Chapter

Novel Technologies and Their Application for Protected Area Management: A Supporting Approach in Biodiversity Monitoring

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Abstract

State-of-the-art tools are revolutionizing protected area (PA) manager approaches to biodiversity monitoring. Effective strategies are available for test site establishment, data collection, archiving, analysis, and presentation. In PAs, use of new technologies will support a shift from primarily expert-based to automated monitoring procedures, allowing increasingly efficient data collection and facilitating adherence to conservation requirements. Selection and application of appropriate tools increasingly improve options for adaptive management. In this chapter, modern biodiversity monitoring techniques are introduced and discussed in relation to previous standard approaches for their applicability in diverse habitats and for different groups of organisms. A review of some of today's most exciting technologies is presented, including environmental DNA analysis for species identification; automated optical, olfactory, and auditory devices; remote sensing applications relaying site conditions in real-time; and uses of unmanned aerial systems technology for observation and mapping. An overview is given in the context of applicability of monitoring tools in different ecosystems, providing a theoretical basis from conceptualization to implementation of novel tools in a monitoring program. Practical examples from real-world PAs are provided.

Keywords: protected area management, biodiversity monitoring system, environmental DNA, camera trapping, electronic nose, passive acoustic monitoring, remote sensing

1. Introduction

1.1 Recent history of biodiversity loss

Biodiversity is declining globally at an unprecedented rate, a trend that has proceeded unabated since the early 20th century [1–3]. Recognition of the importance and conservation needs of global biodiversity resulted in the proposal of the Convention on Biological Diversity (CBD) in Rio de Janeiro in 1992 [4]. More than 190 nations have since ratified the treaty. At the turn of the millennium, several international initiatives were started with the aim to change the trajectory of biodiversity conservation. Through the United Nations (UN) Millennium Ecosystem Assessment initiative (2001–2005), research was conducted with the goal to identify conservation priorities and set benchmarks for future actions [5]. At the time, the initiative provided a comprehensive summary of ecosystem changes and their effects on human well-being and linked to economic activities. The UN Millennium Development Goals (2000–2015) aimed to mitigate the extent of biodiversity loss. These goals are now addressed by the UN Sustainable Development Goals (SDGs) containing benchmarks for marine and terrestrial biodiversity [6]. In 2012, at the Tenth Meeting of the Conference of the Parties to the Convention on Biological Diversity, a strategic plan for the protection of biodiversity was formulated. The plan included 20 so-called Aichi targets to be addressed during the period 2011–2020. Ultimately, none of the Aichi targets were met on time (**Figure 1**) [7].

Looking forward to 2030, the SDGs provide a global framework toward sustainable development on economic, social, and environmental levels [8]. SDGs 14 and 15 are particularly relevant for biodiversity conservation. Goal 14 aims to protect life below water with a focus on marine pollution, protection, and restoration of ecosystems, reduction of ocean acidification, and sustainable fishing. Goal 15 targets terrestrial biodiversity, with a focus on protection, restoration, and promotion of sustainable forest management while reversing land degradation. To track evidence-based achievement of SDGs, far-reaching state-of-the-art monitoring capacities must be advanced.

1.2 Drivers of biodiversity loss

Despite the formation of the CBD, biodiversity has continued on a downward trajectory for vertebrate and insect species, while trends for many other taxa are unquantified [9, 10]. At least 900 species have gone extinct since 1500, and to date 1,145 species are listed as critically endangered or possibly extinct [11]. Given the considerable knowledge gap, these numbers are likely higher. The Living Planet Report noted a global decline in vertebrate abundance by 60% from the period 1970–2014 [12]. Main causes of biodiversity loss in the past century were associated with human population growth and economic development [13]. In its recent Global Assessment Report, the Intergovernmental Science-Policy Platform on

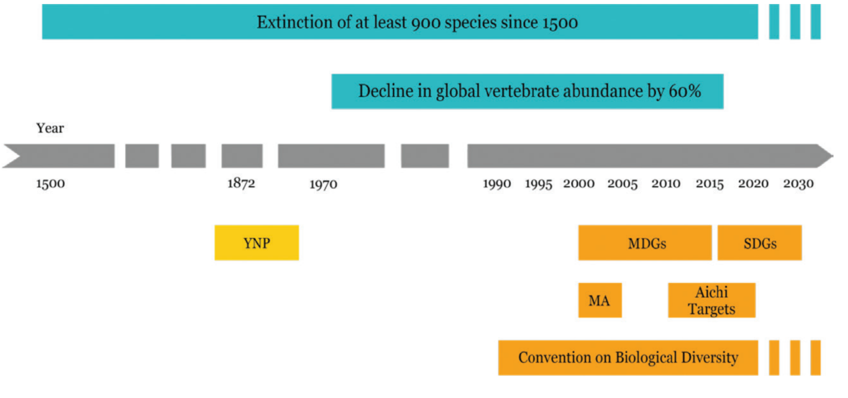

Figure 1.
Global conservation trends over the past 500 years (blue bars) and implementation of conservation treaties (orange bars). MA = millennium ecosystem assessment; MDGs = millennium development goals; SDGs = sustainable development goals; YNP = Yellowstone National Park established in 1872 (yellow bar). Timeline not drawn to scale.

Biodiversity and Ecosystem Services (IPBES) highlighted that terrestrial biodiversity losses were primarily linked to land-use changes caused by agricultural practices, whereas in maritime ecosystems overexploitation of fisheries caused major declines of biodiversity [14]. Other threats for biodiversity include climate change and proliferation of invasive alien species (IAS).

Biodiversity is under pressure due to human activities, and species extinctions will have severe negative feedbacks on human society in the future [15]. The impacts of biodiversity loss on global environmental change are comparable to climate change and need urgent attention. In its recent assessment, IPBES identified major drivers for current biodiversity losses: human-induced land-use changes, climate change, and IAS [16]. A separate study found that climate change, biodiversity loss and biogeochemical flows have already exceeded safe operating space [17]. Rising mean annual temperatures are linked to anthropogenic emissions of greenhouse gases. Temperatures have increased globally by about 0.2°C per decade since the 1970's [18], and climate change-driven impacts on biodiversity are documented across the globe [14]. Projections forecast further changes in the future [19–22].

1.3 Protected areas and biodiversity

The concept of protected areas (PA) may be as old as civilization itself [23]. Throughout the 20th century until today, the number of PAs has grown considerably to over 265,000 sites [24]. The CBD emphasized the importance of PAs for conservation of biodiversity and encouraged further PA establishment to mitigate ongoing biodiversity losses [4].

Some 76 years following the establishment of the world's first national park, Yellowstone, USA, the establishment of the International Union for Conservation of Nature (IUCN) occurred in 1948 and marked a landmark change in global biodiversity conservation [25]. Today, six commissions within the IUCN, including the World Commission on Protected Areas (WCPA) and Species Survival Commission (SSC), actively address environmental and socioeconomic issues related to conservation [23]. The importance of PAs is well-documented, but sufficient data on effectiveness of governance and management status for a majority of PAs are still lacking [26]. Recent studies additionally emphasize that biodiversity is on the decline in many PAs due to persistently high human pressures [27–29]. However, the advent of new technologies, with the possibility to provide fast and highly automated species identification and analysis across large spatial areas, points toward new perspectives in nature conservation [30].

True measurement of conservation outcomes requires effective and meaningful biodiversity monitoring systems (BMS). To foster best practice standards in governance and management of PAs, the WCPA released the Green List in 2016 [31]. In it, four components to evaluate the performance of PAs are described: good governance; sound design and planning; effective management; and successful conservation outcomes [32]. The SSC provides updated information on species and the status of ecosystem conservation in the IUCN Red List [11]. In 2009, the Joint Task Force on Biodiversity and Protected Areas was established by the WCPA and SSC. Their work focuses on two major objectives, determining best predictors of success for biodiversity conservation in PAs, and evaluating of key standards to identify sites that contribute significantly to biodiversity conservation.

1.4 Approaches to biodiversity monitoring

Monitoring of biodiversity is a challenge for many reasons, including deficits in the conception, methodologies, and technologies of BMS. Monitoring is expensive and demands significant human effort. Multiple species may require monitoring, but within the framework of data collection only a limited set of indicators can be selected. A sufficient number of specialists must be available to document taxa of expertise. Human resources can be limited by scheduling conflicts, poor weather, and inaccessible or hazardous field sites. BMS must additionally be reliable, reproducible, flexible, and comparable across sites, as well as applicable to different management questions. Perhaps most importantly, BMS should reflect the current state of the habitat or an organism group, providing key metrics to the manager in a timely and comprehensive manner. Solutions should take these limitations into consideration through application of effective technologies.

Novel approaches are now available to complement, or in some cases replace, classical monitoring methodologies. These exciting approaches are in different stages of maturity. In the following sections, we review digital monitoring techniques that are still under development or have become increasingly standardized in PA management in recent years.

Advances in computational technology over the past half century have revolutionized scientific capacity for monitoring of biodiversity. Digital methodologies that seemed unfathomable just a few years ago are now practical to enable rapid and automated collection of species data [33]. Primary among these state-of-the-art approaches are metagenomics through environmental DNA (eDNA) collection, camera trapping (CT) using digital trail cameras, environmental sampling of volatile organic compounds (VOCs) using digital sensors, passive acoustic monitoring (PAM), and earth-based remote sensing (RS) approaches [34]. In the field of biodiversity conservation, digital collection of big data is accomplished through use of data storage platforms such as GBIF; a lagging element is adequate analysis of these often-unstructured data [33, 35].

2. Advanced tools facilitating biodiversity monitoring

2.1 Applications of environmental DNA

Practical considerations constrain a BMS. One challenge is that due to time and cost considerations, often only limited selections of taxa can be monitored. To improve ecological assessments, metagenomics could be used to address sampling deficiencies. Molecular analysis could support a rapid survey of a wide range of taxa, quantify species richness, and measure diversity across different trophic levels of the ecosystem. Analysis of eDNA is increasingly becoming part of PA monitoring and management programs and can contribute to ensuring that conservation measures are implemented in a targeted manner.

Barcoding is a DNA-based taxonomic identification technique that allows a living organism to be identified on a genetic level through molecular analysis of skin, mucus, feces, or other biological samples [36]. Hair sample collection from the elusive European wild cat *Felis silvestris silvestris*, for example, can contribute to conservation activities by documenting species genetic composition across migration routes [37]. DNA metabarcoding combines barcoding and high-throughput DNA sequencing [38] and is applied for eDNA samples from diverse media such as soil, sediment, fresh water and seawater, and even air [39]. The sampling approach of eDNA collection is non-invasive, operator-independent, and flexible in its application for different taxonomic groups. Moreover, Herder and colleagues [40] highlight improved detection probability for rare and secretive species, including higher reliability of negative results, cost efficiency especially for species difficult to monitor with traditional methods, and species specificity without mismatch in identification. These features make metabarcoding attractive to fulfill PA monitoring goals [41]. Whereas morphological identification of immature aquatic insects is particularly challenging, eDNA analysis provides an objective way to differentiate species independent of life stage [42, 43].

Taxon-specific primers targeting highly conserved regions of the genome are used to amplify sample DNA in a thermocycler [44]. The sample is then sent to a Next Generation Sequencer. Species identification is based on output of nucleic acid sequences. Very short DNA primers, so-called mini-barcodes [45], allow amplification of degraded DNA, for example from soil samples [46].

DNA metabarcoding offers diverse applications to conservation, paleobiology, biomonitoring, and invasion biology. Metagenomics technologies under development could in the future provide more comprehensive biodiversity assessment in PAs using bulk samples from the environment. Moreover, interactions between taxonomic groups could be investigated, and detection of changes in these interactions could optimize adaptive management decisions [47]. For instance, aquatic eDNA sample collections are suited to detect pathogens in the environment including the fungus *Batrachochytrium dendrobatidis* in its host frog species [39, 40]. Discovery of incipient pathogens could help guide adaptive measures to limit spread of disease in the environment.

A coarse application of molecular diagnostics is the application of (molecular) operational taxonomic units, or (M)OTUs [48]. These are distinct clusters of reads whose nucleic acid sequences differ by less than a fixed threshold and can be applied as an initial survey of diversity. These OTUs are of particular value for soil biodiversity assessment in PAs, as no taxa of microorganisms need to be known to benchmark the diversity of different soil samples relative to one another.

Although DNA metabarcoding may have a highly supportive function in PA management, several challenges remain [40]. Reproducibility of results is a primary issue. For example, species composition of replicate samples taken from a freshwater stream may provide conflicting results. DNA detection in fresh water may be possible at a distance of 9 to 12 km away from the genetic source [49]. Species determination is influenced by the primers used and is highly dependent on the quality of available reference databases. Additionally, most designs are customized for the particular research question because there is no uniform approach for all applications. Another disadvantage includes limitations on accurate species density estimates. Furthermore, no information can be provided on the life stages or demographic structures of identified organisms, as eDNA analysis typically generates presence/absence data. Concerns exist that rare and endangered species could be reduced to numbers on a species list. But for their respect and protection, they would need support from society.

However, successful applications of eDNA analysis promote further usage of this novel approach in PAs. Much expectation is placed on future application of metabar-coding in a BMS. Favorable comparability of DNA-based and classical approaches has been demonstrated in the context of the European Union Water Framework Directive [50]. For the PA manager, several prerequisites for the workflow must be assessed. When using eDNA, the analytical procedure, which in most cases is carried out in an external laboratory, is not as important as the evaluation of conservation questions of interest. For this purpose, the manager must be familiar with the range of conclusions that could result from metagenomic analyses. Consideration must be given to whether eDNA collection would be the appropriate technique to answer the monitoring question. The next critical step for the manager is to acquire expert interpretation of the data. Yet, with appropriate research questions, analytical approaches using eDNA sampling have great potential to detect target species and contribute valuable insights to a BMS.

2.2 Camera trapping

Nature photography provides an archivable, permanent record on the in-situ occurrence of plants and animals. As a biodiversity research technique, photography dates back to the late 19th century [51]. In the early period of CT development, photographic approaches utilized cumbersome hardware and explosive compounds to create a flash [52–54]. Technological developments including remote triggering of the shutter, improved flash mechanisms, improvements to battery life, and digitization of images have enhanced cameras since the mid-20th century [51, 55]. With trail cameras, social media platforms, and dozens of smartphone apps, scientists and enthusiasts can now contribute to real-time photo documentation of species (**Figure 2**) [33, 56]. As a biodiversity research tool, CT compares favorably to many previously standard methodologies [57].

Formal CT studies for biodiversity monitoring came into existence a century ago [58]. Approaches have since undergone a dramatic evolution, with a wide selection of wildlife cameras now commercially available [55]. Use of remote photography has become standard for documenting species distributions over broad spatio-temporal scales [59]. Photographic approaches are suitable for examination of species occupancy or abundance in aquatic and terrestrial biomes [34] and are suitable for targeting a range of animal species [60–65]. Robust statistical methodologies are available for data analysis, including spatially explicit capture-recapture techniques (SECR), multi-layered robust principal component analysis, occupancy modeling, and predator–prey co-occurrence analysis [66–69]. Photographic and video processing programs are undergoing continual refinement, providing an ever-improving framework for data analysis and allowing inferences into animal behaviors and spatial distribution [70].

The field of big data analytics is advancing rapidly, utilizing machine learning (ML) algorithms to provide automated analysis of digital imagery [35]. Applications include identification of animals in pictures and systematic behavioral descriptions [71]. Today, deep convolutional neural networks (CNN) are applied to

Figure 2.
Trail cameras are widely available, allowing citizen scientists to capture the movement of animals, such as this family of American black bears (Ursus americanus) in Colorado, USA. Photo courtesy of K. Dalton.

image libraries, allowing rapid processing of large datasets using standard computer operating systems and open-source software [70]. Yet, ML works only if the computer is trained using accurately tagged photographs, which demands significant human effort. CNN in the context of CT research can be applied to identify any properly annotated object, from animals in PAs to agricultural pest insects [72–74]. Interconnectivity of hardware with cloud-based software is poised to empower real-time remote data collection in agriculture [75]. A parallel approach could be applied to state-of-the-art CT systems in PAs to provide real-time monitoring of animals or vegetation [76].

Passive infrared sensors (PIR) are the dominant feature used to trigger the camera shutter, while time-lapse (TL) approaches and PIR + TL in combination are also utilized [77]. Sensitivity of PIR is modulated by the camera field of vision and speed of the passing animal. A major shortcoming to PIR-activated cameras is that they often fail to trigger upon encounter by insects or small animals. Modifications of PIR sensor sensitivity or camera focal point distance can be made to improve detection of small-bodied animals [55, 77]. One advancement to PIR sensors, the so-called HALT trigger, utilizes a near-infrared beam to increase camera trapping performance on arthropods and small vertebrates [63]. As an alternative to sensor-based CT activation, automated TL photography has application to document arthropods, squamates, and avian roosting sites [62, 65, 77–79]. In addition to PIR and HALT, infrared technology has been used to create a less invasive flash mechanism for night photography compared to use of xenon or LED flash [55].

The advantages of remote CT are myriad. Today's automated approaches largely eliminate the requirement of human presence at a study site, restricting visitation to plot establishment and removal, and thereby reducing activities that could bias animal behavior. Furthermore, cameras can be deployed in locations that are difficult to access [79, 80]. Traps can be programmed to function at optimal times to detect target species behaviors. Exclusion of empty pictures or videos is enabled through automated image pre-processing [81, 82]. While studies generally focus on one or a small set of animals, the bycatch of unanalyzed photographs additionally serves as a rich source for wider ML training applications or retrospective occupancy analyses [83].

Despite the advancements of CT methodologies, critical logistical challenges remain. Animals may be able to detect CT through sight or sound, even in the absence of field workers [84]. A network of CT, deployed for weeks at a time, is necessary to acquire a robust dataset. The cumulative sampling effort of all cameras in an array, termed CT days, needs to be approximately determined prior to deployment [55]. Data analysis is an obstacle to understanding the value of CT schematics [59]. Another critical hindrance is the lack of standardization of CT technologies due to the wide selection of cameras on the market today [55, 80], although open standards to promote uniform collection of CT images have been proposed [85]. Up-front material costs of CT surveys can be high but are attenuated the longer the camera traps are in place [57]. The photo archive of a single project typically numbers in the thousands of images but requires a rapid turn-around time to inform management decisions. This problem is addressed through ML, but photographs must first be annotated, requiring months or years of technical effort depending on size of the photographic archive [71]. While automated identification of common species is reliable, identification of rare or undescribed species is challenging because photographic archives may not contain enough pictures to effectively train the computer [58].

With the use of appropriate digital camera sampling methodologies, the researcher no longer needs to interact directly with animals in order to gain insights into their behaviors or population structures. Images are either analyzed manually, or with a computer through ML approaches. Large networks of cameras may capture a representative number of individuals or species, allowing scientific inferences. In general, deployment periods need not exceed more than a few weeks to result in acceptable data. Foresight should be made when investigating particular behavioral attributes such as migration phenology or hibernation, because seasonality can affect captures of certain animals.

2.3 Electronic noses

Automated sensing of airborne chemicals is an emerging area of environmental diagnostics with high potential transferability to PA management. The use of electronic noses, or e-noses, is an established technique with diverse industrial and agricultural functions, including determination of the presence of VOCs, volatile inorganic compounds, and heavy metal pollutants in the environment [86]. Applications of e-nose technologies in conservation include monitoring of IAS and pathogenic infection of plants and animals [86–89]. E-nose devices are even capable of identifying species-level differences in plants based on their VOC emission profiles [90]. As such, e-noses are intelligent instruments that have great potential toward plant health monitoring [91], including in PAs.

Communication in mammals is moderated through sensory modalities, including scent. VOC emissions can be acquired from body surfaces, glands, or breath of animals [89, 92]. Insect communication is impacted by antennal detection of semiochemical VOCs [93]. In integrated pest management, this serves as the basis of mating disruption [94]. E-noses are designed to mimic mammalian or insect olfactory systems [86, 93]. First developed in the 1980's [95], e-noses can be equipped today with a variety of sensors. Among the most common sensor types are conductive polymer biosensors [86]. Environmental analysis using these sensors is an established method for ecological, forestry, and taxonomic research [90]. E-noses can be paired with fluorescence technologies and ML algorithms to allow reliable identification or diagnosis of VOC profiles [96]. Miniaturization of next-generation e-nose devices will allow greater utility in the field [86, 97].

Plants and animals emit altered suites of VOCs under biotic or abiotic stresses [86, 89, 97]. Comparison of VOC emissions can be made between field-grown plants and reference electronic aroma signature patterns to determine plant infection or infestation status [90]. In a study of North American ash trees, healthy trees had higher diversity of VOCs compared to trees infested with emerald ash borer *Agrilus planipennis*, a devastating IAS. Analysis of VOC patterns could help managers identify infested trees more rapidly than by using baits or traps for confirmation of infestation [88]. In the case of IAS introductions, such knowledge could advance containment measures and guide further surveillance actions [87]. Early detection of IAS or pathogenic infections of keystone species in PAs could similarly help managers determine adaptive management interventions.

Utilization of e-nose devices suffers from considerable practical limitations. Their bulky size and high price, coupled with difficulties of aroma profile detection, limit their application in the field [97]. E-noses only display raw response unless they are paired with computer-based training datasets [91]. When working with previously uncharacterized species, new computer algorithms and VOC reference libraries must be generated [86]. Moreover, due to geographic variability of abiotic factors, source materials for reference libraries should come from the sampled region [90]. Periodic calibration of e-nose monitors is necessary to maintain accuracy [86]. Sensors must be replaced periodically due to degradation over time [87]. Yet, the objective identification of VOC profiles in the environment represents a clear opportunity for management of plant health in PAs.

2.4 Passive acoustic monitoring

Animals communicate with one another for a number of biologically important reasons including defense, mating, group interactions, and orientation [98, 99]. Sound is recognized as a common means of communication in insects, fish, birds, squamates, and mammals [98, 100]. Call count censusing has long been a standard practice to identify community assemblages [101, 102]. Initially conducted with expensive, cumbersome equipment, census techniques using recorders now allow ecologists to document a wide diversity of species at a far lower cost than continual deployment of field crews [98]. Today, PAM uses autonomous recording units (ARUs), representing a non-invasive means to collect species-level occupancy data, thereby minimizing behavioral impacts or animal stress [103, 104].

Modern ARUs have many advantages over previously standard field techniques, enabling research crews to conduct more site surveys with fewer site visits and allowing improved biodiversity estimation in remote areas [105, 106]. Digital recordings further serve as permanent data records that can be played back for verification of species identity [101, 107–109]. Rapid acoustic surveys using microphone arrays have application in conservation, identifying changes in community species assemblages or migration patterns, phenology, communication, or even presence of IAS [105, 110, 111]. This approach may help to identify environmental impacts of anthropogenic disturbance, for example the impacts of artisanal mining on the local avian community [112].

Methodologies for detection of vocal species are well established, including classic field approaches of physical trapping, playback of audio recordings, point counts, and timed area searches [105, 108, 113, 114]. Bats and birds have been recorded in proximity to wind turbines using radar tracking, infrared imagery, and radio telemetry, [61, 115]. First formalized nearly 20 years ago, SECR techniques provide the statistical framework to document species density across microphone arrays [69, 103, 114, 116]. For some taxa, effectiveness of manual calling surveys has been directly compared to results from ARU methodologies, with both methods providing synergetic benefits to a monitoring program [101]. Manual calling surveys and ARU approaches can support similar conclusions; however, ARUs may provide biodiversity data with dramatically reduced human effort [117]. Similar to CT studies, well-established statistical techniques are available for studies using PAM to provide estimates on animal abundance, density, and occupancy [105, 113, 118, 119].

Species-specific auditory signals can be identified by experienced personnel, or automatically using ML algorithms. Several automated ML techniques are described [99, 100, 107, 120]. Two crucial components of automated bioacoustics analysis are recognized. First, auditory signals are characterized visually through spectrograms; subsequently, signals are extracted from continuous recordings through pairing with a "recognizer" template segment [105]. Spectrograms assist in species identification [106, 115]. Automation coupled with cloud-based technologies now enable remote real-time identification, potentially providing up-to-the-minute conservation information to a PA manager [107, 121].

Expert-based field identification may compare favorably to findings generated from remote microphone arrays linked to species recognition algorithms [108]. Yet, surveys relying on human skill for identification of species are prone to error due to imperfect species detection, confirmation bias, or listener fatigue [102, 103, 119, 122]. Lack of objective classification is especially challenging when a reviewer is charged with identifying rare or unknown species, with animals that are known to employ mimicry, or in complex soundscapes [104, 111]. Multiple factors influence the soundscape, including relative abundance of species, caller density, and community acoustic diversity [123]. Analysis of soundscape profiles can be facilitated through reduction of background noise [104, 109]. Incorporating species time of arrival or activity into a survey using fixed-point microphone arrays can be an approach to reduce bias [102, 114]. Through application of sound filters, automated programs can eliminate sections of uninformative data, facilitating verification of acoustic signals by a reviewer [117].

Important limitations persist for auditory species identification. Use of automated computer recognition of animal calls is currently underutilized [102]. For effective ML, hundreds of labeled sound records are required [115, 120]. Recordings may miss very faint or distant calls and allow overrepresentation of calls by noisy species [115, 117, 122]. Depending on equipment, costs can be high for acquisition and maintenance of a microphone array [105]. Furthermore, effective sampling area is often imprecisely known due to landscape features, thus limiting inference on species occupancy [103]. An effective study design can help alleviate some limitations, for example through strategic placement of microphone arrays providing overlap within species habitat. Certain types of hardware are becoming less expensive, while many software programs and call libraries are deposited in open-source libraries [99].

The generation of large amounts of data is a common feature to many PAM programs [117]. While automated identification of acoustic calls is possible for certain species or analytical processes, big data processing challenges remain [35, 99, 121]. Solutions to data management should be transferrable to personnel of all skill levels, and in a way that acoustic data can be statistically compared across sites [117]. Nonetheless, the recent advancements of automated PAM hold great promise for the future of PA management.

2.5 Applications of remote sensing in protected area monitoring

Management of PAs can be supported by RS applications. A range of different datasets can be produced using RS, including information on climate, characteristics of vegetation, plant phenology, water budget, energy exchange, and terrain models [124]. In order to ensure efficient use of such data, a clear implementation strategy is essential. Analysis of satellite data is a cost-efficient extension to conventional in-situ monitoring in the field, particularly in remote and inaccessible areas. Moreover, analyses can be carried out retrospectively with historic satellite imagery [125]. To detect different ecosystems and habitats, structural and functional attributes can be determined based on various RS technologies [124]. For example, LiDAR- and radar-derived elevation models are often used for forest mapping to assess aboveground structure and biomass [126]. Some RS techniques also provide the possibility to compare different PAs worldwide based on the same dataset, enabling global estimates of habitat availability. Local and regional datasets are often more accurate than global datasets, in particular for the use of unmanned aerial systems, or drones [124]. Drones are flexible vehicles that can be equipped with imaging sensors including thermal vision cameras, visible red-green-blue, near infrared, multispectral, or hyperspectral sensors, as well as ranging sensors including laser scanners and synthetic aperture radars. Drones come in multi-rotor or fixed wing configurations and are used in many conservation-based fields: wildlife monitoring and management, ecosystem monitoring, law enforcement, ecotourism, environmental management, and disaster response [127].

To improve management and monitoring effectiveness in PAs, software programs like Spatial Monitoring and Reporting Tool (SMART) combine geographic information systems (GIS) with database tools and digital field assessment [128]. Through such tools, standardized results of conservation efforts or PA law enforcement activities can be generated in real-time. SMART output shows the spatial distribution of illegal activities while simultaneously tracking patrol efforts and providing a record of the violation [129].

The SMART approach streamlines the time required for quality assessment. A multilingual interface facilitates its implementation in PAs anywhere in the world. The use of pictograms can further simplify the generation of datasets. Preparation of data templates also provides an efficient way to produce standardized reports that can be expressed as a dashboard visualizing monitoring results with only a few clicks [130]. Using cloud-based technology, it is now possible to produce near real-time (NRT) alerts directly from the field [131]. This allows immediate action on incidents of conservation interest, thus improving management of the PA.

A study on the impact of NRT alert systems for conservation concluded that such systems are suitable for identifying fire impact and illegal forest activities [132]. The accuracy and availability of NRT alerts are affected through different factors including spatial resolution or time lag due to cloud cover. Despite these limitations, RS datasets provide an important indication of potential threats [133].

Diverse methodologies and thresholds are used to assess key variables in forest inventories, making data comparison a challenge [134]. In particular, use of

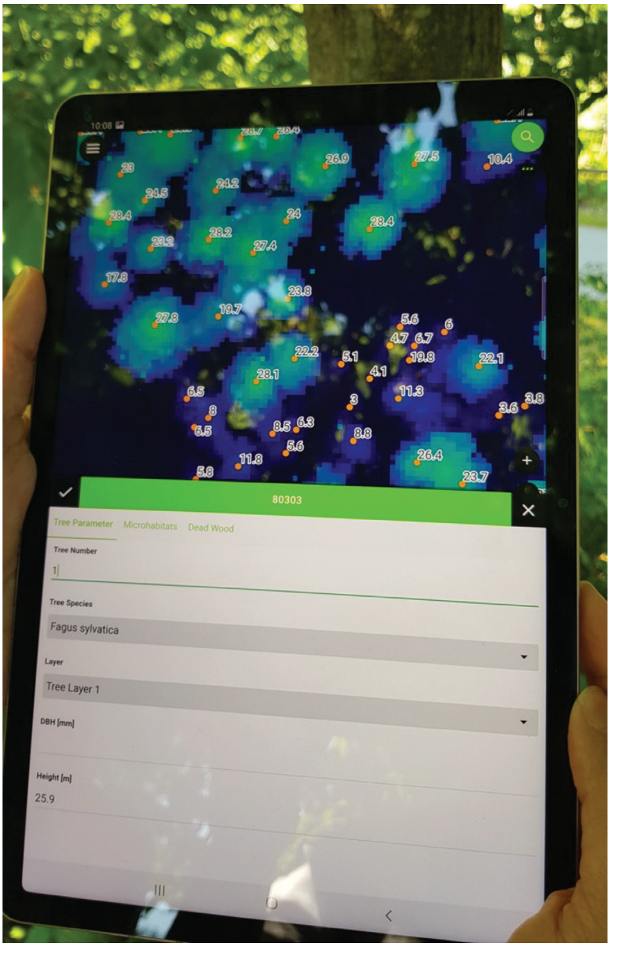

Figure 3.
In-situ single tree assessment with QField. The points represent single tree detections from a remote sensing approach and allow a linkage of tree parameters to the tree itself. Coloration indicates the tree height and crown structure.

subjective techniques can lead to faulty measurements. One solution is to compare parameters using RS such as above-ground woody biomass across national borders [135]. In this instance, generation of cross-comparable information could play an important role in understanding carbon sequestration dynamics of different forests [136]. By identifying, such datasets enable a comparison of individual tree characteristics at the landscape level [137]. The applicability of different methodologies and datasets for single tree detection has been studied for more than three decades [138] and is becoming more accurate. For laser scanner datasets, the point density to detect tree parameters can vary from 2 points m^{-2} up to more than 25,000 points m^{-2} [139, 140]. Furthermore, analysis of datasets with repeat survey dates allows detection of single missing trees. These so-called change detection approaches are already possible using consumer-level drones without post-processing effort, based on multi-temporal ultra-high-resolution orthomosaics (5 cm pixel resolution with a flight altitude of 100 m) and three-dimensional point clouds. The use of such technologies can thus increase the comparability and repeatability of monitoring datasets. With a combination of pre-processed single tree detection it is possible to ground-truth tree parameters or quantify microhabitats directly in the field based on the position of the trees [141].

Applications like QField further allow PA managers to establish digital assessments in the field based on GIS (**Figure 3**). Such applications promote effective workflows encompassing whole data assessment, data input, and digitization, thereby enabling data quality control. The availability of actual RS data in the field can further increase the quality of digitization [142].

3. Conclusion

In this chapter, a review of some of the most exciting technological advances to improve BMS is provided. To meet the urgent demands of international biodiversity conventions, state-of-the-art monitoring approaches must be quickly adopted on a broad scale. In some cases, completely new work flows will be required. Yet, in order to retain the value of historical data, utility of new technologies must be evaluated, compared with previously standard approaches, and visualized for interpretation. In other words, while application of individual novel technologies may be beneficial, no method alone provides a singular solution to improve conservation metrics. Instead, PA managers must select suitable tools as part of a toolkit to allow large-scale assessment and flexibility in an adaptive management program. Using such an integrated approach will assist PA managers to reach conservation goals. Currently, the BioMONITec research team of the UNESCO Chair on Sustainable Management of Conservation Areas Carinthia University of Applied Sciences, Austria, is constructing an online decision-making assistant, or configurator, to guide development of site-specific monitoring toolkits. In coordination with the IUCN WCPA, a comprehensive global biodiversity monitoring guideline that shall be applicable in PAs across the world is being developed (M. Jungmeier, *pers. comm.*).

Implementation of digital monitoring tools is poised to augment biodiversity monitoring programs, economizing both human capital and natural resources. Where monitoring data already exist, usage of new tools must allow valid comparison of data to permit identification of trends. High-throughput DNA metabarcoding techniques using eDNA sampling have proven to be invaluable for rapid and comprehensive biodiversity assessments in PAs. Advances in cloud-based computer frameworks and ML will allow sensor-based technologies to convey data in real-time to a manager. Drones and satellites can already provide NRT data from above the earth's surface, and these capabilities are continually improving. In this context, PA managers of the future should not only be competently qualified scientists, excellent communicators and mediators, but must also be up-to-date technology enthusiasts.

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Conflict of interest

The authors declare no conflict of interest.

Abbreviations

ARU	autonomous recording unit
BMS	biodiversity monitoring system
CBD	Convention on Biological Diversity
CNN	convolutional neural network
CT	camera trapping
eDNA	environmental DNA
GIS	geographical information system
IAS	invasive alien species
IPBES	Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services
IUCN	International Union for the Conservation of Nature
ML	machine learning
(M)OTU	(molecular) operational taxonomic unit
NRT	near real-time
PA	protected area
PAM	passive acoustic monitoring
PIR	passive infrared
RS	remote sensing
SDGs	Sustainable Development Goals
SECR	spatially explicit capture-recapture
SMART	Spatial Monitoring and Reporting Tool
SSC	Species Survival Commission
TL	time-lapse
UN	United Nations
VOC	volatile organic carbon
WCPA	World Commission on Protected Areas

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