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Emerging technologies revolutionise insect ecology and monitoring

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Key words

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Highlights

- We appraise four emerging tools and technologies (computer vision, acoustic monitoring, radar and molecular methods) that provide unprecedented opportunities for insect monitoring and the study of insect ecology.
- These technologies have various benefits over traditional insect monitoring methods, including increased resolution of data collection across space and time, and a broader taxonomic coverage.
- At the same time, each technology has its limitations, some of which can be overcome with further methodological developments.
- Key issues regarding open science and international standards need to be addressed.
- While technology can never replace the knowledge of entomological specialists, we expect that integration of data across technologies, along with expert knowledge, will become commonplace in the future.

Glossary

Term	Definition
Acoustic sensor	A device that detects and records sounds.
AI (Artificial intelligence)	Scientific field of computer science interested in (partially) reproducing human skills, such as thinking, acting, or interpreting data, with computational algorithms. Often used as a synonym for machine learning (see below).
Citizen science	The participation of the general public in scientific processes. Participation can occur at different levels of involvement and expertise, and at different stages of the process (study design, data collection and/or interpretation).
Computer vision	Scientific field of computer science that develops algorithms for analysing image or video data to produce descriptions of the depicted content, e.g., a categorization via numerical representations.
(Convolutional) neural networks	Group of machine learning methods that require large datasets for training, often used for image analysis and pattern recognition, where each network consists of connected nodes and layers that process input data to obtain desired outputs.
Deep learning	General term that denotes the training and application of deep

	(convolutional) neural networks for a specific task, often used as a synonym for machine learning with deep neural networks.
Edge computing	Data processing done near the site of data collection, instead of transferring the data to a remote location for processing and analysis.
Environmental DNA (eDNA)	DNA obtained from environmental samples such as water from lakes or rivers, soil, faeces, air etc.
FAIR data	Data that are findable, accessible, interoperable and reusable.
Machine learning	Scientific field of computer science for developing predictive algorithms that learn patterns in data to make predictions. The algorithms learn from example training data rather than being programmed explicitly.
Metabarcoding	The recognition of species from their genetic structure, applied to multiple taxa contained in bulk or mixed samples. A common genetic region used for barcoding is mitochondrial cytochrome c oxidase subunit 1 (CO1).
Multi-sensor station	Observation device equipped with multiple sensors and recording units.
Radar	Device emitting radio waves in a certain direction to record the time, intensity and other features of the electromagnetic pulses that return from objects

Traditional monitoring	Observations, usually by sight or trap, and species identification by human eye in the field or in the lab.

Abstract

Insects are the most diverse group of animals on Earth, but their small size and high diversity have always made them challenging to study. Recent technological advances have the potential to revolutionise insect ecology and monitoring. We describe the state-of-the-art of four technologies (computer vision, acoustic monitoring, radar, and molecular methods), and assess their advantages, current limitations and future potential. We discuss how these technologies can adhere to modern standards of data curation and transparency, their implications for citizen science, and their potential for integration among different monitoring programs and technologies. We argue that they provide unprecedented possibilities for insect ecology and monitoring but it will be important to foster international standards via collaboration.

Technological advancement for insect monitoring

Insects are the most diverse group of eukaryotic organisms on Earth, comprising an estimated 80% of all animal life [1]. This staggering diversity, of which at least 80% remains undescribed, forms a major challenge to studying insects and monitoring their responses to environmental changes [2]. Recent reports of long-term declines in insect biomass and abundances [3,4], in combination with the emergence of new technologies [5–7], have led to calls for [8], and the establishment of, new research projects for monitoring populations and assemblages of insects and other invertebrates [9,10].

Traditionally, the monitoring of insects involves the killing of insects, followed by time-consuming sorting and species identification by specialists [11]. Often the number of individuals and the taxonomic diversity within a sample are so large that only a subgroup of taxa are identified, or taxa are only identified to a coarse taxonomic level. Hence, there is a heavy bias towards research on well-resolved groups, such as butterflies and ground beetles, whereas the diversity of other taxa, e.g. most Diptera is often ignored [e.g. 12]. Additionally, the required human labour for both data collection and processing limits the number of locations or the frequency of sampling in traditional insect monitoring programs.

Recent development of technologies that employ novel detection and identification methods, often in combination with citizen science, has opened up exciting new avenues for tracking insect populations and assemblages [5–7,13]. These technologies, which include automated image- and sound recognition, radar, and molecular methods, have the potential to radically increase the spatial, temporal and taxonomic coverage of monitoring programs. They also allow new questions to be asked about insect population dynamics, phenology and biotic interactions (Box 1). At the same time, these technologies come with their own set of limitations, and are in parallel development in different projects and countries. To ensure efficient progress, there is a need for large-scale collaboration to develop international databases, metadata standards, and open communication on hardware and software development, to ensure adherence to FAIR data principles.

This paper is a collaborative effort of researchers from different European countries, aiming to review emerging tools and technologies for insect monitoring and outlining a research agenda that harnesses their potential. We provide an overview of (1) the state-of-the-art of these technologies, their advantages, current limitations, and future potential, (2) how the data collected using these technologies can adhere to modern standards of data curation and transparency, (3) how citizens can participate in projects using these new technologies, and (4) the potential for integration and synergies among technologies.

Box 1: Seeing the unseen using new technologies

Species interaction networks:

Interactions between species are often hard to detect due to the time, place or scale at which interactions take place, but modern technologies can help make the unseen visible. Molecular methods are being used to identify both the predators and food of insects directly, i.e. by analysing faeces [14], gut contents [15] (also from blood meals [16]), or parasite presence [17], and indirectly, using DNA left after resource visitation, such as on flowers [18]. Also computer vision has been used to quantify insect resource use and foraging behaviour [19].

Quantifying ecosystem services: Technologies are already being used to quantify insect pollination. Computer vision is applied to images taken by cameras fixed above plants [19–21] and metabarcoding can be used on pollen or flowers to identify flower visitors [19,22,23]. Computer vision or acoustic monitoring may also prove useful in studying the decomposition of dung, carrion or dead plant matter, but has to our knowledge not yet been applied.

Tracking species movements and occurrences from local to continental scales:

For many ecological questions, as well as for biodiversity conservation, public health and crop protection, it is essential to track the whereabouts of specific insect species. Several of the technologies we discussed can help doing this. At the smallest scales, computer vision can track insects, such as pollinators, as they forage for resources [19,20], and eDNA can detect traces of past insect visits [18]. At regional to continental scales, different technologies can be used to detect the occurrence and movement of beneficial species [24], pest species [25–27], disease vectors [28], invasive species [29–31], and protected species [32].

Energy and biomass fluxes within and across habitats:

The movement of insects creates fluxes of nutrients and energy across large distances and across ecosystem boundaries (linking e.g. aquatic and terrestrial systems). Tracking these fluxes is now possible in 4 dimensions in a non-invasive and unbiased way [33,34]. Vertically-looking radar has been used to quantify high altitude insect migrations [35], and vertical photography and lidar can show insect biomass fluxes at closer ranges [33,36].

Four technologies that are revolutionising entomology

Computer vision

Computer vision is a field of computer science that develops algorithms to extract information from digital images and video (Fig. 1A). In ecology, computer vision is being used in diverse ways to collect observations and automize species identification. For instance, it is being used for automated and standardised sampling of biodiversity, using cameras aimed at an environmental feature [19] or at a screen placed in the field (see Box 2), often in combination with traps (e.g., light traps [37], sticky traps [38] or pheromone traps [39]) to increase detection rates. Computer vision is also helping to digitise the vast museum collections of specimens to mobilise historic occurrence records [40,41]. Images are also being collected by citizen scientists and uploaded to portals for opportunistic observations [42]. Several of these applications (e.g. www.iNaturalist.org, www.observation.org/apps/obsidentify/, and www.pictureinsect.com) support automated identification. While the technology has yet to be applied at a large scale for insect monitoring, the first applications show promising results (Box 2).

There are a number of potential advantages to using computer vision for sampling and identifying insects over traditional techniques. First, computer vision methods are often non-destructive, so individuals don't need to be interfered with or killed. Second, computer vision technology can count and classify insects with less human labour and observer bias [6]. Third, by reducing the necessity for taxonomic expertise, computer vision is creating opportunities to expand the engagement of citizen scientists (Box 3). Last, computer vision can be used to collect information on insect behaviour and interactions. For instance, fixed cameras have been mounted over resources such as flowers to record the activity of insects, including plant-pollinator interactions [19,20].

Computer vision uses machine learning algorithms, such as convolutional neural networks (CNNs), which are trained to identify insects using a library of pre-classified images. Accuracy rates can be over 90% at the species-level for some taxa, but strongly depend on taxon group size and morphological similarity [43–48]. In addition to taxonomic identification, algorithms are being used to count individuals in an image and estimate individual size, biomass and movement [49,50].

Several technical challenges are currently hindering the widespread application of computer vision in entomological research. A main challenge is the large amounts of training data (reference libraries) needed, which may be taxon, region, and project specific. Computers have difficulties identifying species with limited training data (typically rare species), and tend to overpredict species with a disproportionately large amount of training data (typically common species). One solution to expand reference libraries is the development of apps for local experts and citizens to submit training image data of species at different angles [51]. Another challenge is the power consumption for the cameras and subsequent data transfer. This difficulty may be reduced by the use of solar panels (Box 2), but this increases the risk of theft. For on-site classification, internet connectivity is important, however, edge computing (local data processing) enables classification directly on the device (e.g. the Seek app by iNaturalist (https://www.inaturalist.org/pages/seek_app) with the potential for real-time monitoring [19]. Hence, while there still are challenges [6], already the opportunities of computer vision are numerous and will likely transform insect monitoring in the coming decade (Fig. 2A).

Acoustic monitoring

A diverse range of insect taxa emit sounds that can be used for efficient monitoring. Like computer vision, acoustic monitoring uses a field recorder to collect information (i.e., sounds), in combination with machine learning algorithms for species identification (Fig. 1B). Insect sounds may be sampled using stationary recorders or by mobile transects from cars or trains [52,53]. So far, these methods have mostly been applied to detect the chirping of insects such as orthopterans and cicadas (Box 2), and have been tested on freshwater invertebrates [54,55], and bees, hornets and mosquitoes based on their flight sounds [56,57], but they have a much broader range of possibilities (Fig. 2B).

One of the main advantages of acoustic monitoring over other sampling approaches, is that insects can be detected over much longer ranges - sometimes more than 100 m [53]. Additionally, like computer vision, acoustic monitoring is nondestructive, rapid, and inexpensive [58], and machine learning algorithms applied to the recorded sound circumvent observer biases [53,59]. In addition to species presence, acoustic signals contain information on insect behaviour, such as phenology, activity and courtship behaviour [52,53,60], and can provide direct measures of ecological functions, such as pollination or wood-boring [57,61]. Recordings of composite environmental sounds [62] - soundscapes - also contain rich information about the state of biological assemblages related to species diversity [63].

Identification of species from their sounds is still limited by the size of the reference libraries, which are poorly developed compared to those for vertebrates [59]. Currently, these libraries are only sufficiently large in temperate regions for some terrestrial vocalising insect groups, whereas for the use of other insect sounds (especially flight sounds), reference libraries are largely lacking (but see [56]). Citizen science schemes could, however, help build these acoustic reference libraries [64]. There is also a strong need for research into the factors that influence the detectability of insect sounds, including microphone type, weather, and vegetation attenuation, to understand the sampling ranges. Nevertheless, acoustic monitoring has underexplored potential for low-cost but large-scale monitoring (Fig 2B).

Radar

The application of remote sensing technologies for biodiversity monitoring has rapidly expanded over the last decade. In entomology, radar monitoring uses terrestrial radar systems, including weather surveillance radar, to detect insects in the airspace (Fig. 1C). It has been long known that radar can detect large swarms of insects, but modern radar can provide detailed information on flying insects, including size, shape, speed, trajectory and wing beat frequency [65]. Specialised entomological radars can detect insects far above the ground, from 150 m above ground level, with the potential to detect larger insects (i.e., >15 mg) up to 1.2 km above ground level [65].

Advantages of monitoring insects by radar are that it's non-invasive, has large detection radius, and can operate day and night. Hence, radar observations are especially useful to study biomass fluxes [35], migratory behaviour [65], and population dynamics [24] (Box 1). Radar can also be used to reveal insect presence indirectly, by detecting signs of vegetation damage [25] or nest structures [66]. Data from weather surveillance radars have already been combined with local monitoring programs to document population declines in mayflies [67] and the movement of locust swarms [26].

Radar technologies have significant potential for large-scale monitoring of insects, even at the continental-scale, using the existing networks of weather surveillance radars [34]. However, they would benefit from improved algorithms for filtering biological targets from other airborne particles, as well as increased knowledge of the reflective properties of insect taxa [68,69].

LiDAR (laser radar) has only recently been applied in entomology, but can be used to detect insects much closer to the ground than most radar systems, over sampling ranges of 10-600 m. Moreover, it has the potential to use the spectral reflectance to identify insects to much lower taxonomic levels [28,70,71]. As the technology develops, better taxonomic classification can be achieved when libraries on spectral scatter become available for more taxa [13].

Molecular methods

Out of the modern technologies, molecular methods using genetic information are the most developed and most widely used so far. These methods can be used for many goals including the quick discovery of new species [72], the detection of endangered [32], invasive or pest species [73], the characterization of species interaction networks [18,74], and assessment of taxonomic [22,75] and genetic diversity of whole assemblages [76,77].

The most common use of genetic information is based on DNA barcoding, i.e. amplification of a short section of DNA from a specific gene or genes, providing adequate separation between focal taxa. Barcoding was originally proposed for the identification of individual specimens [78]. Yet, advancements in laboratory protocols and high-throughput sequencing technologies now enable DNA isolation, amplification and taxon identification from complex mixture samples (DNA metabarcoding; Fig. 1D) [29]. Compared to traditional monitoring, metabarcoding can be time- and cost-efficient [72]) and is highly scalable, enabling simultaneous processing of many samples and species. Metabarcoding methods can be applied directly to organismal samples, using the storage medium [79] or homogenised bulk samples of collected insects [80]. Alternatively, it is possible to detect the presence of species from DNA fragments in environmental samples (eDNA), such as water [32], soil [81] or air [82]. Interactions between insects and other taxa can be identified by using samples derived from animals guts, blood or faeces [74] (Box 1). One of the most recent advances is the use of eRNA [83] to distinguish the presence of living from dead individuals, since RNA is only present in metabolically active cells, whereas DNA may derive from the remains of dead individuals.

Molecular methods overcome many of the observation biases associated with traditional monitoring, however, they bring a new set of biases. Differences in DNA amounts and extractability among insect taxa [79], or taxa-specific variation in PCR amplification [84,85], may result in some species not being detected even when present in the sample. Size sorting within a sample can help DNA amplification of small and rare species [86]. However, commonly used markers, such as the CO1 gene, sometimes still fail to detect some insect taxa such as Hymenoptera [87]. Amplification biases may also be circumvented by bypassing the PCR step and directly sequencing the complete extracted DNA [75,88] or RNA (metatranscriptomics). RNA sequencing also brings the potential to detect metabolic capacities and gene expression of individuals or assemblages at the moment of sampling [89].

The primary outputs of DNA-technologies are gene-based operational units (operational taxonomic units [OTUs] and amplicon sequence variants [ASVs]; e.g. [90]), which represent clusters of organisms with similar DNA sequences. To link with existing knowledge of species and their ecology, these units must be mapped to reference databases, such as BOLD or GenBank.

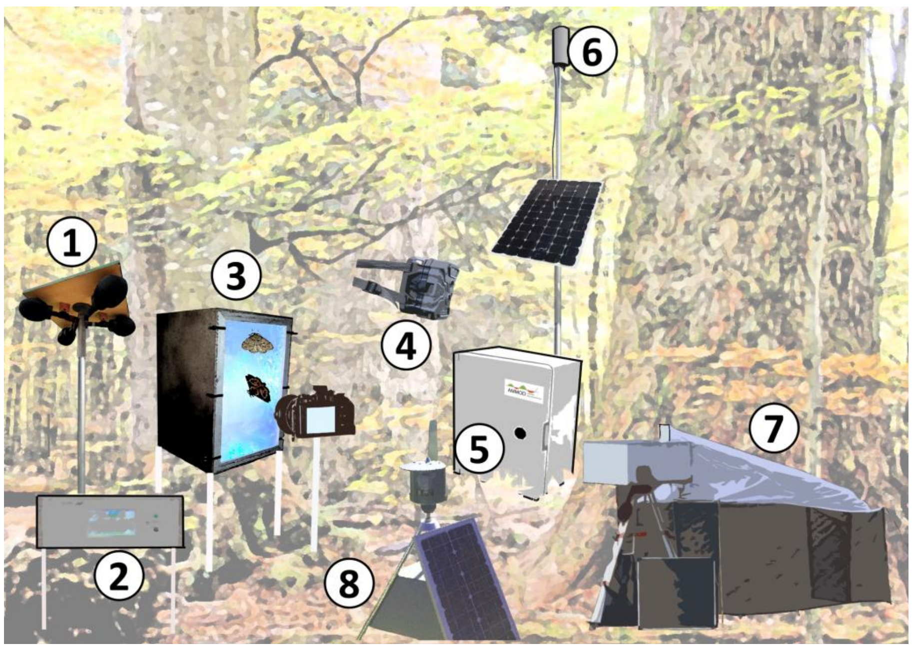
These reference databases are rapidly growing, BOLD now containing genetic data on 213,344 publicly available insect species. However, errors, synonymy, misidentifications and missing species can cause misclassifications. Nevertheless, international, national and taxon-specific initiatives are currently making strong progress on improving the taxonomic coverage of such reference libraries [80,91].

Box 2: Case in point: Pioneering monitoring projects

Case study	Brief description
DIOPSIS (Netherlands)	 Fig .I. DIOPSIS. DIOPSIS (Digital Identification Of Photographically Sampled Insect Species) takes regular photos of a yellow screen that attracts insects and uses machine learning to recognize and count the photographed insects [92]. Photos are taken every 10 seconds or when movement is detected. If a photo is different from the previous one, it is stored locally and/or sent to a

	server through 4G. Individual tracking across pictures is applied to remove duplicates. Since 2019, about 80-100 DIOPSIS cameras have been deployed each year in the Netherlands.
INPEDIV (Germany)	 Fig. II. INPEDIV (Image credit: Livia Schäffler) The project „Integrative analysis of the influence of pesticides and land use on biodiversity in Germany“ (INPEDIV) aims at investigating effects of organic and conventional farming on biodiversity in open calcareous grasslands at 20 protected sites in western and eastern Germany. The project combines traditional and modern methods to examine impacts of agricultural land use on biodiversity across trophic levels along trap lines reaching from agricultural fields into adjacent protected areas. Flying insects caught in Malaise traps are determined by metabarcoding of bulk samples. Additionally, the pesticide load is analysed at each trap location.

Suivi des Orthoptères Nocturnes (France)	SON Suivi des orthoptères nocturnes Fig. II. Suivi des Orthoptères Nocturnes. In France, nocturnally vocalising bush crickets have been monitored by citizen scientists since 2006, as an add-on to the acoustic bat monitoring scheme Vigie-Chiro. For this purpose, Tadarida software was developed to detect both bat and insect calls and classify them into 79 classes including all common bat and bush-cricket species, using a random forest algorithm [93]. This nationwide monitoring scheme, with so far 16 349 individual sampling locations, has detected significant declines of four bush-cricket species, and an increase of *Phaneroptera nana.*
Insektmobilen (Denmark / Germany)	 Fig. III. Insektmobilen (Image credit: Anders Drud, Natural History Museum of Denmark.)

	InsektMobilen uses nets mounted on car rooftops (car nets) to sample flying insects, followed by DNA metabarcoding and image classification to quantify biomass, richness and diversity [94]. In Denmark and Germany, volunteers sampled insects over 250 five-km routes during June/July 2018 and 2019. In Denmark, the project detected 319 species not known for Denmark and 174 species included in the Danish Red List.
AMMOD (Germany)	 Fig IV. Illustration of the modular AMMOD monitoring station design. (1) Acoustic monitoring, (2) Smellscapes (pVOCs), (3) Visual monitoring: Moth scanner, (4) Visual monitoring: Wildlife camera trap, (5) Base station, (6) Data transfer and management, (7) Metabarcoding: Automated Malaise trap, (8) Metabarcoding: Automated pollen sampler. Figure draft and design: J. Wolfgang Wägele.

	AMMODs are Automated Multisensor stations for Monitoring of species Diversity [9]. Analogous to weather stations, these are autonomous samplers that monitor plants, birds, mammals and insects. The technology consists of six modules: (i) automatized visual monitoring and image analyses (mammals and moths), (ii) detection of smellscapes using volatile organic compounds, (iii) Malaise and pollen traps for metabarcoding, (iv) automated bioacoustic monitoring (birds and bats), (v) development of a base station, and (vi) data management and cross-platform analysis. Since 2020, AMMOD is being tested at three sites in Germany.

Box 3: New technologies as opportunities to advance citizen science

About 70-80 % of species records in Europe are collected by volunteers [95]and these data underpin many national and regional assessments of biodiversity change [96,97]. Historically, most insect monitoring was organised outside academia, especially by taxonomic specialists and natural history societies [98], and there is a long tradition of including lay people in the scientific data collection process for various insect taxa including butterflies and mosquitoes [95]. Recent technological developments have increased the opportunities for people,

including non-specialists, to get involved, for example helping with digitization of museum collections (e.g. Denmark).

Out of the new technologies, computer vision has been most often integrated into citizen science; for example, a range of smartphone applications use computer vision to help users identify species (e.g. iNaturalist, ObsIdentify, and Picture Insect, lepsnap). Many of these applications use a so-called ‘human-in-the-loop’ approach - the technology helps users narrow down the likely species by suggesting the most visually similar species. Another way citizens have contributed to computer vision-based science is by helping to compile the training data needed for machine learning, for example in the PollinatorWatch project. In projects using DNA-technology, some rely on citizen scientists for the collection of the insect samples [94], which are subsequently processed by scientists. A few citizen science projects are starting to include citizens in the analysis steps e.g., the DNA&life project in Denmark [99].

Ecologists often debate the reliability of species observations from citizen science. However, the development of AI based apps [100] and DNA based methods [31] may help increase identification accuracy. For instance, AI tools may allow instant feedback on the likelihood of an observation. AI methods can also be used to develop intuitive field guides that may deviate from classic dichotomous identification keys. Some citizen science platforms already use crowd-sourced expert identification for validation of observation (such as expert crowd verification of iNaturalist or iRecord observations); however, the rate of manual validation is unable to keep pace with the rapidly growing number of submissions. In these cases, technologies could use active learning AI algorithms, which select only a subset of images for human validation for i) groundtruthing or training of the AI classifier, and ii) where the AI classifier was most uncertain in its decision. Citizens with taxonomic expertise may also help compile the training datasets by identifying species on images or sounds.

New technologies have the potential to increase the accessibility and diversity of entomological citizen science. For instance, citizen science activities could be extended to volunteers with expertise in joint software development and data visualisation. Care, however, needs to be taken to avoid access barriers and unintended exclusion due to possible technology barriers or disconnect of data, people and wildlife. Overall, there could be considerable benefits from involving citizen scientists in the development and application of the tools through co-created projects and community partnerships [98].

Fig. V. Using automated identification technology to monitor insects can be a win-win situation for citizens and scientists. Using such tools, citizens can learn about species identity and ecology, and scientists can use the data collected to study, for example, species interactions, such as this lady beetle feeding on aphids on their host plant.

The road forward

The development of new technologies for insect ecology and monitoring is no goal in itself, but must be guided by the needs of society, policy makers, as well as the scientific questions scientists address (Box 1). Furthermore, they must meet the demands of modern science in terms of data curation and transparency [101], and consider the possibility of involvement of other stakeholders, such as citizens (Box 3), who have contributed 70-80 % of species occurrence records in Europe [95]. There are also un(der)explored possibilities for integration among technologies. In the next sections, we will outline the opportunities for how these technologies can revolutionise insect ecology and monitoring.

Open Science

Insect data collected by traditional monitoring schemes or derived from museum specimens are becoming increasingly accessible via data discovery platforms such as www.GBIF.org. However, for data collected using the technologies discussed here, the norms and practices of open science, as well as standards for data publishing have yet to evolve and to be agreed upon. To make these new technologies open and reproducible, both the underlying data and processing steps must be FAIR: findable, accessible, interoperable, and reusable [101] .

While generalist data repositories may function sufficiently well for basic data access and retrieval, specialist repositories are often needed for the most efficient data re-use. Data openness has been fostered for DNA-based technologies through International Nucleotide Sequence Database Collaboration (www.INSDC.org) data portals such as the Sequence Reed Archive (SRA). GBIF has also led the development of protocols to deal with sequence data to improve discoverability of DNA derived data [102]. For sharing species images, there are various citizen scientist platforms, but fewer for audio recordings (but see www.iNaturalist.org).

New technologies face practical problems about which form of data should be stored due to the typically large file sizes or novel data attributes. To ensure comparability over time, data should be stored in their original form, so the data can be reprocessed when reference libraries or technologies improve and enable better species detection and/or classification.

Standardisation and quality of data and metadata are key for interoperability and reusability. Among the most widespread are Ecological Metadata Language (EML [103]) and Darwin Core [104]. Yet, it is still unclear what metadata would be sufficient for reproducibility of data collected by different technologies or different protocols [105]. Technological reproducibility also needs to involve openness of hardware (type, model, as well as mechanical, electrical and optical settings), and software (version, documentation), and the availability of analytical code as a community norm. For DNA technologies, specific steps of the laboratory protocols, such as preservation buffer, DNA polymerase, PCR enhancer, are essential for reproducibility [106] and automated workflows are being proposed for standardisation [102,107].

The potential of technological integration

Each of the reviewed technologies has its own strengths and weaknesses, and new studies should seek to combine the strengths of the different technologies, as well as integrate the continued value of traditional monitoring methods. Combining different technologies could bring a range of benefits: increased spatial, temporal or taxonomic coverage, a broader range of biodiversity metrics, or simply more confident taxonomic assignment. Integration is also likely to be the optimal solution for effective large-scale and long-term insect monitoring. Some examples of complementary use of methods already exist. Below, we outline some possibilities:

(1) Quantification of different biodiversity metrics in insect bulk samples

A combination of technologies applied to the same sample can increase the range of produced biodiversity metrics. While molecular methods provide reliable biodiversity metrics such as richness and diversity, traditional methods [108] and computer vision [50] still provide more robust quantitative metrics such as biomass and abundance. Although we note that methods are being tested to quantify species abundances and biomass from DNA samples [109].

The onset of robotic techniques for the processing of individual insects from bulk samples [110] may to a large extent replace the laborious work of manual species identification. Together, computer vision, robotic sorting, and DNA-based identification may add both images and DNA-sequences of previously unencountered taxa to reference libraries, provide all desired biodiversity metrics, and discover new and rare species for further processing by taxonomic specialists. So far, only a prototype for this approach exists [110], but this combination of technologies can upscale biodiversity monitoring to unprecedented levels.

(2) Increasing confidence of species identification

The integration of different technologies may improve identification accuracy and coverage of the insects in a sample. Integration could occur either during the taxonomic classification step, as a multi-sensor input for the neural networks (so-called cross-modal perception), which may work especially well for combined visual and acoustic monitoring. Alternatively, integration may occur as a final step to check for overall concordance of the classifications between the technologies; for instance, following analysis of insect bulk samples by computer vision and DNA analysis. Integrating optical and acoustic sensors may be especially useful for developing pollinator indicators, which are especially urgent given their key role in ecosystems, but difficult to accurately identify based on each technology alone.

(3) Filling the gaps: increased spatial, temporal and taxonomic coverage

Due to the decreased human labour needed, new technologies can increase the spatial, temporal and taxonomic coverage of monitoring programs. To align with existing schemes, new technologies could be initially set up to target current spatial and temporal gaps e.g., when and where fewer people are active, such as in remote areas. Another way of upscaling monitoring to large spatial scales with great potential is the use of (weather) radar. Although radar currently largely lacks certainty about species identity, it could also be combined with vertical photography [33] and aerial eDNA [82] to sample the same aerospace.

For assessment of whole ecological assemblages within a region, multi-sensor biodiversity ‘weather’ stations [9] may become particularly useful. These stations simultaneously use multiple technologies and trap types to monitor a broad range of organisms, including insects, plants and vertebrates (see AMMOD project in Box 2). Such monitoring is especially useful to understand trophic links and for monitoring overall ecosystem health.

On-going role of traditional monitoring

Regardless of technological developments, new technologies cannot replace specialist taxonomic knowledge and traditional methods [111]. Instead, new technologies should seek to complement traditional monitoring, to alleviate workload and tedious tasks, and to increase the spatial, temporal and taxonomic coverage of existing monitoring schemes. Furthermore, combining metabarcoding and microscopy has been shown to increase the level of species identification [108].

Entomological expertise is also needed for building and improving reference libraries and the validation of the results from automated monitoring. Moreover, there are still some groups that can be poorly distinguished by modern technology, e.g. morphologically similar taxa (such as ants) or taxa that are poorly distinguishable by commonly used barcoding genes [112]. As novel methods continue to emerge and may eventually dominate the records, expert checks will become crucial to ensure data quality.

Another area where human labour will remain essential is the detection of protected species, which are rare and not allowed to be trapped, such as those under the European Commission Habitats Directive for Annex I. For aquatic species, eDNA may be a viable option, but for monitoring rare terrestrial habitat specialists, such as the hermit beetle *Osmoderma eremita* or the Great Capricorn Beetle *Cerambyx cerdo*, human observations will remain essential.

Outstanding questions

- **What standards are needed to ensure interoperability of data and reproducibility of methods using each technology? How should these standards be fostered by the scientific and biodiversity informatics community?**

- **How do these new technologies compare to traditional methods in accuracy and informativeness? Are new technologies just quicker and cheaper? When should we still use traditional taxonomy and sampling, and how can new technologies and traditional sampling best complement each other?**

- **What are the sampling biases of new technologies, in terms of both taxonomic accuracy (which groups can be monitored by each technology) as well as species traits (which kinds of species might be missed by each technology)?**

- **How should the technologies be optimised to maximize both data quantity and data quality, bearing in mind that many of the new technologies may rapidly increase the rate of data collection, outpacing storage capacities and/or the rate at which the data can be validated, processed and analysed?**

- **How should data aggregation services (such as GBIF and national records) define and label data from novel identification techniques, including the uncertainty in species identity and non-validated insect records, so that these uncertainties are transparent to the end-user?**

- **How can new technologies overcome common biases associated with the effects of insect activity on monitoring indices and provide unbiased density estimates?**

- **What is the best sampling design to upscale and integrate different technologies for large-scale and long-term insect monitoring?**

- **How can new technologies facilitate and enhance engagement with society, promote experience of and learning about insects, and foster meaningful and innovative citizen science?**

- **How can we ensure that the outputs of these technologies align with policy-relevant indicators for ecological states and trends at relevant spatial and temporal scales?**

Concluding remarks

The technological developments described in this paper provide unprecedented possibilities for entomological research and monitoring. However, most of them are still in a proof-of-concept stage and are not ready for large scale deployment, and none of them is free of biases (see Outstanding Questions). While these technologies cannot replace specialist taxonomic knowledge, they can help save time on species identification, and some can enable non-lethal monitoring. Existing monitoring programs using traditional methods have proven invaluable for understanding the extent of recent insect declines [3], and should be maintained to extend historic time-series. Before new technologies can be deployed for large-scale insect monitoring, international standards need to be developed via collaboration across borders, projects and technologies. It will also be crucial to involve different stakeholders to develop policy-relevant indicators, so that the data collected can be truly and broadly useful. The future of entomology will be a collaboration between human and machine.

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References

1 Chapman, A.D. (2009) *Numbers of Living Species in Australia and the World. 2nd edition*, Australian Biological Resources Services.

2 Cardoso, P. *et al.* (2011) The seven impediments in invertebrate conservation and how to overcome them. *Biol. Conserv.* 144, 2647–2655

3 Van Klink, R. *et al.* (2020) Meta-analysis reveals declines in terrestrial but increases in freshwater insect abundances. *Science* 368, 417–420

4 Hallmann, C.A. *et al.* (2017) More than 75 percent decline over 27 years in total flying insect biomass in protected areas. *PLoS ONE* 12, e0185809

5 Bálint, M. *et al.* (2018) Environmental DNA Time Series in Ecology. *Trends Ecol. Evol.* 33, 945–957

6 Høye, T.T. *et al.* (2021) Deep learning and computer vision will transform entomology. *Proc. Natl. Acad. Sci.* 118, 2002545117

7 Tosa, M.I. *et al.* (2021) The Rapid Rise of Next-Generation Natural History. *Front. Ecol. Evol.* 0, 480

8 Saunders, M.E. *et al.* (2020) Moving On from the Insect Apocalypse Narrative: Engaging with Evidence-Based Insect Conservation. *BioScience* 70, 80–89

9 Wägele, J.W. *et al.* (2022) Towards a multisensor station for automated biodiversity monitoring. *Basic Appl. Ecol.* DOI: 10.1016/j.baae.2022.01.003

10 Lehmann, G.U.C. *et al.* (2021) Diversity of Insects in Nature protected Areas (DINA): an interdisciplinary German research project. *Biodivers. Conserv. 2021 308* 30, 2605–2614

11 Montgomery, G.A. *et al.* (2021) Standards and Best Practices for Monitoring and Benchmarking Insects. *Front. Ecol. Evol.* 0, 513

12 Van Klink, R. *et al.* (2015) Effects of large herbivores on grassland arthropod diversity. *Biol. Rev.* 90, 347–366

13 Brydegaard, M. and Jansson, S. (2019) Advances in entomological laser radar. *J. Eng.* 2019, 7542–7545

14 Mata, V.A. *et al.* (2021) Combining DNA metabarcoding and ecological networks to inform conservation biocontrol by small vertebrate predators. *Ecol. Appl.* 31, e02457

15 Masonick, P. *et al.* (2019) No guts, no glory: Gut content metabarcoding unveils the diet of a flower-associated coastal sage scrub predator. *Ecosphere* 10, e02712

16 Massey, A.L. *et al.* Invertebrates for vertebrate biodiversity monitoring: Comparisons using three insect taxa as iDNA samplers. *Mol. Ecol. Resour.* n/a,

17 Hrcek, J. *et al.* (2011) Molecular detection of trophic links in a complex insect host–parasitoid food web. *Mol. Ecol. Resour.* 11, 786–794

18 Tiusanen, M. *et al.* (2019) Flower-visitor communities of an arcto-alpine plant—Global patterns in species richness, phylogenetic diversity and ecological functioning. *Mol. Ecol.* 28, 318–335

19 Bjerge, K. *et al.* Real-time insect tracking and monitoring with computer vision and deep learning. *Remote Sens. Ecol. Conserv.* n/a,

20 Ratnayake, M.N. *et al.* (2021) Tracking individual honeybees among wildflower clusters with computer vision-facilitated pollinator monitoring. *PLOS ONE* 16, e0239504

21 Pegoraro, L. *et al.* (2020) Automated video monitoring of insect pollinators in the field. *Emerg. Top. Life Sci.* 4, 87–97

22 Thomsen, P.F. and Sigsgaard, E.E. (2019) Environmental DNA metabarcoding of wild flowers reveals diverse communities of terrestrial arthropods. *Ecol. Evol.* 9, 1665–1679

23 Lucas, A. *et al.* (2018) Generalisation and specialisation in hoverfly (Syrphidae) grassland pollen transport networks revealed by DNA metabarcoding. *J. Anim. Ecol.* 87, 1008–1021

24 Wotton, K.R. *et al.* (2019) Mass Seasonal Migrations of Hoverflies Provide Extensive Pollination and Crop Protection Services. *Curr. Biol.* 29, 2167-2173.e5

25 Ghulam Rasool, K. *et al.* (2020) Evaluation of some non-invasive approaches for the detection of red palm weevil infestation. *Saudi J. Biol. Sci.* 27, 401–406

26 Amarjyothi, K. *et al.* (2022) Identification and Tracking of Locust Swarms by Indian Doppler Weather Radar. *IEEE Geosci. Remote Sens. Lett.* 19, 1–4

27 Wang, R. *et al.* (2022) An automatic system for pest recognition and forecasting. *Pest Manag. Sci.* 78, 711–721

28 Brydegaard, M. *et al.* (2020) Lidar reveals activity anomaly of malaria vectors during pan-African eclipse. *Sci. Adv.* DOI: 10.1126/sciadv.aay5487

29 Piper, A.M. *et al.* (2019) Prospects and challenges of implementing DNA metabarcoding for high-throughput insect surveillance. *GigaScience* 8, giz092

30 Comtet, T. *et al.* (2015) DNA (meta)barcoding of biological invasions: a powerful tool to elucidate invasion processes and help managing aliens. *Biol. Invasions* 17, 905–922

31 Larson, E.R. *et al.* (2020) From eDNA to citizen science: emerging tools for the early detection of invasive species. *Front. Ecol. Environ.* 18, 194–202

32 Doi, H. *et al.* Detection of an endangered aquatic heteropteran using environmental DNA in a wetland ecosystem. *R. Soc. Open Sci.* 4, 170568

33 Ruczyński, I. *et al.* (2020) Camera transects as a method to monitor high temporal and spatial ephemerality of flying nocturnal insects. *Methods Ecol. Evol.* 11, 294–302

34 Bauer, S. *et al.* (2017) From Agricultural Benefits to Aviation Safety: Realizing the Potential of Continent-Wide Radar Networks. *BioScience* 67, 912–918

35 Hu, G. *et al.* (2016) Mass seasonal bioflows of high-flying insect migrants. *Science* 354, 1584–1587

36 Brydegaard, M. *et al.* (2015) , Daily evolution of the insect biomass spectrum in an agricultural landscape accessed with lidar. , presented at the ILRC27, New York

37 Bjerge, K. *et al.* (2021) An Automated Light Trap to Monitor Moths (Lepidoptera) Using Computer Vision-Based Tracking and Deep Learning. *Sensors* 21, 343

38 Gerovichev, A. *et al.* (2021) High Throughput Data Acquisition and Deep Learning for Insect Ecoinformatics. *Front. Ecol. Evol.* 9,

39 Yalcin, H. (2015) , Vision based automatic inspection of insects in pheromone traps. , in *2015 Fourth International Conference on Agro-Geoinformatics (Agro-geoinformatics)*, pp. 333–338

40 Wilson, R.J. *et al.* Applying computer vision to digitised natural history collections for climate change research: temperature-size responses in British butterflies. . 22-Dec-(2021) , bioRxiv, 2021.12.21.473511

41 Carranza-Rojas, J. *et al.* (2017) Going deeper in the automated identification of Herbarium specimens. *BMC Evol. Biol.* 17, 181

42 Wäldchen, J. and Mäder, P. (2018) Machine learning for image based species identification. *Methods Ecol. Evol.* 9, 2216–2225

43 Martineau, M. *et al.* (2017) A survey on image-based insect classification. *Pattern Recognit.* 65, 273–284

44 Knyshov, A. *et al.* (2021) Pretrained Convolutional Neural Networks Perform Well in a Challenging Test Case: Identification of Plant Bugs (Hemiptera: Miridae) Using a Small Number of Training Images. *Insect Syst. Divers.* 5, 3

45 Spiesman, B.J. *et al.* (2021) Assessing the potential for deep learning and computer vision to identify bumble bee species from images. *Sci. Rep. 2021 111* 11, 1–10

46 Milošević, D. *et al.* (2020) Application of deep learning in aquatic bioassessment: Towards automated identification of non-biting midges. *Sci. Total Environ.* 711, 135160

47 Valan, M. *et al.* (2019) Automated Taxonomic Identification of Insects with Expert-Level Accuracy Using Effective Feature Transfer from Convolutional Networks. *Syst. Biol.* 68, 876–895

48 Korsch, D. *et al.* (2021) *Deep Learning Pipeline for Automated Visual Moth Monitoring: Insect Localization and Species Classification*, Gesellschaft für Informatik, Bonn.

49 Bruijning, M. *et al.* (2018) trackdem: Automated particle tracking to obtain population counts and size distributions from videos in r. *Methods Ecol. Evol.* 9, 965–973

50 Schneider, S. *et al.* Bulk arthropod abundance, biomass and diversity estimation using deep learning for computer vision. *Methods Ecol. Evol.* n/a,

51 Boho, D. *et al.* (2020) Flora Capture: a citizen science application for collecting structured plant observations. *BMC Bioinformatics* 21, 576

52 Newson, S.E. *et al.* (2017) Potential for coupling the monitoring of bush-crickets with established large-scale acoustic monitoring of bats. *Methods Ecol. Evol.* 8, 1051–1062

53 Jeliazkov, A. *et al.* (2016) Large-scale semi-automated acoustic monitoring allows to detect temporal decline of bush-crickets. *Glob. Ecol. Conserv.* 6, 208–218

54 van der Lee, G.H. *et al.* (2020) Freshwater ecoacoustics: Listening to the ecological status of multi-stressed lowland waters. *Ecol. Indic.* 113, 106252

55 Linke, S. *et al.* (2018) Freshwater ecoacoustics as a tool for continuous ecosystem monitoring. *Front. Ecol. Environ.* 16, 231–238

56 Kiskin, I. *et al.* (2021) HumBugDB: A Large-scale Acoustic Mosquito Dataset. *ArXiv211007607 Cs Eess* at <http://arxiv.org/abs/2110.07607>

57 Kawakita, S. and Ichikawa, K. (2019) Automated classification of bees and hornet using acoustic analysis of their flight sounds. *Apidologie* 50, 71–79

58 Hill, A.P. *et al.* (2018) AudioMoth: Evaluation of a smart open acoustic device for monitoring biodiversity and the environment. *Methods Ecol. Evol.* 9, 1199–1211

59 Gibb, R. *et al.* (2019) Emerging opportunities and challenges for passive acoustics in ecological assessment and monitoring. *Methods Ecol. Evol.* 10, 169–185

60 Sueur, J. *et al.* (2021) Acoustic biodiversity. *Curr. Biol.* 31, R1172–R1173

61 Mankin, R.W. *et al.* (2011) Perspective and Promise: a Century of Insect Acoustic Detection and Monitoring. *Am. Entomol.* 57, 30–44

62 Burivalova, Z. *et al.* (2021) The sound of logging: Tropical forest soundscape before,

during, and after selective timber extraction. *Biol. Conserv.* 254, 108812

63 Aide, T.M. *et al.* (2017) Species Richness (of Insects) Drives the Use of Acoustic Space in the Tropics. *Remote Sens.* 9, 1096

64 Aodha, O.M. *et al.* (2018) Bat detective—Deep learning tools for bat acoustic signal detection. *PLOS Comput. Biol.* 14, e1005995

65 Chapman, J.W. *et al.* (2011) Recent Insights from Radar Studies of Insect Flight. *Annu. Rev. Entomol.* 56, 337–356

66 Rhodes, M.W. *et al.* (2022) Recent advances in the remote sensing of insects. *Biol. Rev.* 97, 343–360

67 Stepanian, P.M. *et al.* (2020) Declines in an abundant aquatic insect, the burrowing mayfly, across major North American waterways. *Proc. Natl. Acad. Sci.* 117, 2987–2992

68 Drake, V.A. *et al.* (2017) Ventral-aspect radar cross sections and polarization patterns of insects at X band and their relation to size and form. *Int. J. Remote Sens.* 38, 5022–5044

69 Mirkovic, D. *et al.* (2019) Characterizing animal anatomy and internal composition for electromagnetic modelling in radar entomology. *Remote Sens. Ecol. Conserv.* 5, 169–179

70 Gebru, A. *et al.* (2018) Multiband modulation spectroscopy for the determination of sex and species of mosquitoes in flight. *J. Biophotonics* 11, e201800014

71 Kirkeby, C. *et al.* (2021) Advances in automatic identification of flying insects using optical sensors and machine learning. *Sci. Rep.* 11, 1555

72 Srivathsan, A. *et al.* (2021) ONTbarcoder and MinION barcodes aid biodiversity discovery and identification by everyone, for everyone. *BMC Biol.* 19, 217

73 Batovska, J. *et al.* (2021) Developing a non-destructive metabarcoding protocol for detection of pest insects in bulk trap catches. *Sci. Rep.* 11, 7946

74 Clare, E.L. *et al.* (2019) Approaches to integrating genetic data into ecological networks. *Mol. Ecol.* 28, 503–519

75 Ji, Y. *et al.* (2020) SPIKEPIPE: A metagenomic pipeline for the accurate quantification of

eukaryotic species occurrences and intraspecific abundance change using DNA barcodes or mitogenomes. *Mol. Ecol. Resour.* 20, 256–267

76 Elbrecht, V. *et al.* (2018) Estimating intraspecific genetic diversity from community DNA metabarcoding data. *PeerJ* 6, e4644

77 Zizka, V.M.A. *et al.* (2020) Can metabarcoding resolve intraspecific genetic diversity changes to environmental stressors? A test case using river macrozoobenthos. *Metabarcoding Metagenomics* 4, e51925

78 Hebert, P.D.N. *et al.* (2003) Biological identifications through DNA barcodes. *Proc. R. Soc. Lond. B Biol. Sci.* 270, 313–321

79 Marquina, D. *et al.* (2019) Establishing arthropod community composition using metabarcoding: Surprising inconsistencies between soil samples and preservative ethanol and homogenate from Malaise trap catches. *Mol. Ecol. Resour.* 19, 1516–1530

80 Roslin, T. *et al.* (2022) A molecular-based identification resource for the arthropods of Finland. *Mol. Ecol. Resour.* 22, 803–822

81 Noguerales, V. *et al.* Community metabarcoding reveals the relative role of environmental filtering and spatial processes in metacommunity dynamics of soil microarthropods across a mosaic of montane forests. *Mol. Ecol.* n/a,

82 Roger, F. *et al.* Airborne environmental DNA metabarcoding for the monitoring of terrestrial insects - a proof of concept. . 27-Jul-(2021) , bioRxiv, 2021.07.26.453860

83 Cristescu, M.E. (2019) Can Environmental RNA Revolutionize Biodiversity Science? *Trends Ecol. Evol.* 34, 694–697

84 Elbrecht, V. *et al.* (2019) Validation of COI metabarcoding primers for terrestrial arthropods. *PeerJ* 7, e7745

85 Marquina, D. *et al.* (2019) New mitochondrial primers for metabarcoding of insects, designed and evaluated using in silico methods. *Mol. Ecol. Resour.* 19, 90–104

86 Elbrecht, V. *et al.* (2021) Pooling size sorted Malaise trap fractions to maximize taxon

recovery with metabarcoding. *PeerJ* 9, e12177

87 Krehenwinkel, H. *et al.* (2017) Estimating and mitigating amplification bias in qualitative and quantitative arthropod metabarcoding. *Sci. Rep.* 7, 17668

88 Greenfield, P. *et al.* (2019) Kelpie: generating full-length ‘amplicons’ from whole-metagenome datasets. *PeerJ* 6, e6174

89 Cordier, T. *et al.* (2021) Ecosystems monitoring powered by environmental genomics: A review of current strategies with an implementation roadmap. *Mol. Ecol.* 30, 2937–2958

90 Ratnasingham, S. and Hebert, P.D.N. (2013) A DNA-Based Registry for All Animal Species: The Barcode Index Number (BIN) System. *PLOS ONE* 8, e66213

91 Morinière, J. *et al.* (2019) A DNA barcode library for 5,200 German flies and midges (Insecta: Diptera) and its implications for metabarcoding-based biomonitoring. *Mol. Ecol. Resour.* 19, 900–928

92 Hogeweg, L. *et al.* (2019) Smart Insect Cameras. *Biodivers. Inf. Sci. Stand.* 3, e39241

93 Bas, Y. *et al.* (2017) Tadarida: A Toolbox for Animal Detection on Acoustic Recordings. *J. Open Res. Softw.* 5, 6

94 Svenningsen, C.S. *et al.* (2021) Detecting flying insects using car nets and DNA metabarcoding. *Biol. Lett.* 17,

95 Schmeller, D.S. *et al.* (2009) Advantages of Volunteer-Based Biodiversity Monitoring in Europe. *Conserv. Biol.* 23, 307–316

96 Hayhow, D.B. *et al.* Oct-(2019) , State of nature 2019. . [Online]. Available: https://nbn.org.uk/stateofnature2019/reports/. [Accessed: 31-Jan-2022]

97 WWF (2020) *Living Planet Report Nederland. Natuur en landbouw verbonden*, Wereld Natuur Fonds.

98 Gardiner, M.M. and Roy, H.E. (2022) The Role of Community Science in Entomology. *Annu. Rev. Entomol.* 67, 437–456

99 Berg, T.B. *et al.* (2021) The Role and Value of Out-of-School Environments in Science

Education for 21st Century Skills. *Front. Educ.* 6,

100 Mäder, P. *et al.* (2021) The Flora Incognita app – Interactive plant species identification. *Methods Ecol. Evol.* 12, 1335–1342

101 Wilkinson, M.D. *et al.* (2016) The FAIR Guiding Principles for scientific data management and stewardship. *Sci. Data* 3, 160018

102 Andersson, A. *et al.* (2020) *Publishing DNA-derived data through biodiversity data platforms. v1.0*, GBIF Secretariat.

103 Jones, M. *et al.* (2019) *Ecological Metadata Language (EML) version 2.2.0*, KNB Data Repository.

104 Wieczorek, J. *et al.* (2012) Darwin Core: An Evolving Community-Developed Biodiversity Data Standard. *PLOS ONE* 7, e29715

105 Arribas, P. *et al.* (2021) Connecting high-throughput biodiversity inventories: Opportunities for a site-based genomic framework for global integration and synthesis. *Mol. Ecol.* 30, 1120–1135

106 Zaiko, A. *et al.* (2022) Towards reproducible metabarcoding data: Lessons from an international cross-laboratory experiment. *Mol. Ecol. Resour.* 22, 519–538

107 Mousavi-Derazmahalleh, M. *et al.* (2021) eDNAFlow, an automated, reproducible and scalable workflow for analysis of environmental DNA sequences exploiting Nextflow and Singularity. *Mol. Ecol. Resour.* 21, 1697–1704

108 Pereira, C.L. *et al.* (2021) Fine-tuning biodiversity assessments: A framework to pair eDNA metabarcoding and morphological approaches. *Methods Ecol. Evol.* 12, 2397–2409

109 Bista, I. *et al.* (2018) Performance of amplicon and shotgun sequencing for accurate biomass estimation in invertebrate community samples. *Mol. Ecol. Resour.* 18, 1020–1034

110 Wührl, L. *et al.* DiversityScanner: Robotic handling of small invertebrates with machine learning methods. *Mol. Ecol. Resour.* n/a,

111 Bianchi, F.M. and Gonçalves, L.T. Getting science priorities straight: how to increase the

reliability of specimen identification? *Biol. Lett.* 17, 20200874

112 Jinbo, U. *et al.* (2011) Current progress in DNA barcoding and future implications for entomology. *Entomol. Sci.* 14, 107–124

Figure captions

Figure 1. Workflows, from data collection to end product, of each of the four covered technologies.

Figure 2. Current and potential future scope of the four technologies A non-exhaustive list of current, in development and expected future possibilities for insect ecology and monitoring using the four technological developments discussed in this paper. Colours refer to different aspects of each technology: taxonomic precision and groups (orange), the metrics for biodiversity that can be obtained (light blue), the size, scale and type of samples that can be processed (gold) and the technological challenges for data processing (dark blue). Terms that transgress the borders between technologies are applicable to both.

Highlights

- We appraise four emerging tools and technologies (computer vision, acoustic monitoring, radar and molecular methods) that provide unprecedented opportunities for insect monitoring and the study of insect ecology.
- These technologies have various benefits over traditional insect monitoring methods, including increased resolution of data collection across space and time, and a broader taxonomic coverage.
- At the same time, each technology has its limitations, some of which can be overcome with further methodological developments.
- Key issues regarding open science and international standards need to be addressed.
- While technology can never replace the knowledge of entomological specialists, we expect that integration of data across technologies, along with expert knowledge, will become commonplace in the future.

Outstanding questions

- **What standards are needed to ensure interoperability of data and reproducibility of methods using each technology? How should these standards be fostered by the scientific and biodiversity informatics community?**

- **How do these new technologies compare to traditional methods in accuracy and informativeness? Are new technologies just quicker and cheaper? When should we still use traditional taxonomy and sampling, and how can new technologies and traditional sampling best complement each other?**

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- **How can we ensure that the outputs of these technologies align with policy-relevant indicators for ecological states and trends at relevant spatial and temporal scales?**

Figure 1

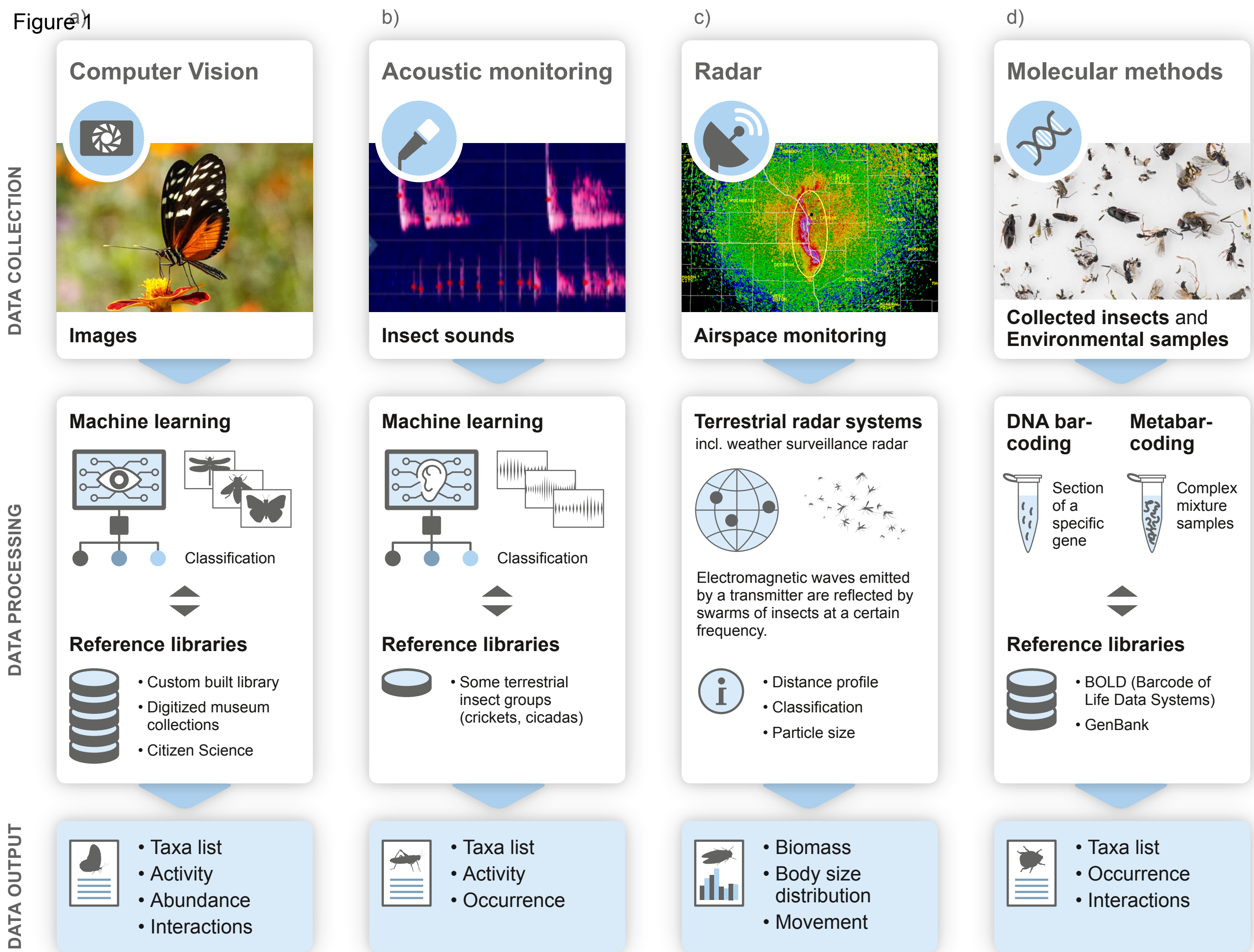
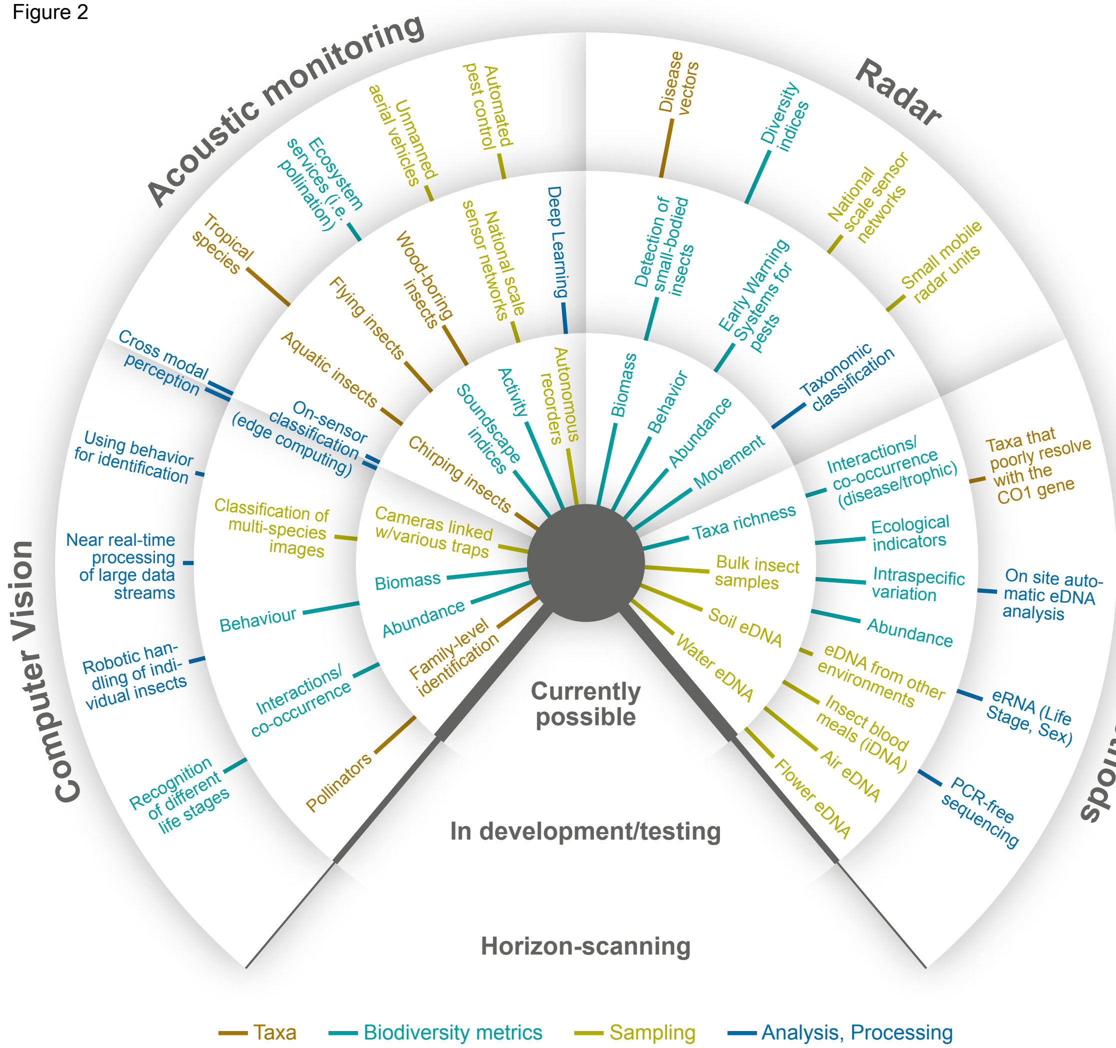

a)
b)
c)
d)
DATA COLLECTION
DATA PROCESSING
DATA OUTPUT
Computer Vision
Images
Acoustic monitoring
Insect sounds
Radar
Airspace monitoring
Molecular methods
Collected insects and Environmental samples
Machine learning
Classification
Reference libraries
• Custom built library
• Digitized museum collections
• Citizen Science
Machine learning
Classification
Reference libraries
• Some terrestrial insect groups (crickets, cicadas)
Terrestrial radar systems
incl. weather surveillance radar
Electromagnetic waves emitted by a transmitter are reflected by swarms of insects at a certain frequency.
• Distance profile
• Classification
• Particle size
DNA bar-coding
Section of a specific gene
Metabar-coding
Complex mixture samples
Reference libraries
• BOLD (Barcode of Life Data Systems)
• GenBank
• Taxa list
• Activity
• Abundance
• Interactions
• Taxa list
• Activity
• Occurrence
• Biomass
• Body size distribution
• Movement
• Taxa list
• Occurrence
• Interactions

Figure 2



Acoustic monitoring
Radar
Molecular methods
Computer Vision
Currently possible
In development/testing
Horizon-scanning
Automated pest control
Unmanned aerial vehicles
Ecosystem services (i.e. pollination)
Tropical species
Wood-boring insects
National scale sensor networks
Deep Learning
Flying insects
Aquatic insects
Activity
Autonomous recorders
Soundscape indices
Chirping insects
Disease vectors
Diversity indices
National scale sensor networks
Small mobile radar units
Detection of small-bodied insects
Early Warning Systems for pests
Taxonomic classification
Biomass
Behavior
Abundance
Movement
Taxa that poorly resolve with the CO1 gene
Interactions/ co-occurrence (disease/trophic)
Ecological indicators
Intraspecific variation
Abundance
On site auto-matic eDNA analysis
eRNA (Life Stage, Sex)
PCR-free sequencing
Taxa richness
Bulk insect samples
Soil eDNA
Water eDNA
eDNA from other environments
Insect blood meals (iDNA)
Air eDNA
Flower eDNA
Cross modal perception
On-sensor classification (edge computing)
Using behavior for identification
Near real-time processing of large data streams
Robotic han-dling of indi-vidual insects
Recognition of different life stages
Classification of multi-species images
Behaviour
Interactions/ co-occurrence
Pollinators
Cameras linked w/various traps
Biomass
Abundance
Family-level identification
Taxa
Biodiversity metrics
Sampling
Analysis, Processing