biological sounds[225–230]. This line of reasoning typically argues that conservation is mostly species focused; therefore, individual species recognition algorithms are largely sufficient, and resources should be directed towards the improvement thereof[231]. By contrast, some scientists argue that acoustic indices provide a valid metric of the soundscape as a whole and that their use should be further refined and researched under different contexts. Typically, these scientists point to the diversity of indices, many of which were not designed to correlate with species richness to begin with; instead, these indices aim to be reflective of, for example, the ratio of biological to anthropogenic sound, overall soundscape diversity in terms of frequency and time, and the amount of invertebrate chorusing, among others[226,232,233]. Guidelines and best practice publications on acoustic indices highlight the importance of ground-truthing an index if it is to be used as a proxy of a specific biodiversity metric[226,227]. Many scientists use acoustic indices to visualize large datasets in terms of temporal patterns and major outliers, for quality checking and to track whether the soundscape is changing over time, space and in response to anthropogenic impacts[37,234,235].

We believe that, in fact, the dichotomy between species identification using machine learning and soundscape analysis using acoustic

Glossary

Acoustic indices
A numerical summary of an environmental sound recording based on amplitude, time and frequency. Acoustic indices are typically used with the goal of extracting ecologically meaningful information from soundscapes.

Autonomous recording units
A self-contained sound recording device with an internal or external microphone or hydrophone, designed for unattended, often long-term environmental sound recording. Other commonly used terms are acoustic device, sensor and recorder.

Bioacoustics
An interdisciplinary science combining biology and acoustics to study the production, transmission and reception of sound in animals. It investigates how organisms use sound for communication and echolocation and how these sounds interact with the environment.

Conservation bioacoustics
An applied branch of bioacoustics that channels the study of sounds towards understanding, managing, restoring and protecting species and ecosystems. In this Review, we, at times, refer to conservation bioacoustics simply as bioacoustics.

Convolutional neural networks
Deep learning models that use convolutional layers to automatically learn hierarchical patterns (edges, textures and shapes in images) by sliding small filters (kernels) over input data, extracting features into feature maps and then progressively building complex representations through pooling and activation functions, ultimately classifying or detecting objects.

Ecoacoustics
Interdisciplinary science that investigates natural and anthropogenic sounds and their relationship with the environment over a wide range of spatial and temporal scales, including populations, communities and landscapes.

Occupancy modelling
Hierarchical statistical models used to estimate the probability that a species occupies a site while explicitly accounting for imperfect detection.

Passive acoustic monitoring
A technique that uses autonomous recording equipment to record environmental sounds or soundscapes.

Soundscapes
All biological, geophysical and anthropogenic sounds present at a particular site.

indices is unnecessary. Conservation needs and questions are as diverse as the socio-ecological contexts they address, and it is simply unlikely that one (species-based) approach will answer all such needs or that another (soundscape analysis using acoustic indices) will answer none of those needs. Therefore, our recommendation is for conservation practitioners to carefully consider their goals and the evidentiary strength and limitations of the potential methods, and for scientists to embrace the fact that conservation bioacoustics is an emerging field, with space for growth and innovation. Conservation problems need creative solutions, which might require more than one approach to data analysis.

Summary and future directions

Bioacoustics is a near-mainstream technology used across the full spectrum of conservation bioacoustics. For the purpose of identifying new threats, it is commonly used to detect problem species and human activities, as well as changes in soundscapes or species indicative of a new conservation problem. In conservation prioritization, PAM has particularly been used at the landscape scale, for instance, to determine the areas in which management should be applied or energy infrastructure installed. Whereas bioacoustics is predominantly a monitoring technology, applications in active conservation interventions using sound have been demonstrated, from acoustic attraction of seabirds and soundscape enrichment in coral reef restoration to acoustic deterrence of wildlife from wind turbines and agricultural areas. The most common uses of bioacoustics are in evaluating impacts of human-related activities, including logging, habitat degradation, or noise and light pollution, and assessing the effectiveness of conservation interventions such as habitat restorations or species translocations.

For researchers and practitioners deciding whether, when and how to use bioacoustics, our Review details the evidentiary strength of the major bioacoustic data types used in conservation. Beyond the fundamental constraint that bioacoustics can only detect species or events that produce sounds, and only when they do so, the approach is transforming biodiversity monitoring by creating permanent, re-examinable and potentially multi-taxonomic evidence. Currently, most uncertainty at the individual species level stems from the sound identification process at scale. Here, a lack of sound libraries and the high acoustic diversity of many natural ecosystems make species-level sound identification challenging, but enormous progress has been made for birds through ever-improving machine learning models' accuracy. At the diversity metric level, species-agnostic acoustic indices enable evaluation of the overall soundscape, bypassing the uncertainty of species identification. However, no single index that would generalize well as a direct proxy for common biodiversity metrics, such as species richness, currently exists. At present, machine learning models can be reliably used for presence and absence, and acoustic indices can be used to visualize overall soundscape properties and quantify changes therein. In the future, ecological, natural history and systematic field acoustic studies will be crucial to maximize the potential of bioacoustics in conservation, even as AI continues to improve researchers' ability to recognize species sounds.

PAM's capacity for continuous monitoring over time and the relative ease of monitoring many sites simultaneously distinctively position the approach to allow for causal inference in biodiversity conservation studies. The need to show causation, instead of simply correlation, has been widely recognized in conservation but remains largely elusive beyond remote sensing studies using quasi-experimental methods and a small collection of randomized controlled trials. Whereas true experiments are likely to remain rare in large-scale conservation (for example, new protected areas are not going to be assigned randomly), large soundscape datasets could make quasi-experimental techniques more achievable in three ways. First, explicit consideration of more confounding variables can become possible with larger sample sizes, and techniques such as matching might become feasible. Second, regional baselines or general acoustic observatories could serve as control sites for projects or interventions that lack suitable control areas. Towards this end, future research can invest into better interoperability principles (in lieu of standardized sampling, which is not yet achievable or desirable). Third, through time series of acoustic data, before–after–control–intervention study designs might become more accessible even for researchers studying interventions of which the timing is unknown or beyond their control.

As bioacoustics, together with camera trapping, eDNA and remote sensing, generates increasingly detailed broad-scale biodiversity data, and AI allows for new and faster analyses, conservation decision science will need to navigate heterogeneous or contradictory evidence reflecting a multitude of biodiversity responses to a single threat or intervention. This challenge will require not just better detection algorithms and statistical models but also better frameworks for interpreting and communicating uncertainty and aligning the types of metrics available with decision-making needs. Navigating these value-laden interpretations and decisions will be fundamental for the effective and responsible use of bioacoustic data in nature-based climate solutions, biodiversity credits, the Kunming–Montreal GBF, and any future schemes for climate and biodiversity.

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