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REVIEW AND SYNTHESIS

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# Insect monitoring without pitfalls: Seven steps for robust insect sensing systems

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## Abstract

1. Data shortages fuel controversy about an ongoing insect biodiversity crisis. Insects are immensely diverse and functionally critical for ecosystems, yet data on their trends remain patchy and biased. Sensors, ranging from camera traps and acoustic recorders to weather radar stations, are set to transform data collection in entomology. Meanwhile, AI models that extract biological information from sensors are improving at a startling rate.
2. Realising the potential of automated monitoring means progressing from proof-of-concept studies to scalable insect sensing systems. However, stakeholders face severe operational challenges when adopting a growing suite of sensors, models and protocols for insect surveillance. Deployment of devices is not well co-ordinated, while the risks of relying on AI are overlooked or understated. To achieve monitoring goals, common pitfalls related to sensors and AI need to be exposed and avoided.
3. We trace a seven-step path towards an effective transnational rollout of insect sensing systems. Step (1) reviews strengths, weaknesses and synergies across visual, acoustic, radar and photonic sensors; (2) confronts species determination—a key challenge for sensors and AI—suggesting how to improve identification and

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make use of uncertain data; (3) promotes creating and sharing standardised, labelled data, offering ecological insights and opportunities to train and evaluate AI.

4. Focussing on data processing and scalability, step (4) proposes using AI to complement other resources, both human and digital, given it is not always the best tool for the job; (5) highlights how and why AI models fail, calling for routine evaluations and shrewdness during model training; (6) aims to break barriers to wider uptake of technologies through knowledge sharing, affordable design principles and equitable computing infrastructures, and finally, (7) emphasises that any revolution in insect monitoring must be grounded in good sampling design, with established monitoring schemes at its core.
5. We set a trajectory for coordinated development of insect sensing systems, focussing not only on technical performance but also on integration with human expertise, case-based evaluation and harmonisation with historical long-term datasets. We address fundamental challenges of sensors and AI for biodiversity monitoring, producing recommendations that apply to all branches of the tree of life.

**KEYWORDS**
arthropods, artificial intelligence, computer vision, image classification, invertebrates, machine learning, object detection, pollinators, remote sensing, signal processing

## INTRODUCTION

Insects form the bulk of macroscopic biodiversity on earth (Stork, 2018). They are extraordinarily diverse, but also functionally indispensable, with roles as pollinators, decomposers, predators, pests and pest-control agents (Noriega et al., 2018). As such, recent reports of insect decline have raised both economic and conservation concerns (Hallmann et al., 2017; Wagner, 2020). However, the evidence is mixed: a global meta-analysis suggests decreases in terrestrial insects and increases in freshwater insects (van Klink et al., 2020). Furthermore, the magnitude and generality of trends across biomes, regions and taxa is debated. One thing is clear, though: available data only glimpse the complexity of insect life (Thomas et al., 2019), and are heavily biased towards Europe, North America and certain taxa (e.g., butterflies; Sánchez-Bayo & Wyckhuys, 2019). Meanwhile, international policy instruments such as the Convention on Biological Diversity (United Nations, 1992), UN sustainable development goals (United Nations, 2015) and the EU nature restoration regulation (Directorate-General for Environment, 2022) demand comprehensive monitoring of the diversity and abundance of insects, as well as underlying drivers of change.

Scaling of data collection needs to be cost-effective, as there are limited resources available for insect monitoring (Geijzendorffer et al., 2016). Traditional monitoring methods, including malaise traps, pan traps, pitfall traps, light traps and visual surveys (McCravy, 2018; Montgomery et al., 2021; Southwood, 1966), have built baseline datasets and fundamental understanding of insect status and trends (Brooks et al., 2012; Conrad et al., 2006). However, traditional monitoring schemes are difficult to expand, especially in tropical regions; manual identification is skilled and laborious work, and expertise is often a limiting factor (Sánchez Herrera et al., 2024). Furthermore, most traditional methods, such as visual surveys and traps, suffer from detectability and observer biases (e.g., Brereton et al., 2011), while others involve excessive lethal sampling (Lövei & Ferrante, 2024). Methodological continuity is a priority for any long-term monitoring effort (van Klink, 2024). Given their limitations in terms of human workload, scalability and lethality, traditional methods alone will not be sufficient to address major challenges in entomology (Didham et al., 2020).

Novel technologies offer opportunities for more scalable, standardised and non-lethal insect monitoring (Lövei & Ferrante, 2024; van Klink et al., 2022) and promise datasets that will transform our ecological understanding (Gillespie et al., 2025; Hartig et al., 2024). Molecular methods allow identification of insects to high taxonomic resolution without expert identification (Chua et al., 2023). DNA metabarcoding, in particular, involves extracting, amplifying and sequencing DNA from a sample, followed by taxonomic assignment of sequences according to reference libraries (Chua et al., 2023). This approach has successfully identified insects in bulk samples of specimens (Buchner et al., 2025; Mata et al., 2021), as well as samples of water, soil, air, gut contents or flowers (Bohmann et al., 2014; Thomsen & Sigsgaard, 2019). While molecular methods provide a powerful addition to the insect monitoring toolbox, they also face a number of challenges, such as incomplete reference libraries, taxonomic biases, limited capability to infer abundance, high infrastructure costs and uncertainty about the spatial and temporal origin of detected DNA (Alberdi et al., 2018; Chua et al., 2023; Deagle et al., 2019). Furthermore, because molecular techniques require collecting physical samples, they are limited by the frequency in which data can be collected and analysed; they typically

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provide discrete snapshots in time rather than continuous observations.

Meanwhile, sensor-based methods show great promise to monitor insects continuously through time. Cameras, microphones, radar and lidar can offer real-time, non-invasive data that capture the presence, biomass, movements and behaviours of insects (van Klink et al., 2024). Resulting high-frequency time-series offer novel insights into biotic interactions, such as plant-insect interactions (Mehrotra et al., 2024; Naqvi et al., 2022; Serra-Marin et al., 2025). Furthermore, sensors can be affordable and operate autonomously, offering a very low cost per insect observation (Brydegaard et al., 2024). The volume of data produced by sensors is challenging to work with (Høye et al., 2021), but emerging methods for automation, especially ***artificial intelligence*** (AI; Box 1, Appendix S1), are relieving bottlenecks in data processing. Clearly, insect sensing systems could drive a step change in the spatial and temporal scale of ecological monitoring worldwide (Bauer et al., 2024; Besson et al., 2022).

However, coordination is needed for insect sensing systems to reach their full potential. Hardware designs and deployments are currently fragmented, and species identification remains unfeasible for many taxa and technologies (Chiranjeevi et al., 2025; Hansen et al., 2020; Hüppop et al., 2019). Many datasets are published, but they are not always easy to find, use or combine (Schneider et al., 2023). AI models are improving rapidly, but are still not used effectively to complement human expertise. Crucially, AI outputs are often viewed with scepticism, so guidance is needed to deal with AI uncertainty transparently and systematically (Cowans et al., 2022). Furthermore, automated methods developed in high-income countries may not be sufficiently affordable and accessible to support insect monitoring schemes at a global scale (Brydegaard et al., 2024). Of course, decades of practice using sensors to monitor vertebrates can already be applied to insect sensing systems (Tuia et al., 2022), including lessons on the risks of opportunistic sampling (Burton et al., 2015). However, insect monitoring also presents unique challenges, particularly those related to extreme densities of tiny, highly diverse organisms.

Here, we provide seven steps for fruitful implementation of insect sensing systems, whether for small scientific projects or global monitoring initiatives (Figure 1). We provide guidance for choosing the right sensors (Step 1) and set expectations for dealing with taxonomic uncertainty (Step 2). We promote good practices for generating and sharing data (Step 3) and advocate a cautious approach when integrating AI into a data processing workflow (Step 4). We highlight potential pitfalls when training and using AI and suggest how to avoid them and train more useful AI models (Step 5). Finally, we consider the global accessibility of insect sensing systems (Step 6), which we see as an extension to—not a replacement for—ongoing monitoring initiatives (Step 7). Readers seeking in-depth discussion of AI concepts are strongly encouraged to consult Boxes 1–8 (Appendix S1) referenced throughout the review. We also include a glossary with detailed descriptions of *bold italic* terms in the main text (Table 1).

## Scope

This synthetic review focuses on ***insect sensing systems***. We define these as acoustic or electromagnetic wave sensors that continuously record insects in-situ (under field conditions), including associated hardware, software and data processing pipelines. We prioritise systems that sense a broad range of insect taxa, while giving some consideration to systems specialised on a few species (e.g., agricultural pests). We do not include systems that tag insects, for example with radio frequency identification (Barlow & O'Neill, 2020). While we centre our review on the topic of insect monitoring, our guidelines (and many of the sensing systems) are applicable for a range of other invertebrates and small animals.

Our scope excludes molecular methods (e.g., DNA metabarcoding), lab-based sensing systems (e.g., imaging museum specimens or dead insects in preservative liquid) and traditional methods (e.g., malaise trapping). However, these methods have their own strengths, provide important context and can often complement or enable insect sensing systems. For example, molecular methods may provide taxonomic resolution not available to insect sensing systems. Meanwhile, lab-based sensing can generate vital training data for in-situ sensing. Finally, traditional monitoring has massively progressed our understanding of insects and will continue to do so; novel methods must build on this legacy, for example by providing a spatio-temporal resolution and coverage that is not achievable with traditional monitoring alone (van Klink et al., 2024).

# LEVERAGE THE STRENGTHS OF SENSORS

Different sensors, including cameras, microphones, radar and lidar, offer distinct strengths for automated insect monitoring (Figure 2). Some excel at detecting and counting large numbers of insects, while others provide more detailed information about taxonomic identity or ecological traits. Understanding these differences is crucial to design effective monitoring strategies, and the correct choice of sensor(s) depends greatly on the purpose and goals of monitoring. Furthermore, the use of attractants can increase the efficiency of data collection by drawing more insects within range of the sensor (Bjerge et al., 2021; Sittinger et al., 2024). However, attractants can also introduce biases, as the mechanisms and extent of attraction can vary between taxa. Below, we examine the relative strengths of four sensor categories (Figure 2) and consider how diverse technologies can complement each other to achieve monitoring goals.

Overall, sensors excel in consistency and continuity of data collection through time (van Klink et al., 2022). However, they also share a set of common challenges. Beyond challenges of species identification and taxonomy (see Step 2), devices face risks of theft, damage or disturbance, particularly in areas densely populated by humans or other animals. These risks scale with the value and visibility of devices and can be alleviated through strategic placement (Clarin et al., 2014; Meek et al., 2019). Sensors are also complex; off-the-shelf systems are not always available or suitable, while

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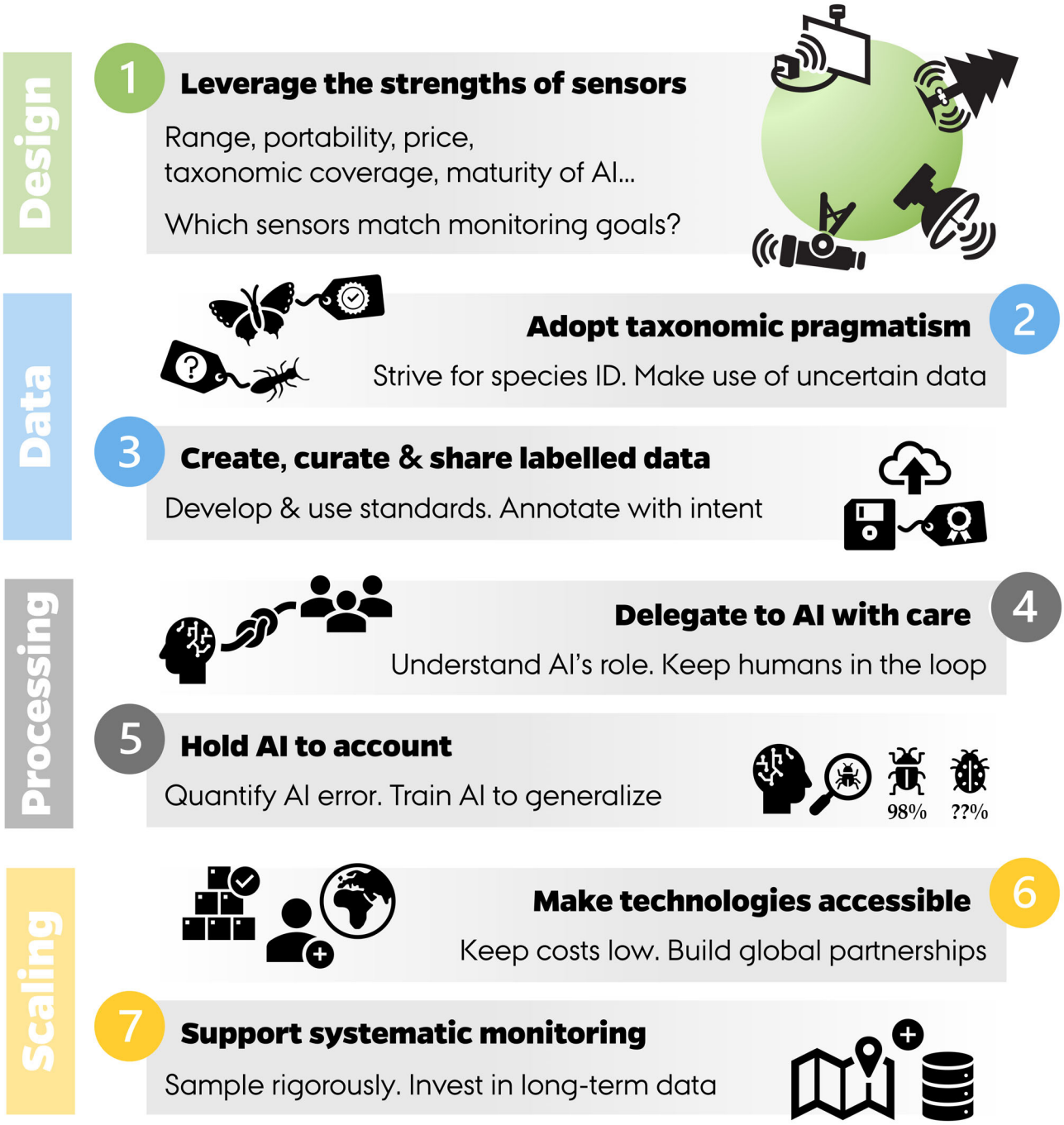


**FIGURE 1** Insect monitoring without pitfalls: Seven steps for robust insect sensing systems.

more adaptable do-it-yourself (DIY) systems require technical expertise to assemble and use (Bjerge et al., 2021; Droissart et al., 2021; Sittinger et al., 2024). Customs, transport and tax regulations complicate the transport of DIY systems: lithium batteries are often restricted on aeroplanes, and locally available alkaline batteries are usually not a viable alternative. Sourcing deep-cycle batteries locally and opting for solar power can mitigate these issues.

A universal challenge for insect sensing devices is the lack of standardisation (van Klink, 2024). Scalable, commercial solutions for automated insect monitoring are mostly absent, and many designs rely on custom hardware and have limited user support (e.g., Bjerge et al., 2021; Chen et al., 2024; Droissart et al., 2021; Sittinger et al., 2024). The most established devices for insects include the DIOPSIS (van Klink et al., 2022) and UKCEH AMI (Roy et al., 2024), both of which have a high price tag and require technical skills to maintain. While a range of devices are necessary to monitor different taxa and environments, the fragmentation of system designs hinders standardisation and data integration. Work is ongoing to build an ontology of insect sensing devices, so that their parameters and quirks

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**TABLE 1** Glossary.

| Term | Explanation |
|---|---|
| Annotation, Label | Biological information attached to sensor data (e.g., species presence, identity or behaviour), often used for training, validating or evaluating AI models. Human-generated labels are often called annotations. |
| Algorithmic Processing, Signal Processing | Extracting meaningful information from raw sensor data using rule-based, mathematical and statistical techniques. One example could be filtering or modification of digital images by means of algorithms and filter matrices (kernels). |
| Artificial Intelligence (AI) | Computational systems that perform tasks typically requiring human intelligence. Often refers to machine learning models that learn complex patterns from large training datasets to carry out data processing tasks. |
| Benchmark (dataset) | A curated dataset with associated annotations. Used to compare performance of data processing tools for a specific task, under a set of known constraints and assumptions. |
| Domain | Entities, contexts and data structures that are in scope for a given data processing task. Can include taxa, backgrounds, environmental conditions, recording parameters and file types. An AI model has a source domain, captured by the training dataset, but is tested and applied in target domains. Where source and target domains differ (domain shift) performance may decline. |
| Embedded processing, Edge processing | Data processing done locally to the sensor device, for example, on a compact computer. Used to prioritise which data to store or transfer, and for real-time updates or changes to system behaviour. |
| Foundation models | Large AI models, trained on vast and often multimodal datasets (e.g., text, audio, images), well-suited to general tasks. |
| Ground truth, Ground reference | Direct observations considered to be true, as opposed to inferred. Can be derived using meticulous calibration or expert annotation. |
| Generalisation | The ability of a model or monitoring system to perform well when applied to taxa, environments or conditions that differ from those seen during training or calibration. |
| Insect sensing systems | Acoustic and/or electromagnetic sensors that continuously record insects in-situ (under field conditions), including associated hardware, software and data processing pipelines. |
| Human-in-the-loop | A workflow where human expertise is incorporated to validate, correct or refine outputs of automated data processing. Permits verified records, quality control and feedback loops to train AI. |
| Machine Learning (ML) | A class of algorithms to train models that learn complex patterns from data to make predictions. |
| Multimodality | The use or integration of multiple data types or sensing modalities (e.g., imagery, audio, radar, optical signals, DNA, text descriptors) within a single monitoring system or analytical framework. |
| Segmentation | A data processing task that involves separating or "segmenting" regions of an image based on shared properties, for example separating foreground insects from one another, and from their background. The output is often a set of bounding polygons or pixel masks. |
| Signal-to-noise ratio | The relative strength of biologically relevant signals compared with irrelevant environmental or sensor noise. |
| Standards | Sets of terms, structures and formats for storing and sharing data relevant to a specific field or application. |
| Transfer learning | The process of re-training an AI model for a new task while leveraging features learned for a previous task. |

can be easily and transparently retrieved using data exchange ***standards***.

## Cameras

Modern cameras operate by focusing light through a lens onto an image sensor, converting it into an electrical signal and storing it as a digital image or video. Image quality depends on lens type, sensor resolution and onboard image processing, all of which affect the capacity to detect and identify insects or interpret their behaviours (Seimandi-Corda et al., 2024).

Camera setups are typically tailored to specific goals, such as observing flowers (Droissart et al., 2021), nests (Calvus et al., 2025), screens or platforms (Bjerge et al., 2021; Sittinger et al., 2024) or baited locations (Preti et al., 2021). They can also be connected to traditional capture methods, including sticky cards or Malaise traps (Chiavassa et al., 2024; Geissmann et al., 2022). Suitable devices range from trail and compact cameras (Naqvi et al., 2022; Steen, 2017) to action and security cameras (Seimandi-Corda et al., 2024; Varga-Szilay et al., 2024), smartphones (Ratnayake et al., 2021; Ștefan, Workman, et al., 2025) and DIY builds based on single-board computers like Raspberry Pi (Serra-Marin et al., 2025; Szczygieł et al., 2026; Wittmann et al., 2024) or microcontrollers (Darras et al., 2024). The DIY options support add-ons like environmental sensors, light sources, solar panels and customisable software. Image capture can be scheduled or triggered by motion or on-device AI-based detection (Gardiner, Rowlands, & Simmons, 2026; Steen, 2017).

Camera traps excel at non-invasive, continuous monitoring of insect presence, activity or abundance, phenology, behaviour and morphology, particularly at times or in locations that are difficult for human observers to reach. They support studies on pollination, predation and habitat use (Droissart et al., 2021; Ștefan, Workman, et al., 2025) and enable fine-scale temporal analyses (Geissmann et al., 2022). High-resolution imagery allows species-level classification where distinctive features are visible (Bjerge et al., 2025; Chiranjeevi et al., 2025). It also enables a potential by-catch of ecological and environmental information (Alison et al., 2024; Pernat

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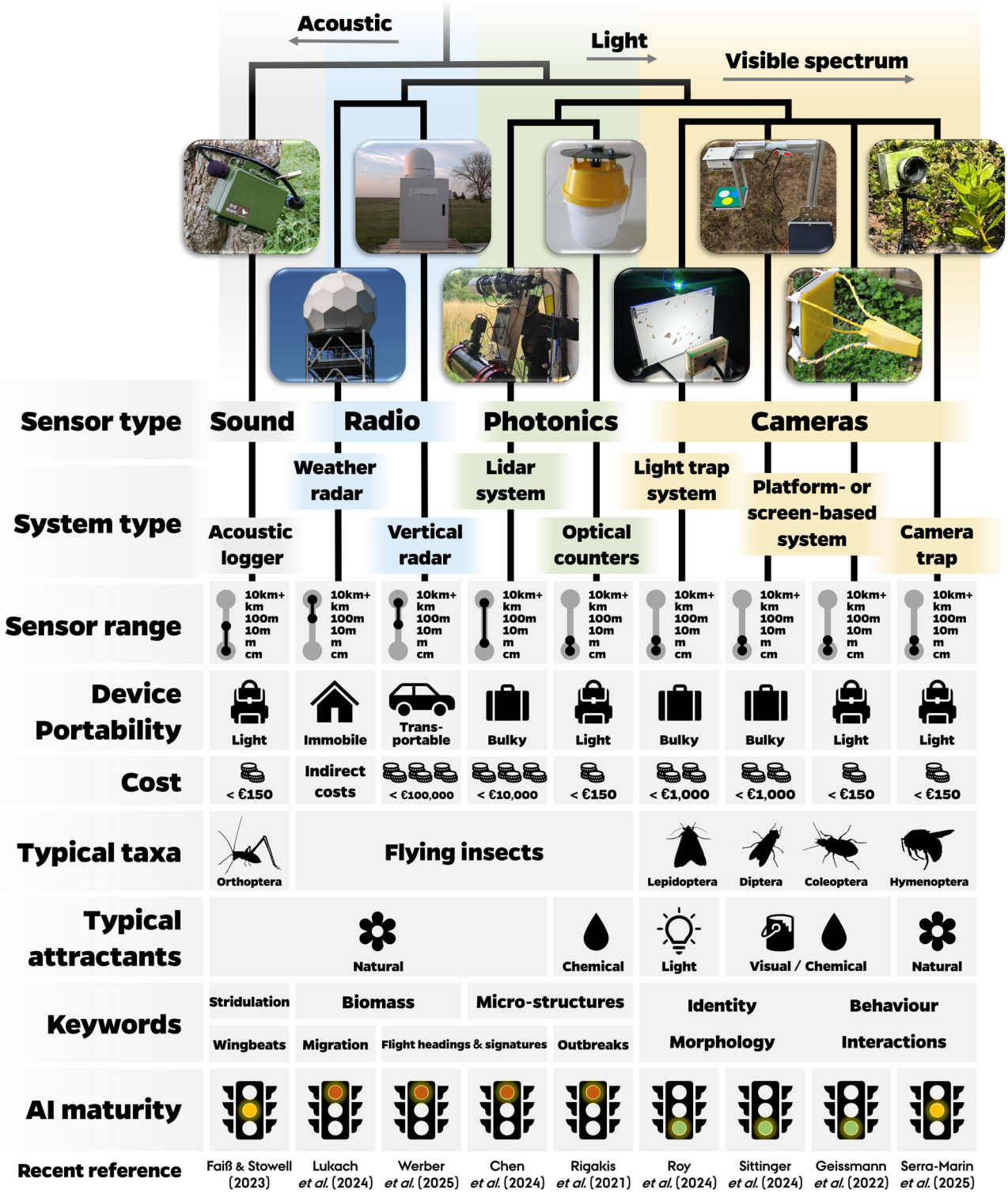


**FIGURE 2** Insect sensing systems vary in their range, portability, cost, taxonomic scope and resolution. Some capture insects in natural contexts, while others lure them with chemical or visual attractants. Data from different sensors provide information on unique aspects of insect life, exemplified here under "Keywords". Some systems can leverage AI more readily than others, and traffic lights represent the maturity of AI systems: **(Red)** Annotated datasets are not widely available, but AI is occasionally used for coarse identification or unsupervised hierarchical clustering. Identification usually relies on ***algorithmic processing***. **(Yellow)** Datasets exist to train AI, but coverage of taxa and contexts is a strong limiting factor. Studies demonstrate reasonable performance for specialised AI, but models generalise poorly to novel communities and conditions. **(Green)** Large datasets support training of AI models which reliably identify higher insect taxa and distinctive species. Generalisable AI is deployed at scale, and some models are suitable for ***embedded processing***. Image credit from left to right: Jamie Alison (Song Meter Mini 2); Philip Halling (weather radar); Baptiste Schmid (BirdScan MR1 radar); Meng Li (Scheimflug lidar); Rigakis et al. (e-funnel trap; Rigakis et al., 2021); Jarek Scanferla (UKCEH AMI trap); Max Sittinger (DIY camera trap); Quentin Geissmann (Sticky Pi); Pau Serra-Marin (automated camera system).

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et al., 2024). However, detection and classification are usually less reliable for smaller insects.

Commercial trail cameras often lack fine control over scheduling and are not optimised to detect small, fast-moving insects (Pegoraro et al., 2020). DIY systems, while adaptable, usually require expertise for assembling components and configuring software, posing a barrier for non-specialists. Open hardware platforms and community-developed projects (e.g., Droissart et al., 2021; Sittinger et al., 2024; Szczygieł et al., 2026) enable flexible, modular designs and can improve reproducibility and uptake in the community, especially in conservation and citizen science efforts (Sheard et al., 2024). Most systems are stationary, capturing imagery of an area smaller than 1 $m^2$.

Video and image data can quickly exceed storage and processing capacity, and scheduled recording may capture long stretches of irrelevant footage. On the other hand, motion-triggers or real-time detection models can reduce data volume (Bjerge et al., 2025; Darras et al., 2024; O'Shea-Wheller et al., 2024; Sittinger et al., 2024), but could introduce bias to data collection. Detection tends to be easier against simple backgrounds than in complex natural settings (Ștefan, Stark, et al., 2025). Detection models are often task-specific, but new generalisable AI tools are emerging (Svenning et al., 2025), as are platforms on which to apply them (e.g., Antenna). Classification models, powered by citizen science datasets, are able to identify some larger-bodied taxa to species level (Spiesman et al., 2021).

## Acoustics

Passive acoustic monitoring (PAM) is the use of autonomous sound recording units to record vibrations in air (Ross et al., 2023), water (Lamont et al., 2022), or solid substrates such as plant tissues (Mehrotra et al., 2024). It is widely used in terrestrial and aquatic ecosystems to detect and analyse animal sounds (Darras et al., 2025; Deichmann et al., 2018; Gibb et al., 2019). Advances in affordable, programmable recording units and software tools have contributed to a surge in PAM studies (Hill et al., 2018; Kohlberg et al., 2024; Sugai et al., 2019), although invertebrates remain underrepresented, with only 23 of 460 terrestrial PAM studies targeting insects (reviewed by Sugai et al., 2019; see also Mankin et al., 2011).

PAM devices capture sound across a variety of frequencies: Audible-range units (<20 kHz) can capture crickets, bees and some aquatic insects, while ultrasonic devices (>20 kHz) capture signals from moths and katydids. Higher sampling rates allow recording of higher frequency sounds, but increase storage demands and drain batteries, which limits deployment duration. Devices range from lightweight, low-cost units like Audiomoth (~80 g) to professional-grade recorders like the SM4 (~1.2 kg with batteries). Microphone quality can limit detection of insects, especially in the ultrasonic range, where low-end microphones can miss subtle insect sounds (Riede & Balakrishnan, 2025). Whilst there are several automated hardware options for terrestrial recording, the hydromoth is the principal low-cost option for freshwater environments, which suffers from poor recording quality and low ***signal-to-noise ratio*** (Lamont et al., 2022). Contact microphones and laser vibrometers can record vibrations in a substrate, revealing the presence of insects living on plants (Mehrotra et al., 2024; Šturm et al., 2022), in tree trunks, or underground (Robinson et al., 2024).

PAM excels for loud or "soniferous" taxa, and where visual monitoring is difficult, for example in habitats with dense vegetation, aquatic systems and forest canopies (Desjonquères et al., 2020; Sugai et al., 2019). It enables large-scale, long-term surveys with low disturbance and recording effort (Browning et al., 2017; Linke et al., 2018; Penar et al., 2020). While research has focused on Orthoptera and cicadas (Bennett et al., 2025; Do Nascimento et al., 2024), there is growing interest in other soniferous taxa, such as aquatic insects (Desjonquères et al., 2024), bees (Bota et al., 2022) and flies (Mukundarajan et al., 2017). Combined with ***machine learning***, PAM can uncover diel and seasonal activity patterns and support behavioural or ecological inference (Lawson et al., 2022; Riede & Balakrishnan, 2025; Scarpelli et al., 2023; Symes et al., 2024).

Data processing is a major bottleneck. The breadth and performance of automated processing tools are improving; AI models are able to distinguish select Orthoptera and cicada species with some success (Madhusudhana et al., 2024; Okamoto & Oguma, 2025). However, background noise is a major challenge, and models often perform poorly in new settings (Tang et al., 2022). A limiting factor is the lack of training data for most species, especially in tropical ecosystems (Riede & Balakrishnan, 2025). For manual processing, several software options exist (Audacity, Raven, Whombat, (Rhinehart et al., 2024)), but insect-specific workflows remain scarce. Labelled insect sounds are often not shared (but see Acosta et al., 2024; Rivas et al., 2025; Zefa et al., 2022; Branding et al., 2024), so reference libraries are limited. However, repositories like Xeno-canto facilitate data sharing, while open-source R packages like Rthoptera (Rivas et al., 2025) enable generation of metrics and intuitive visualisations. Solutions that expedite and standardise manual processing would support the development of reference libraries, as well as characterisation of distinct types of bioacoustic signals (sonotypes).

## Radar

Radar is an active remote sensing technology that emits radio waves and interprets the returning signals reflected by objects. Initially developed for military use, radar has become a powerful tool for studying aerial ecology, including insects (Bauer et al., 2024; Chapman et al., 2011; Rhodes et al., 2022; Shamoun-Baranes et al., 2021). Technological and algorithmic advances have enabled radar to deliver continuous data on insect flight patterns, timing, direction, altitude and spatial distribution, often reaching several kilometres into the atmosphere (Chapman et al., 2015; Drake & Reynolds, 2012; Tielens & Kelly, 2024). These data support research on insect migration (Werber et al., 2025), orientation (Shi et al., 2021), phenology (Haest et al., 2024), behaviour (Gao et al., 2020), biomass dynamics (Hu

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et al., 2016; Wotton et al., 2019) and environmental drivers (Knop et al., 2023). However, a key limitation is that individuals can rarely be identified to a high taxonomic resolution (Hüppop et al., 2019; Jeffries et al., 2013).

Two radar types are primarily used in insect monitoring: small-scale vertical-looking radars and large-scale weather surveillance radars (Bauer et al., 2024). Vertical-looking radars track individual insects and record flight trajectories, wingbeat frequencies and body size (Drake et al., 2024; Zaugg et al., 2008) and are increasingly portable and commercially available. In contrast, weather radars capture biomass (Mungee et al., 2025) and movements (Lukach et al., 2022, 2024; Stepanian et al., 2016) at regional scales but lack the resolution for individual tracking.

Species identification remains challenging: weather radars inherently lack resolution (Drake, 2016; Hao et al., 2020), while vertical-looking radars show promise but require improvements to radar technology, signal interpretation (Addison et al., 2022; Gauthreaux & Diehl, 2020) and more labelled datasets (Haest et al., 2021). Direct species-level identification will remain inherently difficult, but can be achieved under certain conditions—for example using supplementary trait data (e.g., Chapman et al., 2012; Hao et al., 2020). While insect detection with radar may be more reliable for larger-bodied insects, size-biases can be mitigated by simultaneously using complementary radar types (Lochmann et al., 2024).

Radar data are generally processed using open-source tools (Dokter et al., 2019; Haest et al., 2024; Kranstauber et al., 2025), usually through a combination of rule-based and statistical approaches. However, AI methods are being developed, and stored recordings will enable retrospective processing with new models (Sun et al., 2024). Meanwhile, ongoing initiatives, including HiRAD, aim to consolidate radar entomology knowledge, developing open-access tools and datasets for ecological applications (Bauer et al., 2024).

## Photonics

Photonic sensing of insects involves recording how emitted photons, typically from lasers or LEDs, reflect from insect bodies in-situ (Brydegaard & Svanberg, 2018). This method leverages principles from optical modulation spectroscopy and laser remote sensing to detect insects based on how they scatter, absorb or reflect light. While passive methods using scattered sunlight are possible (Jansson & Brydegaard, 2018), most systems rely on active illumination to ensure reliability across lighting and weather conditions (Brydegaard et al., 2020; Rydhmer et al., 2024).

Photonic sensors can be deployed at various scales (Li, Han, et al., 2023; Saha et al., 2023), ranging from compact e-traps based on simple photo-interruption (Potamitis et al., 2017, 2018; Preti et al., 2021; Rigakis et al., 2021), to short-range monitoring devices (Rydhmer et al., 2024), to lidar systems that survey kilometre-long transects (Brydegaard et al., 2016). The latter enables non-invasive monitoring of insect fluxes (individuals and biomass), flight headings (Li et al., 2020) and dispersal (Månefjord et al., 2024). While generally recording smaller volumes of space than radar, lidar captures fine-scale optical signatures such as wing membrane nanostructures (Li, Runemark, et al., 2023; Müller et al., 2023) and melanin absorption (Goh et al., 2021). While many such features have primarily been studied under controlled conditions, they could be quantified under field conditions in the future.

While they can be made weather-resistant (Chen et al., 2024), lidar systems are not yet standardised, so comparison across studies is difficult. Comparability can be improved by presenting general metrics like chitin or melanin pathlength (Li, Runemark, et al., 2023). Lidar systems also require specialised maintenance and, like radar, can suffer from atmospheric interference. Photonic sensors can generate hundreds of thousands of observations daily but, as for other sensor types, detectability varies with the size and shape of insects (Li, Runemark, et al., 2023; Månefjord et al., 2024; Yamoa et al., 2025).

A lack of training data limits the utility of AI for data processing, though unsupervised methods like hierarchical clustering can help to estimate diversity and reveal ecological patterns (Rydhmer et al., 2024; Yamoa et al., 2025). Data processing generally focuses on extracting oscillation frequencies (Brydegaard et al., 2020), spectral profiles (Li et al., 2022; Månefjord et al., 2024), polarimetric properties (Genoud et al., 2019) and physical parameters of insects (Müller et al., 2023). Species identity can sometimes be derived based on these properties, but is limited by the absence of comprehensive optical property databases. An important step forward is to express sensor-derived traits (e.g., body size, wing thickness and area, spectral properties) in SI units so that they can be matched with future measurements derived manually in the lab.

## Multimodal sensing

Sensing systems that combine data collection modalities can form more than the sum of their parts. Several studies demonstrate technological synergies for in-situ biodiversity monitoring, for example between cameras and environmental DNA (Stothut et al., 2024; Tetzlaff et al., 2024). However, studies that combine multiple sensor types are surprisingly rare—especially for insects (Buxton et al., 2018; Kline et al., 2025; Wägele et al., 2022).

Multimodal sensing can offer synchronous and asynchronous synergies for biodiversity monitoring. Synchronous synergies involve multiple sensor types recording in the same time and place. For example, recording the same individual insects with multiple sensor types could improve identification using multimodal AI (in line with previous work complementing images and DNA; Badirli et al., 2021) and even create coveted labelled datasets for acoustics, radar and lidar sensing (Giuntini et al., 2024). On the other hand, while multimodality generally increases both cost and complexity, using one type of sensor to trigger another, for example using an infrared beam to trigger a camera, can offer savings in terms of power and storage (Hobbs & Brehme, 2017).

Asynchronous synergies involve complementary insights from sensors that are not perfectly aligned in space and time. For example,

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cameras and acoustics might capture complementary sets of taxa (Buxton et al., 2018), while radar and lidar data might be complementary in terms of spatial scale. Similarly, aerial environmental DNA (Roger et al., 2022) could provide taxonomic context for entomological radar data, which have high taxonomic uncertainty (Haest et al., 2024). Beyond light, sound and radio, other sensing modalities can also generate complementary understanding. For example, changes in capacitance can be used to detect insects walking over a surface (Scherer et al., 2022), crawling through tubes (Campbell et al., 2005) or feeding (Itskov et al., 2014).

## ADOPT TAXONOMIC PRAGMATISM

Species identification has always been a major challenge in entomology. There are at least 5.5 million insect species globally, of which 80% remain undescribed (Stork, 2018). Furthermore, species compositions of insect communities are highly uneven, meaning that most species are rare, and thus difficult to record (Preston, 1962). Monitoring of insects is also severely biased towards certain geographic regions and taxa (Rocha-Ortega et al., 2021). Small-bodied taxa are rarely monitored, and even meticulous morphological identifications can result in aggregation or "lumping" of cryptic species complexes (Li & Wiens, 2023).

The challenge of identifying insect species is amplified when using only sensor data, which can lack fine-grained morphological features. It can be very difficult for human specialists to distinguish species in visual imagery (Ștefan, Workman, et al., 2025), let alone lidar or radar signals (Drake et al., 2024; Rydhmer et al., 2022). Identification is further complicated with the use of AI. AI models inevitably make errors, especially for rare species, owing to bias, missing taxa and class imbalances in training datasets (Buda et al., 2018; Gharaee et al., 2023). Overall, taxonomy is probably the single greatest challenge faced by insect sensing systems. This challenge calls for taxonomic pragmatism: in other words, we need to strive to identify species wherever possible and seek effective ways to make use of taxonomically uncertain data.

Species-level data are the top priority. Many applications, from species conservation to surveillance of pests and invasives, cannot be achieved without species identification. To that end, we need to develop and promote tools that reliably generate species-level records. Fortunately, some species can be successfully identified through AI processing of images and sounds (Jain et al., 2025; Symes et al., 2024). Furthermore, in photonics, multi- and hyper-spectral analysis reveals features of insects that are invisible to the human eye, offering new ways to distinguish species and even sexes (Li et al., 2025; Müller et al., 2023). Still, to maximise the species-level recognition of AI models, it is vital to develop and use training datasets verified by morphological or DNA-based identification (Step 3; Gharaee et al., 2023; Kirkeby et al., 2021).

Species identification is paramount, but when this is not possible, there are usually opportunities to leverage the temporal scale and resolution of sensor data. Higher taxa or functional groups are usually distinguishable; cameras can record visits by different pollinator guilds through seasonal or day-night cycles (Alison et al., 2022; Anderson et al., 2023). Acoustic complexity indices or sonotypes help to reveal broad patterns in the activity and diversity of insects (Scarpelli et al., 2023). Similarly, radar data capture mass migrations of insects in a range of size classes (Wotton et al., 2019). Some of the most striking examples of insect decline have involved taxonomically coarse data (Brooks et al., 2012; Hallmann et al., 2017), which insect sensing systems generate in unprecedented quantities (Werber et al., 2025). However, such coarse indicators of insect abundance can mask the subtleties of changes in insect communities; the best solution probably integrates species-level and taxonomically aggregated data, producing indicators that are both inclusive and interpretable (Outhwaite et al., 2019, 2020).

Importantly, taxonomic pragmatism does not involve analytical shortcuts. Working with taxonomic uncertainty means training models that effectively identify insects at both high (Mazen, 2023) and low taxonomic ranks (Bjerge et al., 2022), producing outputs at the highest reasonable taxonomic resolution (Step 5). Species-level records help to build species abundance indicators (Kissling et al., 2018), while higher-level records shed light on wider community biomass, composition and function—for example, by cross-referencing with insect trait databases (Hörren et al., 2022). Trait-based approaches can capture ecosystem processes using data spanning multiple taxonomic ranks (Moretti et al., 2017). However, such analyses rely heavily on transparent use of taxonomic backbones (Step 3; August et al., 2015).

Above all, taxonomic pragmatism depends on quantification of uncertainty during identification. It is rare for AI models to communicate uncertainty effectively (Gawlikowski et al., 2023), and they sometimes express higher confidence when they are out of their comfort zone (Box 2, Appendix S1). More reliable uncertainty measures could reduce the impact of AI identification errors during downstream analyses, but also flag uncertain records for expert review within a ***human-in-the-loop*** workflow (Step 4).

## CREATE, CURATE AND SHARE LABELLED DATA

Labels are essential, representing biological information to sensor data. They can be generated by humans or AI models and take many forms; for example, species IDs attached to bounding boxes, or behavioural descriptors attached to time segments. Human-generated labels, often called ***annotations***, are generally treated as ***ground truth***; they are the gold-standard for training and validating AI models, though sometimes associated with error of their own (Austen et al., 2016; Foody, 2024). However, manual annotation is costly, demanding many human working hours, and forms a severe bottleneck for data processing. Despite advances in AI for machine-generation of labels, the demand for annotations is greater than ever (Box 3, Appendix S1). The question is not *whether* to annotate, but *what* to annotate and *how*: the answer depends on what annotations will be used for, as well as which labelled datasets are already available (Blair et al., 2024).

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It is rarely feasible to manually annotate all data generated by a sensor. Instead, it is often necessary to select strategic subsets of the data to achieve annotation goals. Annotations can be used (i) to train AI models, (ii) to evaluate AI outputs, or (iii) as a direct source of biological data. Where the aim is to improve AI model performance, a good strategy is to increase representation of species or conditions where models perform poorly (Koch et al., 2022). If annotations are used to evaluate an AI model in a new context (Cowans et al., 2022; Wood & Kahl, 2024), a good strategy is to subset data evenly across space, time or taxa to fully represent the new context. When annotations are for biological analysis, a good strategy is to target regions and periods of ecological interest, such as open flowers for pollinators (Alison et al., 2022). Furthermore, it is always important to annotate some sensor data where insects are absent, providing true negatives that form a counterfactual for training and evaluation of AI.

Well-documented annotation protocols are vital to ensure quality and reproducibility. Processing tasks include classification, detection, ***segmentation***, measurement or description of insects (Figure 3), with outputs ranging from a taxonomic ID linked to a recording (Madhusudhana et al., 2024) to a pixel mask highlighting insects in an image (Svenning et al., 2025); see Figure 3: Segmentation. Protocols should capture methodological choices that affect reproducibility, especially details related to annotation scope. For example, when is a signal considered too small or weak to annotate? How are the boundaries of an annotation defined? A gold-standard approach is to consult multiple annotators, allowing uncertainty in the human-defined ***ground truth*** to be quantified. This gives context when evaluating an AI model: if two human annotators only agree in 90% of cases, models should not be expected to exceed 90% accuracy.

There are a wide variety of viable software tools for annotation, many of which are free and open source (LabelStudio, CVAT, VIA, RoboFlow, Whombat, WildTrax), while platforms like Zooniverse allow crowdsourced ***annotations*** from multiple users (Willi et al., 2019). However, for non-visual methods, the generation of reliable ***ground truth*** annotations can be particularly intricate. For example, the process may involve proactively recording known species in the field (Gradišek et al., 2017) or in cages (Rydhmer et al., 2024), or combining multiple recording methods to guarantee taxonomic identity (Giuntini et al., 2024; Van Doren et al., 2023).

Large volumes of data and labels are already being generated by insect sensing systems, both in research and in industry, yet they are not always shared according to FAIR principles: Findability, Accessibility, Interoperability and Reusability (Wilkinson et al., 2016). While some datasets are published specifically for AI applications (Gharaee et al., 2023), other AI-relevant datasets become available as side effects of research, education and community engagement (August et al., 2015; Unger et al., 2021; Wilson et al., 2023). Datasets accompanying scientific publications are often persistent and findable in general-purpose data repositories, such as Zenodo. Data sharing platforms such as Agouti or Wildlife Insights (Ahumada et al., 2020) have extended reach, catering to a broad ecological audience, but place no emphasis on insects. A catalogue of annotated insect datasets would help to leverage synergies between them, especially to train generalised entomological AI models that perform in a wide variety of contexts (Schneider et al., 2023). For example, Svenning et al. (2025) curated 23 arthropod image datasets, enabling a highly generalised model for arthropod detection and ***segmentation***. Similarly, the TreeOfLife-10 M dataset collates the iNat21, BioScan-1 M (Gharaee et al., 2023) and Encyclopedia of Life datasets to advance general organism classification, especially at higher taxonomic ranks (Stevens et al., 2023).

Still, the accessibility, interoperability and reusability of data ultimately depends on consistent and well-defined metadata and ***standards*** (Box 4, Appendix S1). While metadata provides context or details about data, ***standards*** provide common terminology and structure with which to store and share data. At the heart of a data standard is a set of well-defined terms, such as *scientificName* and *captureMethod*, that link to established ontologies, such as community agreed taxonomic, life-history or anatomical concepts (Yoder et al., 2010). A data standard can also define structures and formats for data: for example, the CamTrapDP standard provides tables for Deployments, Media and Observations, with a JavaScript Object Notation (JSON) format to describe and connect them (Bubnicki et al., 2024). Development of, and adherence to, community ***standards*** that can accommodate the density of data generated by automated monitoring systems is absolutely vital for scalability, yet remains an under-resourced frontier.

## DELEGATE TO AI WITH CARE

Given the hype around AI (Pollock et al., 2025), it is easily seen as the solution to every data processing challenge (Placani, 2024). However, AI is not a panacea for insect sensing systems: some sensors are less "AI-enabled" than others (Figure 2), and integrating AI into monitoring pipelines is far from trivial (Schneider et al., 2023). AI models are costly to develop, energy intensive (Luccioni et al., 2023) and not well suited to all situations or tasks. Furthermore, there are many ethical issues around the development and use of AI (Taffel et al., 2022). Before rushing to assign every task to AI, proper consideration must be given to non-AI or hybrid solutions. We recommend always asking two key questions: (1) Is AI best suited for the task? (2) What is the role of AI in the workflow?

### Is AI best suited for the task?

AI models are candidates for many data processing tasks (e.g., Figure 3), but their availability and performance vary across sensors, tasks and ***domains***. Furthermore, they must be measured against their competition—for example ***algorithmic processing*** (Box 5, Appendix S1) and human processing. The suitability of AI for data processing depends on the context; for some tasks, such as insect detection using radar, annotated data are not widely available to train AI models (Gauthreaux & Diehl, 2020; Haest

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et al., 2021). As such, ***algorithmic processing***, with calibration by experts, remains the standard approach to extract entomological data from radar and lidar (Chen et al., 2024; Dokter et al., 2019). On the other extreme, annotated images of insects are so abundant that ***foundation models***—large AI models that can perform a variety of tasks—are now extremely useful for image-based monitoring (Box 6, Appendix S1).

Task complexity also determines the suitability of AI for data processing (Figure S1). For simple, repetitive tasks with a high ***signal-to-noise ratio***, ***algorithmic processing*** can automate analysis with minimal training data (Lürig et al., 2021). As the complexity and scope of the task increases, and more sensor data are created, annotated and shared, AI gradually becomes a viable solution. For example, it is much harder to detect insects in images of flowers and vegetation (Bjerge, Alison, et al., 2023; Ştefan, Stark, et al., 2025) than in images of an illuminated screen (Roy et al., 2024); the former task is currently not always achievable with AI, while the latter is possible using a simple algorithmic thresholding method (Bjerge et al., 2021). When tasks lack sufficient training data for AI and are too complex for ***algorithmic processing***, human processing becomes necessary to expand the training data and generate ecological insights (Figure S1; Step 3).

## What is the role of AI in the workflow?

AI models can be characterised based on their task—for example, detection, classification and measurement of insects (Figure 3)—but also their role; that is, how they complement other elements, including humans, to achieve monitoring goals (Figure 4). This affects how, when and where AI models should be deployed. For example, if AI predictions are used to directly generate a population index for an annual report, models can run long after data collection on a high-performance computer, while training should prioritise accuracy over speed (Figure 4). On the other hand, AI can assume the role of a "trigger mechanism" to enable reactive monitoring of ecological phenomena, such as pollinator behaviour (Ratnayake et al., 2022). This role demands an AI that runs in real time, perhaps even on-device for ***embedded processing*** (also known as edge processing; Sittinger et al., 2024; Smith et al., 2026). ***Embedded processing*** is trending across animal ecology (Vuilliomenet et al., 2026) and entomology (Bjerge et al., 2025) but it has many limitations. We advise caution before adopting on-device AI processing, as it increases device cost, complexity and power consumption, and is not necessary for all applications (Box 7, Appendix S1). Where ***embedded processing*** is used to decide whether to retain or discard data, we strongly recommend withholding a subset of unfiltered data for ongoing evaluation (Figure 5).

**FIGURE 3** Data processing tasks such as classification, detection, segmentation, measurement and description can be performed by humans, or using automated processing tools such as AI. These tasks output labels in various formats: Classification may produce a table with the ID of the insect in each input image; detection may produce an output for each input image, with coordinates of the bounding boxes of each detected object. Outputs can also be more complex: In segmentation, image masks or polygons are generated for each object. For measurement, the objects are assigned a value according to the trait desired. Tasks exemplified here for visual imagery exist in similar forms for acoustic, radar and lidar sensing. Detections, segmentations and measurements in the Figure were derived using the flatbug model Svenning et al., 2025), while the description was generated using the Gemini 2.5 Pro model Comanici et al., 2025).

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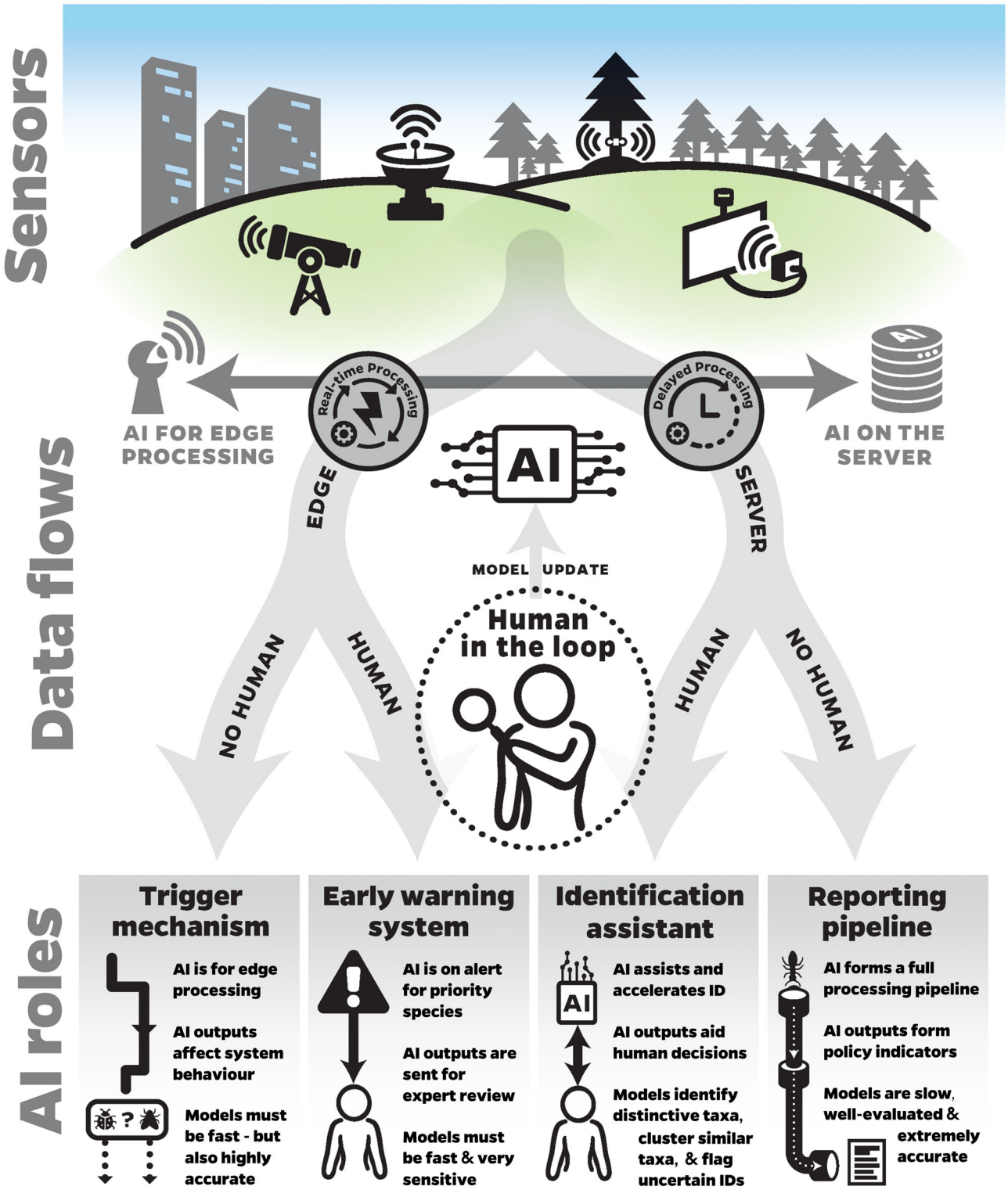


**FIGURE 4** AI can take on a variety of roles in an insect monitoring workflow. In some roles, lightweight models process data in real-time—perhaps even adjacent to the sensor for ***embedded*** (or edge) ***processing*** (left side). In others, larger models are run sometime after data collection on high-performance computing servers (right side). Some roles demand independent working (outer routes); others demand frequent interaction with humans (inner routes). Understanding the role of AI in insect sensing systems is crucial to optimise when, where and how models are deployed.

AI is often seen as displacing humans in data processing workflows. However, using ***human-in-the-loop*** approaches, humans and AI can work as a team to perform distinct, complementary roles. Frequent interactions between humans and AI models can enhance the learning process through active learning feedback loops (Kath et al., 2024). AI systems accommodate human validation or

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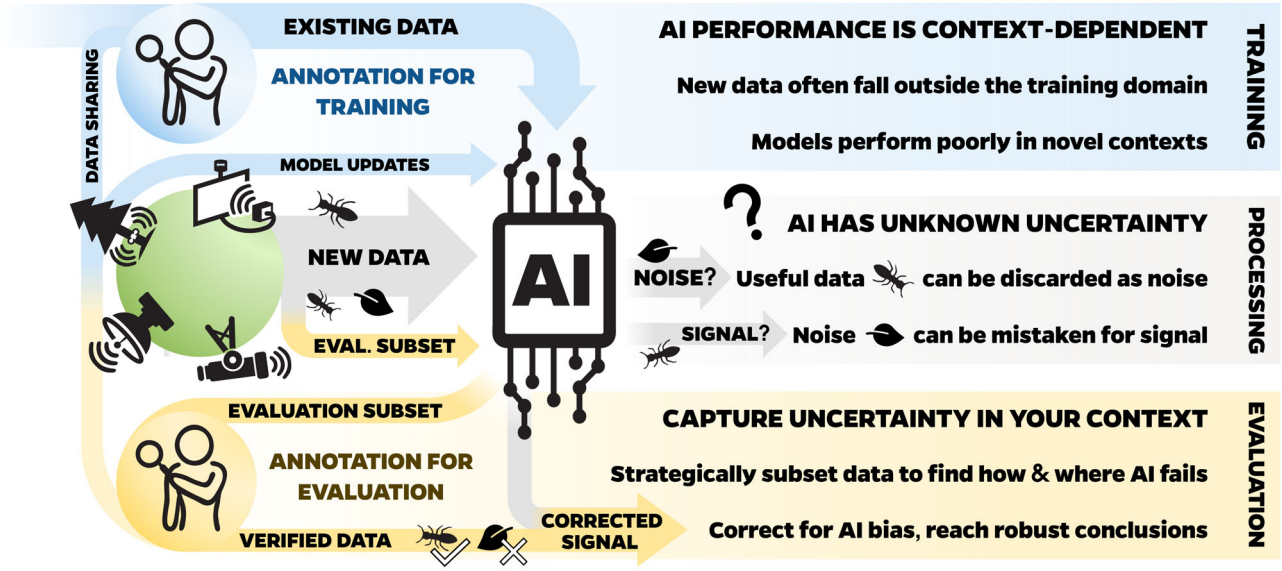


**FIGURE 5** **Annotation isn't just for model training—it also helps to capture uncertainty**. Strategically annotating a subset of recorded data (golden arrows) can allow bias correction, for example by calibrating AI confidence scores (Wood & Kahl, 2024) or using false-positive models (Cowans et al., 2022). Even where AI predictions are uncertain, a good evaluation can permit robust ecological conclusions.

consultation not only during training but during application (Mosqueira-Rey et al., 2023). It is vital that humans take responsibility for critical decisions, and that we leverage their experience and taxonomic expertise (Dyer et al., 2024). To that end, AI can be usefully cast in a supporting role, and even error-prone models can simplify and accelerate human processing. Operational examples of ***human-in-the-loop*** workflows are still rare in insect monitoring, though some are in development (Welch et al., 2026). Importantly, different data processing roles call for different qualifications, with implications for AI model selection and training.

We highlight two examples of ***human-in-the-loop*** workflows that exploit AI efficiency, but also human expertise (Figure 4, middle pathways). The first, the early warning system, focuses on detecting pests or other priority species in real-time, with human experts on-call to manually validate AI detections. An example application is to detect outbreaks of pests such as the red palm weevil (*Rhynchophorus ferrugineus*) in palm plantations (Passias et al., 2024). Development of AI for early warning systems may imply specific training targets: a high ***recall*** model would make sure pest outbreaks are not missed, at the cost of a few more false-positives. These false-positives could be efficiently filtered out by human experts and even improve model performance in an active learning feedback loop.

The second example, the identification assistant, sees AI taking on a less time-critical role of detecting and pre-sorting insects in recordings to facilitate human identification (Figure 4). AI can help with simple tasks, such as flagging images or audio files that contain animal signals (Sheard et al., 2024; Willi et al., 2019), or propose species identifications, as on the iNaturalist platform (Campbell et al., 2023). However, species-level AI identifications are not reliable across many taxa, sensors and ***domains*** (Step 2), and can introduce bias to human determinations. On the other hand, a general order-level image classifier is within reach for insects (Schneider et al., 2023). The MothBot software tool demonstrates how to use AI tools to effectively facilitate identification by experts. By accurately classifying insects at order-level using BioCLIP, then clustering them based on visual similarity, MothBot explicitly prioritises ease of human verification over fine-grained AI classification (Szczygieł et al., 2026). The ideal identification assistant would readily process the most highly distinctive taxa or species, but flag unfamiliar ones for further review (Hogeweg et al., 2024). Future developments should build taxonomically tiered and partially automated sorting systems, drawing inspiration from high-throughput traditional monitoring programmes (Karlsson et al., 2020).

## HOLD AI TO ACCOUNT

If applied with care, AI is an increasingly useful processing tool. However, AI models can fail in surprising ways, in spite of—and sometimes owing to—their efficiency and complexity. Some AI pitfalls have roots in statistical autocorrelation; much like statistical models, AI readily exploits non-generalisable correlations in space and time, so we must be vigilant when splitting training and test datasets (Box 8, Appendix S1). Despite advances in the field of explainable AI (Chiaburu et al., 2024; Mosqueira-Rey et al., 2023), it is not always clear how AI models function and why they make mistakes. However, flawed AI is still useful if errors can be quantified and understood (Funosas et al., 2026). Robust evaluation improves interpretation of uncertain AI outputs and helps us train more reliable models for the future.

To properly confront AI uncertainty, we need to be more open about it. A key issue is that models are trained and evaluated using

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similar data, giving an unrealistic impression of performance in novel contexts. Crucially, there is a lack of accepted ***benchmark datasets*** to fairly evaluate different models (Schneider et al., 2023; but see Nguyen et al., 2024 for vision; Branding et al., 2024 for acoustics). Bjerge, Alison, et al. (2023) demonstrate issues with siloed evaluation: they trained a model to detect insects in images, achieving an F1 score of 0.932 on their own test dataset. However, when evaluating the model for insect classes not present in training and test data, only ~80% of insects were detected. Similarly, Ștefan, Stark, et al. (2025) found considerable drops in model performance when exposing models to background conditions and insect sizes that differed from the training data. In general, it is good practice to report evaluation results in detail. Publishing performance for each class, context or specimen in a ***benchmark dataset*** helps to clarify how often models fail, and for which types of inputs (Burnell et al., 2023).

Crucially, to understand AI uncertainty, we need to encourage evaluation using out-of-distribution (o.o.d.) data. Validation and test datasets are assumed to be independent and identically distributed (i.i.d.) to training data. Ideally, real-world data would also meet this assumption, but this is very rarely the case (Geirhos et al., 2020). Real-world data are often o.o.d.: they differ from the training data based on distinct background conditions, new locations or even shifts in the rank-abundance of taxa. Evaluation with o.o.d. data helps determine whether an AI model has learned the intended features, so that it can generalise well to new conditions within the target ***domain***. Svenning et al. (2025) evaluate their arthropod detection model across 23 distinct imaging systems, highlighting how o.o.d. evaluation can be carried out and presented during model development.

Importantly, o.o.d. evaluation is not just for model developers; it may be most useful during model deployment, using data from the context in which AI is being applied (see Appendix S2 for a hypothetical example). Annotating a subset of data processed by a model enables quality control of AI outputs (Figure 5, golden arrows), allowing quantification of false-positives and false-negatives (Cowans et al., 2022) and even calibration of confidence scores (Wood & Kahl, 2024; Box 2, Appendix S1). This evaluation and quality control process generates annotations to train new AI models (see Step 3), but also helps us make sense of unverified AI predictions. Error rates can be accounted for, and it is even possible to explicitly model the AI-detectability of species (Cowans et al., 2022). While o.o.d. evaluation is always insightful, it can be expensive. As a minimum, AI users should consider whether training data differ from the application context and how this may impact model performance.

Holding AI to account means assessing its reliability, but also improving its performance. A very common approach is fine-tuning—a kind of ***transfer learning*** where an existing model is re-trained on a dataset relevant to a specific task (Kumar et al., 2022). However, there is room for innovation to address more fundamental weaknesses of AI for insect monitoring. For example, models often struggle to perform well against unseen backgrounds. Algorithms that leverage frame-to-frame motion could improve detection in novel contexts (Bjerge, Frigaard, & Karstoft, 2023; Ratnayake et al., 2021). Alternatively, unlabelled data from novel backgrounds could be used to improve model ***generalisation*** through unsupervised domain adaptation (Kay et al., 2025). Data augmentation is also crucial, artificially increasing the variability of the training data through rotation, cropping, colour-shifting or inclusion of synthetic data (Beery et al., 2020; Schneider et al., 2023). In acoustics, augmentation can involve playback re-recordings or simulation of target and non-target sounds (Madhusudhana et al., 2024; Okamoto & Oguma, 2025).

Many breakthroughs in AI for insect monitoring involve ***multimodal*** approaches, such as supplementing sensor data with taxonomic or text descriptors (Gu et al., 2025; Stevens et al., 2023) or DNA sequences (Badirli et al., 2021; Gharaee et al., 2024). By leveraging the hierarchy of the tree of life, ***multimodal*** learning can improve inference based on sensor data alone. Hierarchical classification can enable coarse taxonomic labels to be attributed to species or phenotypes not present in the training data (Bjerge, Geissmann, et al., 2023; Grele & Richards, 2026). Alternatively, models can be trained to flag specimens that fall outside of their comfort zone (called novelty or o.o.d. detection; Lee et al., 2018), highlighting where annotation could rapidly improve model performance (Koch et al., 2022). Zero-shot learning is an important tool for AI to detect and classify entities not seen during training, and usually involves learning relationships between known entities, or leveraging auxiliary information such as text or DNA sequences (Geng et al., 2021). Beyond descriptive or genetic labels, geographic and temporal labels can also improve AI model performance. They can be used, as by human experts, to effectively narrow the list of possible taxa based on distribution and phenology (Terry et al., 2020).

Finally, an important innovation in AI for insect monitoring is embedding-based modelling. Existing AI, including ***foundation models*** (Box 6, Appendix S1), can be used to generate compressed representations—or embeddings—of sensor data. Then, further models can rapidly explore high-dimensional relationships across those embeddings. This enables effective and computationally efficient novelty detection, as well as classification of new taxa with very few additional training data (Hogeweg et al., 2024). Furthermore, training small linear classifiers using embeddings from pre-trained models is an efficient form of **transfer learning**. So-called "linear probing" trains new models for specific insect monitoring tasks, while retaining some of the generality of the original models (Kumar et al., 2022). BioCLIP 2 embeddings are useful for insect classification (Gardiner, Mougeot, et al., 2025), while BirdNet and Perch embeddings could be useful for acoustic monitoring of insects (Ghani et al., 2023).

## MAKE TECHNOLOGIES ACCESSIBLE

In order to be useful, automated monitoring technologies need to be accessible to researchers and practitioners on the ground. However, technology and AI development for biodiversity monitoring is highly concentrated in the global North (Chan et al., 2021). This limits access to technology and training in the global South and for marginalised groups (Speaker et al., 2022), and reduces the availability and

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relevance of AI models for tropical ecosystems (Pollock et al., 2025). There is a clear risk for existing disparities to be made worse, so that the most biodiverse regions of the world continue to have reduced capacity for biodiversity monitoring (Collen et al., 2008; Ocampo-Ariza et al., 2023).

A variety of technical, financial and socio-economic barriers threaten global adoption of sensors and AI for insect monitoring. First, the complexity of AI, software and hardware is a major barrier to uptake. Many ecologists lack training in not only AI but also handling of large datasets involved in AI training and data-processing (Kendall-Bar et al., 2025). A lack of training compounds with a fast-evolving landscape of both software and hardware related to sensors for insects (van Klink et al., 2024). Most hardware setups are custom-made rather than off-the-shelf products, so that even collection of data requires considerable expertise. Scaling insect sensing systems means more focus on training and community feedback, and a greater emphasis on ease of use and technical support (including sustainable software development; Durdik et al., 2012). Specifically, overcoming deployment biases depends on equitable Global North–South partnerships that include capacity building, skills sharing, community engagement and knowledge exchange (Haelewaters et al., 2021; Sánchez Herrera et al., 2024).

Financial costs related to sensors and AI form another major barrier. For PAM, relatively affordable sensors are available, with commercial devices costing <€150 (Hill et al., 2018). However, other systems are much more expensive; high-end camera systems can cost upwards of €5000 per device. This is prohibitively expensive in many parts of the world, where there may be added costs for insurance, security and replacement of damaged or stolen equipment; a recent deployment of 20 time-lapse cameras on a mountain in South Africa involved hiring guards for 24-h security (Alison et al., 2024). Radar and lidar sensors are often even more expensive (Figure 2), resulting in large gaps in coverage at global scales (Heistermann et al., 2013). To ensure coverage in low-income countries, system development should use a process of "innovation through simplification", while automated monitoring programmes should converge on the most affordable hardware (Brydegaard et al., 2024).

Even if hardware-related costs are reduced, for example through industrial production of sensors (Hill et al., 2018), costs related to data processing and storage may still be prohibitive. Deploying AI is costly in terms of both computation and energy consumption, especially when using highly generalised ***foundation models*** (Luccioni et al., 2023). Training or fine-tuning AI models is also expensive and sometimes cost-prohibitive without suitable computing infrastructure (Hellendoorn & Sawant, 2022). Use of smaller, task-specific AI models—including specialised image classifiers—can help to make systems affordable and energy-efficient. However, access to computing infrastructures is a far-reaching issue that is exacerbated by needs to store and access increasing volumes of data. Growing datasets bring rising costs for insect sensing systems, with some already occupying terabytes (Gu et al., 2025). Such barriers could be addressed fundamentally through more equitable international sharing of computational resources.

## SUPPORT SYSTEMATIC MONITORING

Systematic monitoring involves repeated, standardised surveys of insect biodiversity, ideally at strategically or randomly selected sites, and is the gold-standard for long-term biodiversity monitoring (Brereton et al., 2011; Conrad et al., 2006). A key example of this is the UK Butterfly Monitoring Scheme, which has monitored butterflies repeatedly at sites across the UK since 1976 (Brereton et al., 2011). Systematic monitoring underpins key indicators used to track the biodiversity crisis (Butchart et al., 2010). Furthermore, international policy structures, such as the Kunming-Montreal Global Biodiversity Framework decision 15/5 (Conference of the Parties, 2022) and the European Nature Restoration Law (Directorate-General for Environment, 2022), emphasise the need for systematic monitoring to track progress towards biodiversity targets. Patterns and trends in biodiversity can be derived using opportunistic data (Outhwaite et al., 2020; van Strien et al., 2013), but fixed-effort, systematic observations are more repeatable and information rich (Isaac & Pocock, 2015). Crucially, systematic random sampling is the most direct way to make unbiased inferences about unsampled areas (Boyd et al., 2023).

How can automated methods support systematic monitoring of insects? First, they can be deployed much more widely, and according to rigorous sampling strategies. Until now, sensors for insects and other wildlife have mostly been placed opportunistically (Burton et al., 2015). While some sensors have practical constraints on their placement, contributing to spatial biases (Bowler et al., 2025), there is clear scope to target deployments of smaller sensors to better achieve monitoring goals. When scaling up deployments, we should strive to delineate spatial sampling units (for example, habitats or features of interest) and deploy sensors so that we represent them evenly and transparently. Automated methods allow for scalable monitoring with lower person-hour costs, increased sampling frequency and reduced need for lethal sampling (van Klink et al., 2022). Rigorous sampling strategies are the last piece of the puzzle to maximise the scientific contribution of sensors and fully leverage their potential for standardisation (Høye et al., 2025).

Second, insect sensing systems should build on existing monitoring schemes, according to established site selection protocols. We echo previous assertions that automated methods should improve and expand on, rather than replace, existing insect monitoring initiatives (Dyer et al., 2024). By building on and harmonising with existing datasets, sensor deployments deliver much greater value—both immediately and in the derivation of trends in future. Furthermore, long-term monitoring faces a constant funding crisis, despite calls to expand collection of long-term data to understand insect biodiversity change (Didham et al., 2020; Harvey et al., 2020; Mammola et al., 2020). Automated monitoring and AI are proving highly fundable areas of research, not least due to their potential for biocredit markets (Ford et al., 2024). Well-aligned automated monitoring should scale-up existing monitoring schemes, but also help fund the continuation of traditional monitoring and coveted long-term datasets.

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Third, work is needed to integrate data collected by automated methods, which often differ from many traditional approaches. Some of the longest-running time series of insect populations were produced using traditional methods such as light traps (moths; Conrad et al., 2006; Macgregor et al., 2021), suction traps (Bell et al., 2020) and line transects (butterflies; Brereton et al., 2011). Traditional datasets are clearly not replicated by automated systems (but see Chiavassa et al., 2024), so calibrating new datasets with old ones is crucial. Data integration refers to statistical approaches that analyse multiple data sources within a single analytical framework, leveraging all available information to improve ecological inference (Isaac et al., 2020; Miller et al., 2019). It involves integrated modelling approaches that account for differing assumptions, biases and scales of data collection (Yen et al., 2019). It has been successfully used in species distribution modelling, for example to combine presence-only and abundance data (Fithian et al., 2015; Pagel et al., 2014). However, studies integrating time series from multiple sources are still rare (e.g., Bowler et al., 2019; Hertzog et al., 2021), and we need to move beyond ensemble or synthesis-based approaches towards modelling frameworks that draw on multiple sources of data.

Finally, we need to recognise that sensors are not a panacea in insect monitoring. In most cases, sensors alone do not capture features necessary for species-level identification (see Step 2). Many insect monitoring questions will continue to demand the time of taxonomic specialists, and may gain little from sensor-based approaches (Engel et al., 2021). Here, sensors might support systematic monitoring by focussing on identification and monitoring of common species, freeing up taxonomists for tasks beyond the scope of current AI (Alison & Høye, 2024). Systematic monitoring schemes of the future might build on the strengths of both traditional and automated approaches using a tiered approach: many low-cost, high-frequency, taxonomically coarse sentinel sensor stations could support a network of core monitoring stations, which combine traditional approaches with molecular methods and high-cost sensors.

## CONCLUSIONS

1. Automated biodiversity monitoring with sensors promises to massively increase the availability and affordability of data, whether for biodiversity assessments, trend estimation, agricultural monitoring or ecological research. Companies promising to provide automated monitoring services are already emerging worldwide.
2. However, coordinated action is needed: researchers need to confront and communicate harsh realities of sensors and AI to bring them up to standard for large-scale deployment; developers should focus on affordable hardware design and transparent protocols; project managers should strive to produce standardised, annotated datasets.
3. There are limits to what we can expect from AI. We highlight some often neglected caveats and ethical concerns. Crucially, AI identification is constrained to morphologically distinct species with large quantities of labelled sensor data. Practitioners must not blindly trust AI models, which are most useful when paired with shrewd, case-based judgements.
4. Human resources are an underappreciated component of insect sensing systems. Policymakers must bear in mind that, while sensors and AI can contribute to species monitoring and discovery, human expertise remains a key limiting factor. In short, AI should complement human workflows—not consume them.
5. Creative use of sensors and AI can improve species detection and identification, whether by leveraging hyperspectral signals, multimodal methods or data augmentation. On the other hand, uncertain identifications can be explored at coarse taxonomic ranks, exploiting the extraordinary spatiotemporal scales and resolutions of sensor data.
6. Deployed in the right places, and with sufficient investment in data management, insect sensing systems can enhance our knowledge of insect biodiversity beyond imagination. However, funding agencies should anchor investments in established monitoring schemes, aiming to extend and expand existing long-term insect monitoring datasets.

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## CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

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## DATA AVAILABILITY STATEMENT

Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

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