Emerging technologies revolutionise insect ecology and monitoring

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Review

Emerging technologies revolutionise insect ecology and monitoring

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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 programmes 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.

Highlights

Technological developments are opening new possibilities for biodiversity monitoring, but – especially for insects – they come with their own unique set of limitations.

Due to the vast diversity of insects, of which at least 80% remain undescribed, traditional monitoring is unable to provide even basic knowledge of the state of most insect species in most places.

We appraise four emerging tools and technologies (computer vision, acoustic monitoring, radar, and molecular methods) that provide unprecedented opportunities for insect ecology.

These technologies can enhance spatial, temporal, and taxonomic coverage of monitoring, but none can monitor all insects at all scales, and each comes with a set of limitations.

Technological integration, open data, and international standards are needed to harness the full potential of novel technologies for insect monitoring.

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 (with at least 80% of insect species remaining undescribed), combined with our poor knowledge of their distributions and ecology [2] and the spatiotemporal heterogeneity of their occurrence [3], form major challenges to the study of insects and their responses to environmental changes. Recent reports of long-term declines in insect biomass and abundances [4,5], in combination with the emergence of new technologies [6–8], have led to calls for [9], and the establishment of, new research projects for monitoring populations and assemblages of insects and other invertebrates [10,11].

Traditionally, the monitoring of insects usually involves the killing of insects, followed by time-consuming sorting and species identification by specialists [12]. Often the number of individuals and the taxonomic diversity within a sample are so large that only a subset of taxa are identified, or taxa are only identified to a coarse taxonomic level. Hence, there is a heavy bias towards well-resolved groups, such as butterflies, whereas other taxa (e.g., most Diptera) are often ignored (e.g., [13]), since taxonomic expertise is lacking. Additionally, the required human labour for both data collection and processing limits the number of locations and the frequency of sampling in **traditional monitoring** (see Glossary) programmes.

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 [6–8,14]. These technologies – which include automated image and sound recognition, radar, and molecular methods – have the potential to radically

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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 reveal interactions that would otherwise be missed. Molecular methods can identify predators, food, and foraging sites (including flower visitation [65]) of insects by analysing faeces [95], gut contents [96], or parasite presence [97].

Quantifying ecosystem services

Ecosystem services are notoriously difficult to quantify, but technologies offer a way forward. For instance, technologies are already being used to quantify insect pollination. Computer vision is applied to images taken by cameras fixed above plants [15,98], and metabarcoding can be used on pollen or flowers to identify flower visitors [65]. Computer vision or acoustic monitoring may also prove useful in studying the decomposition of dung, carrion, or dead plant matter, but to our knowledge this has 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 necessary to track the location of specific insect species. Several new technologies can help to do this, at spatial scales otherwise impossible. At the smallest scales, computer vision can track insects (e.g., pollinators) as they forage for resources [15,98]. Technologies can also be used to detect large-scale insect movements, so far applied to pollinators [49], crop pests [50,52], disease vectors [57], invasive species [69,99], and protected species [61].

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 (e.g., linking aquatic and terrestrial systems). Tracking these fluxes is now possible in four dimensions in a noninvasive and unbiased way [53,92]. Vertically looking radar has been used to quantify high-altitude insect migrations [48], and vertical photography and LiDAR can show insect biomass fluxes at closer ranges [92,100].

increase the spatial, temporal, and taxonomic coverage of monitoring programmes. 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 sets 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 and metadata standards, and open communication on hardware and software development, to ensure adherence to **FAIR data** principles.

This review aims to evaluate four emerging tools and technologies (**computer vision**, **acoustic sensors**, **radar**, and molecular methods) for insect monitoring, and outline ways to harness their potential. We review (i) the state of the art of these technologies, their advantages, current limitations, and future potential, (ii) how the data collected using these technologies can adhere to modern standards of data curation and transparency, (iii) how citizens can participate in projects using these new technologies, and (iv) the potential for integration and synergies among technologies.

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 (Figure 1A). In ecology, computer vision is being used to automatically collect observations and provide species identifications. For instance, cameras have been aimed at an environmental feature [15] or at a screen placed in the field (Box 2), often in combination with traps (e.g., light traps [16], sticky traps [17], or pheromone traps [18]) to increase detection rates. Computer vision is also helping to digitise the vast museum collections of specimens to mobilise historic occurrence records [19,20]. Images are also being collected by citizen scientists and uploaded to web portals [21], several of which support automated identification (e.g., www.iNaturalist.org, www.observation.org/apps/obsidentify/, and www.pictureinsect.com).

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While the technology has yet to be applied on a large scale for insect monitoring, the first applications show promising results (Box 2).

Computer vision can be applied to both live and dead insects to count and classify insects with less human labour and observer bias, reducing the necessity for taxonomic expertise and creating opportunities for the engagement of citizen scientists (Box 3). When applied to live insects, advantages are that the method is nondestructive and can be completely automatized, providing information on species' occurrences, abundances, individual size, biomass, and movement [22,23], as well as behaviour and interactions [15]. Imaging of dead specimens allows control of lighting conditions and minimises background variation to achieve impressive classification performance and biomass estimation, and allows independent validation of species identity [24,25].

Computer vision uses **machine learning** algorithms, such as **convolutional neural networks (CNNs)**, trained to identify insects using a library of preclassified images, and is thus limited to morphologically classifiable objects (i.e., the objects detected in an image are assigned to a known class). Accuracy rates can be over 90% at the species level for some taxa, but heavily depend on taxon group size and morphological similarity, and only family or genus levels are possible in some contexts [26–31].

Several technical challenges currently hinder the widespread application of computer vision in entomological research. A major challenge is the large amount of training data (reference libraries) needed for CNNs, which may need to be specific for taxon, sensor, region, and background, depending on the extent of morphological variation as well as quality and typical backgrounds of the images. CNNs tend to perform poorly in identification of species with limited training data (typically rare species), and tend to overpredict species with a disproportionately large amount of training data (typically common and conspicuous species). Expanding reference libraries could be done by developing apps for local experts and citizens to submit training image data of species from different angles [32]. However, undescribed species will remain a challenge, since by definition they will not be present in the training dataset. An approach called open-set classification may to some extent solve this problem, but remains to be tested for insect monitoring [7]. Another challenge is camera power consumption and data transfer. This difficulty may be reduced by using solar panels (Box 2), but this increases logistical challenges and risk of theft. **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.

Acoustic monitoring

A diverse range of insect taxa emit sounds that can be used for efficient monitoring. Acoustic monitoring uses a field sensor to collect information (i.e., sounds), in combination with machine learning algorithms for species identification (Figure 1B). Insect sounds may be sampled using stationary acoustic sensors or by mobile transects from cars or trains [33,34]. So far, these methods have mostly been applied to detect orthopterans and cicadas (Box 2), but have also been tested on freshwater insects [35,36] and bees, hornets, and mosquitoes based on their flight sounds [37,38].

Although limited to insects that emit sounds, acoustic monitoring has the advantage that insects can be detected over much longer distances compared to other methods, sometimes more than 100 m [34], although for flight sounds the recording distance will be much smaller. Acoustic sampling is nondestructive and inexpensive [39], and can be fully automatised when machine learning

Glossary

Acoustic sensor: a device that detects and records sounds.
Artificial intelligence (AI): scientific field of computer science involved in (partially) reproducing human skills – such as thinking, acting, or interpreting data – with computational algorithms. Often used as a synonym for machine learning (q.v.).
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, for example, a categorisation via numerical representations.
Convolutional neural networks (CNNs): 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.
Edge computing: data processing done on the site of data collection, instead of transferring the data to a central location for processing and analysis.
eDNA (environmental DNA): DNA obtained from environmental samples such as water, soil, air, faeces, and stomach contents. This term is sometimes also used to refer to DNA derived from the preservative of insect bulk samples (e.g., ethanol).
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: identification of taxa from mixed samples using high-throughput DNA sequencing of one or multiple genes (DNA barcodes). A common genetic region used for barcoding of insects is a part of the mitochondrial cytochrome c oxidase subunit 1 (*CO1*) gene.
Radar: device emitting radio waves in a certain direction to record the time,

is applied to the recorded sound [40]. In addition to species presence, acoustic signals contain information on behaviour, such as phenology, activity, and courtship [33,34,41], and can provide direct measures of ecological functions, such as wood-boring [42]. Recordings of composite environmental sounds [43] (soundscapes) also contain rich information about the state of biological assemblages related to species diversity [44], can be applied in regions where sound libraries are absent, and can include undescribed species.

intensity, and other features of the electromagnetic pulses that return from objects.
Traditional monitoring: observations, usually by sight or trap, combined with morphological species identification in the field or in the laboratory.

Identification of species from their sounds is still limited by the size of the reference libraries, which are poorly developed for insects compared to those for vertebrates [40]. Currently, libraries are only sufficiently large in temperate regions for some terrestrial vocalising insect groups, and are largely lacking for other insect sounds (especially flight sounds) (but see [37]). Citizen science schemes could, however, help build these acoustic reference libraries [45]. 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 large-scale monitoring (Figure 2B and Box 2).

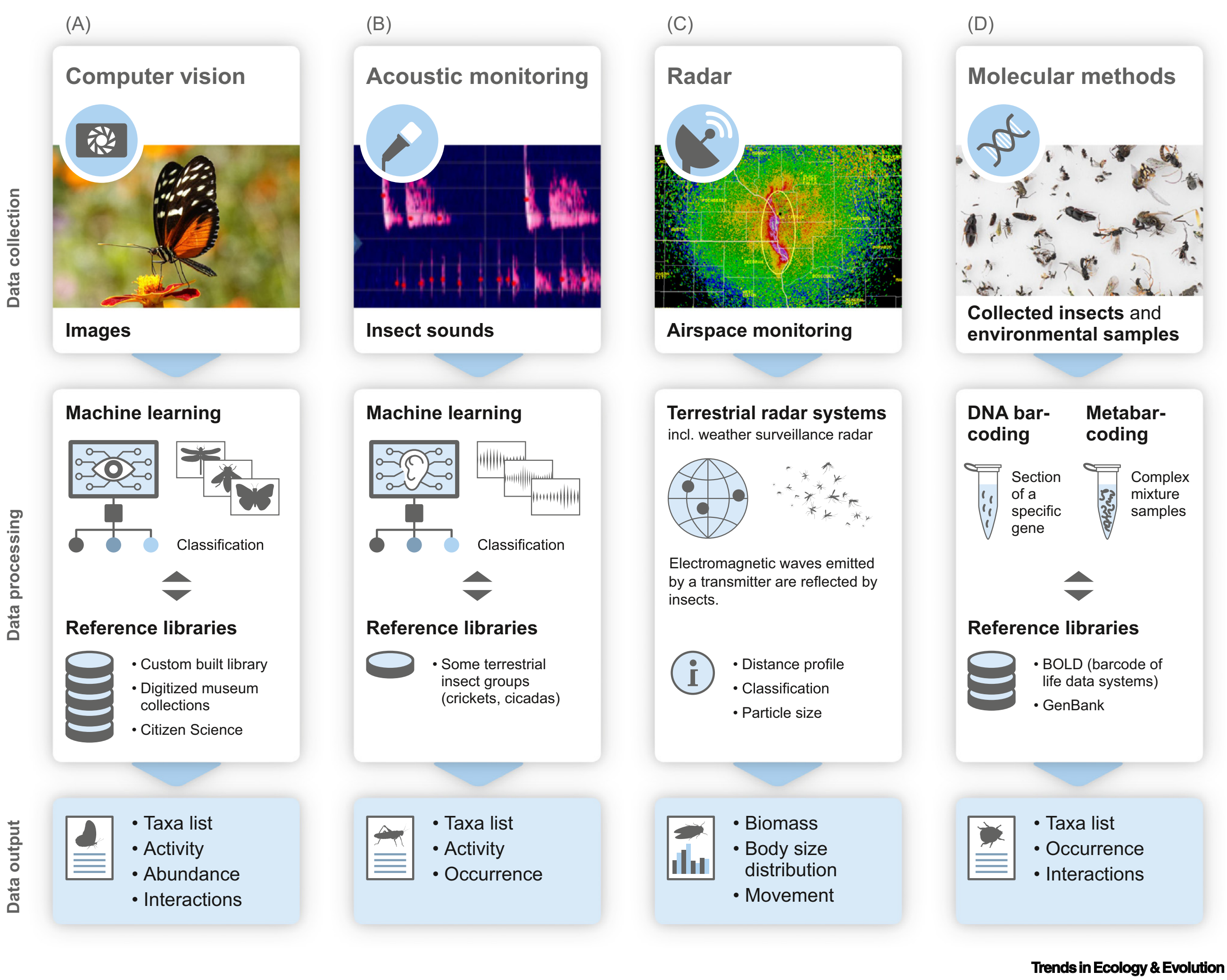


Figure 1. Workflows from data collection to end product of each of the four technologies covered in this review.

Radar

The application of remote sensing technologies for biodiversity monitoring has rapidly expanded over the past decade. In entomology, radar monitoring uses radio waves (including those from weather surveillance systems) to detect insects in the airspace (Figure 1C). It has long been 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 (for larger species) wing beat frequency [46]. 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 [47].

Advantages of monitoring insects by radar are that it is noninvasive, has a large detection radius, and can operate day and night. Hence, radar observations are especially useful to study biomass fluxes [48], migratory behaviour [47], and movement of some species [49] (Box 1). Radar can also be used to reveal insect presence indirectly by detecting signs of vegetation damage [50] or nest structures [46]. Data from weather surveillance radars have already been combined with local monitoring programmes to document population declines in mayflies [51] and the movement of locust swarms [52].

Radar technologies have significant potential for large-scale monitoring of insects, even at the continental scale, using the existing networks of weather surveillance radars [53], but are limited

Box 2. Case in point: pioneering monitoring projects

Case study I: Suivi des Orthoptères Nocturnes (France)

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 (Figure IA). 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 [101]. This nationwide monitoring scheme, with (so far) 16 349 individual sampling locations, has detected significant declines of several bush cricket species [34].

Case study II: DIOPSIS (The Netherlands)

DIOPSIS (digital identification of photographically sampled insect species) (Figure IB) takes regular photos of a yellow screen that attracts insects and uses machine learning to recognize, count and identify the photographed insects [16]. Photos are taken every time movement is detected or at least each minute. Photos are stored locally and/or sent to a server through the 4G network. Individual tracking across pictures is applied to remove duplicates. Since 2019, 80–100 DIOPSIS cameras have been deployed each year in The Netherlands.

Case study III: Australian acoustic observatory (https://acousticobservatory.org/) (Figure IC)

For this 5-year project, the world's largest acoustic sensor network was set up, recording wildlife sounds (including insects) across Australia [102]. The continuously recording solar-powered recorders are installed at 90 sites, covering all Australian ecoregions, including remote places. All raw data are stored for future reprocessing.

Case study IV: AMMOD (Germany)

AMMODs (automated multisensor stations for monitoring of species diversity) [10] (Figure ID) are analogous to weather stations; they are autonomous samplers that monitor plants, birds, mammals and insects. The technology consists of six modules: (i) automatised 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.

Case study V: BIOSCAN (worldwide)

BIOSCAN (https://ibol.org/programs/bioscan/) is a global DNA barcoding project of the International Barcode of Life (iBOL) consortium (Figure IE), coordinated by the University of Guelph, Canada. It currently focuses on catching insects using malaise traps; it aims to barcode 10 million specimens and characterise their parasitic, mutualistic, and symbiotic relationships. It also aims to characterise species assemblages at 2000 locations around the world, including in half of the 867 terrestrial ecoregions.

Figure I. (A) Suivi des Orthoptères Nocturnes, the French nation-wide monitoring scheme for bush crickets. (B) The DIOPSIS (digital identification of photographically sampled insect species) automatic insect monitoring device. (C) The Australian Acoustic Observatory used automatic acoustic sensors to record all environmental sounds. (D) The BIOSCAN project of the International Barcode of Life consortium aims to collect DNA barcodes of 10 million insect specimens and characterise their parasitic, mutualistic, and symbiotic relationships at over 2000 locations worldwide. (E) Illustration of the modular AMMOD (automated multisensor stations for monitoring of species diversity) monitoring station design. (1) Acoustic monitoring. (2) Smellscapes (plant volatile organic compounds). (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.

to detecting flying insects, and taxonomic classification remains limited. Also, monitoring 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 [54,55].

LiDAR (light detection and ranging) uses lasers to detect objects and has only recently been applied in entomology; it can be used to detect insects much closer to the ground than most radar systems, over sampling ranges of 10–600 m. New LED-based methods can detect flying insects at distances shorter than 1 m [56]. LiDAR and LED-based methods have the potential to use spectral reflectance to identify insects to genus or species level [57–59]. As the technology develops, better taxonomic classification can be achieved as libraries on spectral scatter become available for more taxa [14].

Molecular methods

Of the modern technologies, molecular methods using genetic information are the most widely used so far. These methods can be used for many goals, including the quick discovery of new species [60], the detection of endangered [61], invasive, or pest species [62], the characterisation of species interaction networks [63,64], and the assessment of taxonomic [65] and genetic diversity of whole assemblages [66,67]; however, the methods still depend on human labour for sample collection.

The most common use of genetic information is based on DNA barcoding, that is, 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 [68]. However, advancements in laboratory protocols and high-throughput sequencing technologies now enable DNA isolation and amplification and taxon identification from complex mixture samples (DNA **metabarcoding**) (Figure 1D) [69]. Compared to traditional monitoring, metabarcoding can be

Box 3. New technologies as opportunities to advance citizen science

About 25% of insect species records globally are collected by volunteers, and this number may be as high as 80% in Europe (www.gbif.org). Historically, most insect monitoring was organised outside academia, especially by taxonomic specialists and natural history societies [103], and there is a long tradition of including lay people in the scientific data collection process for various insect taxa [104]. Recent technological developments have increased the opportunities for people, including nonspecialists, to get involved, for example, helping with digitisation of museum collections.

Out of the new technologies, computer vision has been most often integrated into citizen science (Figure I); for example, a range of smartphone applications use computer vision to help users identify species (e.g., www.iNaturalist.org, https://observation.org/apps/obsidentify/). 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. Citizens have also helped to compile the training data needed for machine learning, for example, in the PollinatorWatch project (https://www.zooniverse.org/projects/tokehoye/pollinatorwatch). In projects using DNA technology, some rely on citizen scientists for the collection of the insect samples [105], 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) [106].

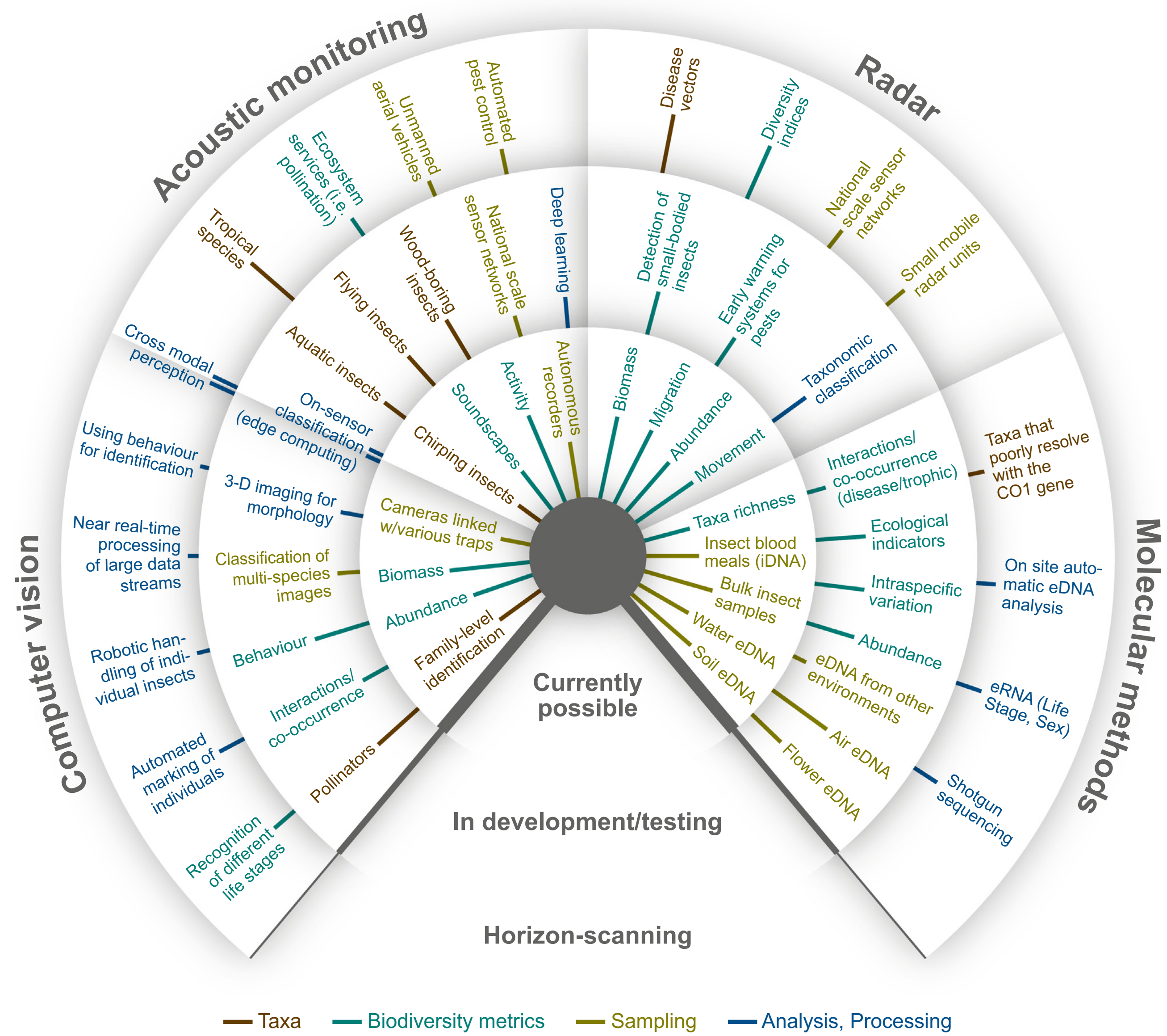
Ecologists often debate the reliability of species observations from citizen science. However, the development of **artificial intelligence (AI)**-based apps [107] and DNA-based methods [99] may help to increase identification accuracy. For instance, AI tools could be used to provide feedback on observation likelihood. Some citizen science platforms already use crowd-sourced expert identification for validation of observation (e.g., iNaturalist); however, manual validation is unable to keep pace with the rapidly growing number of submissions. Technologies could help by using active learning AI algorithms that 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 to compile the training datasets by identifying species on the basis of 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 a 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 cocreated projects and community partnerships [103].

Trends in Ecology & Evolution

Figure I. 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 (*Coccinella septempunctata*) feeding on aphids on their host plant. Photo: Helen E. Roy.

time- and cost-efficient [60] and is highly scalable, enabling simultaneous processing of many samples and species. DNA metabarcoding methods can be applied directly to organismal samples, using the storage medium [70] or homogenised bulk samples of collected insects [71]. It is also possible to detect the presence of species from DNA fragments in environmental samples (**eDNA**), such as water [61], soil [72], or air [73]. Interactions between insects and other taxa can be identified using



Trends in Ecology & Evolution

Figure 2. Current and potential future scope of the four technologies A nonexhaustive list of current, in development, and expected future possibilities for insect ecology and monitoring using the four technological developments discussed in this review. 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. Abbreviations: eDNA, environmental DNA; eRNA, environmental RNA.

samples derived from animals' guts, blood, or faeces [63] (Box 1). One of the most recent advances is the use of eRNA [74] to distinguish the presence of living from dead individuals, since RNA is present only in metabolically active cells, whereas DNA may be derived from the remains of dead individuals.

Metabarcoding facilitates the identification of a larger portion of the species in a sample compared to traditional methods that are limited by taxonomic expertise. However, differences in

DNA amounts and extractability among insect taxa [70], or taxa-specific variation in PCR amplification [75,76], may result in some species not being detected even when present in the sample, and commonly used markers, such as the c oxidase subunit 1 (*CO1*) gene, sometimes fail to detect some taxa such as Hymenoptera [77]. Yet, size sorting within a sample can help DNA amplification of small and rare species [78], and amplification biases may also be circumvented by bypassing the PCR step and directly sequencing the complete extracted DNA [79,80] or RNA (metatranscriptomics). RNA sequencing also has the potential to detect metabolic capacities and gene expression in individuals or assemblages at the moment of sampling [77].

The primary outputs of metabarcoding are amplicon sequence variants (ASVs) and/or operational taxonomic units (OTUs), depending on the bioinformatics used. To link with existing species knowledge, these units must be mapped to reference databases, such as the Barcode of Life Data System (BOLD) or GenBank. BOLD now contains genetic data on 214 390 publicly available insect species, which, nevertheless, represents only about 4% of the expected 5.5 million species of insects on earth [1]. When using these reference libraries, sequencing errors, synonymy, misidentifications, and missing species can cause misclassifications. Nevertheless, international, national, and taxon-specific initiatives are improving the taxonomic coverage of such reference libraries [71,81].

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, and the scientific questions scientists address (Box 1). Furthermore, they must meet the demands of modern science in terms of data curation and transparency [82], and consider the possibility of involvement of other stakeholders, such as citizens (Box 3) [83]. There are also un(der)explored possibilities for integration among technologies. In the following 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 the Global Biodiversity Information Facility (www.GBIF.org). However, for data collected using the discussed technologies, 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 [82].

Data openness for DNA-based technologies has been fostered through International Nucleotide Sequence Database Collaboration (www.INSDC.org) data portals such as the Sequence Read Archive (https://submit.ncbi.nlm.nih.gov/about/sra/). The GBIF has also led the development of protocols to handle sequence data to improve discoverability of DNA-derived data [84]. For sharing species images there are various citizen scientist platforms, but fewer for audio recordings (but see www.iNaturalist.org), and the large quantities of automated monitoring data can currently only be stored institutionally.

New technologies face practical problems about which form of data to store 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 assurance of data and metadata are key for interoperability and reusability. Among the most widespread are the Ecological Metadata Language (EML) [85] and Darwin Core [86]. However, it is still unclear what metadata would be sufficient for reproducibility of data collected by different technologies or different protocols [87]. 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 an analytical code as a community norm. For DNA technologies, specific steps of the laboratory protocols – such as preservation buffer, DNA polymerase, and PCR enhancer – are essential for reproducibility [88], and automated workflows are being proposed for standardisation [84,89].

The potential and challenges of technological integration

Each of the reviewed technologies has its own strengths and weaknesses, and new studies should combine the strengths of the different technologies, as well as with 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. We outline some possibilities in the following sections.

Quantification of different biodiversity metrics in insect bulk samples

A combination of technologies applied to the same sample can increase the range of biodiversity metrics produced. While molecular methods can provide estimates of taxon richness, they do not easily provide information on the number of individuals of each species, although new methods are being tested [90]. Traditional methods [91] and computer vision [25] provide more robust quantitative metrics such as biomass and (relative) abundances, but are more taxonomically limited.

Robotic techniques for the processing of individual insects from bulk samples [24] may potentially replace the laborious work of manual species identification. Together, computer vision, robotic sorting, and DNA-based identification of samples 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 prototypes or components of this approach exist [24,25], but this combination of technologies can significantly upscale species discovery and biodiversity monitoring.

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 during the taxonomic classification step, as a multisensor 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 after each technology has independently classified taxa, to check for concordance. The combination of DNA analysis and computer vision can even reveal new morphological characteristics for identification [29]. Integrating optical and acoustic sensors may be especially useful for monitoring pollinators, which is especially urgent given their key role in ecosystems.

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 programmes. To align with existing schemes, new technologies could be initially set up to target current spatial and temporal gaps, for example, 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 lacks certainty about species identity, it could be combined with short-range LiDAR, vertical photography [92], and aerial eDNA [73] to sample the same aerospace.

For assessment of whole ecological assemblages within a region, multisensor biodiversity 'weather' stations [10] 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 the AMMOD (automated multisensor stations for monitoring of species diversity) project in Box 2]. Such monitoring is especially useful to understand trophic links and for monitoring multitaxon biodiversity.

Ongoing role of traditional monitoring

Regardless of technological developments, new technologies cannot replace specialist taxonomic knowledge and traditional methods [93]. Instead, new technologies should seek to complement traditional monitoring, to reduce workload, to automate the most taxonomically trivial tasks, and to fill gaps in existing monitoring schemes.

Entomological expertise is still needed for describing new species, for building and improving reference libraries, and for validating results from automated monitoring. Moreover, there are still insect groups that are poorly distinguishable by modern technology, for example, morphologically similar taxa or taxa that are poorly distinguishable by commonly used barcoding genes [94].

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.

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 nonlethal monitoring. Existing monitoring programmes using traditional methods have proven invaluable for understanding the extent of recent insect declines 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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Outstanding questions

If upscaled, these technologies could provide data on insect population at high spatial and temporal resolution, but choices still have to be made about sampling design. How can we design monitoring schemes to ensure that the outputs of these technologies produce outputs that are relevant for modelling and policy making?

Most insect biodiversity is found in low- to middle-income countries, but remains undescribed. How can these technologies be made accessible and useful across the world, for the good of biodiversity conservation and for local communities?

Ideally, data generated in different monitoring programmes and countries should be interoperable, reusable, and comparable. What international standards are needed to ensure interoperability of data and reproducibility of methods using each technology?

Biodiversity data are compiled by data aggregators, such as the GBIF, for use in research and conservation. Metadata that describe the data, including uncertainties about taxonomic assignment, are important to ensure that the data are understood by end-users. What metadata are needed for each technology to ensure that the data, and uncertainties within it, are appropriately communicated?

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Declaration of interests

No interests are declared.

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