Mothbox: inexpensive, lightweight, automated light trap for scalable insect biodiversity monitoring

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Abstract

1. Insects represent the most diverse group of organisms on Earth, and comprise the majority of known species, yet they are seldom accounted for in large-scale biodiversity monitoring systems and conservation planning.
2. We have developed the *Mothbox*: an automated light trap that uses open science hardware to make insect monitoring accessible to non-specialists and scalable for scientific and conservation purposes. We have also developed *Mothbot*: a machine learning tool and user interface for processing data from automated light traps. The Mothbox is portable, durable to harsh environments, and low cost to produce, while Mothbot prioritizes human-in-the-loop data validation of computer vision outputs to ensure data quality and aid in developing custom image reference libraries.
3. Mothbox has now been extensively tested in field conditions; with > 185 deployments, spanning > 450 nights and > 100 sampling locations. The two case

studies presented here demonstrate the potential of Mothbox data for behavioural studies and conservation projects.

4. As the young field of automated insect monitoring continues to develop, Mothbox provides an affordable entry point for a wide range of stakeholders. It enables entomologists to explore new research questions by tracking insect diversity in real time and across entire landscapes. Mothbox will help build global insect-monitoring capacity, improving our ability to detect biodiversity loss and guide effective conservation action.

Keywords: biodiversity; monitoring; computer vision; insects; light trap; open source; artificial intelligence

1 Introduction

The majority of the world's species are insects and most insects are active at night (Wong & Didham, 2024). Insects are incredibly valuable ecologically and economically, and rapidly declining in many parts of the world (Basset & Lamarre, 2019; Scudder, 2017; Wagner et al., 2021). However, there are limited options for measuring insect diversity at scale. Traditional approaches require specialised knowledge and considerable time investment (Montgomery et al., 2021), while newer technological approaches have their own limitations. For example, genetic approaches (e.g. DNA metabarcoding) remain expensive, rely on reference libraries with limited coverage for the tropics (Alvarado-Robledo et al., 2024), and are poorly suited to assessing abundance (Sickel et al., 2023),

while satellite-based remote-sensing lacks the resolution for direct monitoring of insects (Rhodes et al., 2022).

Insects present a high-resolution solution for quantifying biodiversity as their high abundance, exceptional taxonomic richness, and relatively limited dispersal mean they often show clear and measurable responses to environmental change. For example, a week of conventional camera trapping at one site for mammals can often yield no data (Kays et al., 2020), in contrast, a week of insect monitoring at the same location can produce hundreds of records for dozens of species (Brehm & Axmacher, 2006). In addition, great diversification of insects is partially the result of specialisation, which makes them particularly relevant biodiversity indicators. For instance, Lepidoptera larvae often feed on only one species or genus of plant (Dyer et al., 2007), and adults can similarly be adapted to pollinating particular host plants (Hahn & Brühl, 2016). Consequently, monitoring Lepidoptera can provide inferences about the plant community (Duran et al., 2022a; Tyler, 2020). Ultimately, insects are rarely included in conservation planning, despite their great diversity, ecological significance, and significant evidence of their global decline, largely because of the difficulty of standardized large-scale insect monitoring (Chowdhury et al., 2023; Høye et al., 2021).

Traditional approaches to monitoring nocturnal insects are time-consuming and require high degrees of specialised knowledge. Moth-sheeting, i.e. attracting moths and other nocturnal insects to lights and setting a sheet for them to land on, is an effective method for visually assessing insect populations or targeting particular taxa. However, documenting every insect that lands on the sheet is often impractical, especially in areas with abundant and diverse insect communities, and requires researchers to attend sheets

throughout the night (Duran et al., 2022a). Bucket traps designed to attract and capture insects do not require ongoing maintenance throughout a night, but do require extensive manual sample processing once collected (Brehm & Axmacher, 2006). To bypass the difficulties with traditional methods, an automated light trap that uses a programmed light source and computer vision for identification was developed in 2021 (Bjerge et al., 2021). This proof of concept inspired the creation of a number of automated light trap devices, including the Automatic Moth Trap (Möglich et al., 2023), Automated Monitoring of Insects (*UKCEH AMI System | UK Centre for Ecology & Hydrology*, n.d.), Insect Detect (Sittinger et al., 2024), DIOPSIS (*Camera | Diopsis.Eu*, n.d.), and others (Beuchert, 2024; Hobern, 2021; Korsch et al., 2023). The field of automated non-lethal insect monitoring is in its infancy, and the devices developed thus far have advantages and disadvantages depending on the monitoring context. There are trade-offs in total cost, portability, image resolution, power consumption, insect attraction lights, 4G capabilities, ease of repair, ease of modification, weather resistance and durability, to name a few.

Here we describe the development and proof-of-concept of the Mothbox, an open-source, automated light trap designed for scalable insect monitoring in challenging field conditions. The Mothbox device integrates a low-cost Raspberry Pi computer, a high-resolution camera, and specialized attractant lighting to capture time-lapse images of nocturnal insects landing on a target sheet. Unlike currently available insect traps, the Mothbox is optimized for portability, adaptability, high-resolution images, and weather resistance. Furthermore, the low materials cost (~$300) makes it possible to deploy many Mothboxes as a part of a sensor network. There are currently two Mothbox versions:

Mothbox 4.5, which is a modular design oriented towards Do-It-Yourself construction and modification, and Mothbox 5.0, which is oriented towards mass production.

We also describe Mothbot, an open-source (MIT license) data processing and organization platform for automated light trap photos. The Mothbot platform detects insects in images, identifies them to a user-defined taxonomic threshold, facilitates rapid human validation and refinement of the automatic identifications, then produces a Darwin Core (Wieczorek et al., 2012) formatted CSV file with the results.

We use two case studies conducted in Panama using the Mothbox and Mothbot to demonstrate potential applications in behavioural research and conservation. The first study investigates patterns in insect activity and community turnover over the night, capturing temporal dynamics often missed by traditional sampling methods. The second study examines the impacts of land-use (teak plantation, secondary and mature forest) on nocturnal insect diversity and composition, providing insights into how land-use change influences community composition.

2 Materials and methods

2.1 Design

2.1.1 Mothbox

The Mothbox is an automated light trap for scalable insect monitoring (Fig. 1). Inspired by initial prototypes developed in 2021 (Bjerge et al., 2021), we set out to design a device that is robust and lightweight enough for use in remote fieldwork. Our vision was to

create a tool that 1. Requires no specialised knowledge to run, 2. Produces real ground-based biodiversity data describing insect communities, 3. Is affordable, durable and sufficiently portable for use in large-scale field-based monitoring and conservation projects. Development has focused on deployment in off-grid, remote tropical forests, as no other automated insect monitoring tools are currently suited to this use case. In addition to housing the most biodiversity, the tropics also present the most hostile conditions for electronics. Thus, if the Mothbox can operate and collect usable data in tropical forest environments, it will be capable of monitoring insects in more forgiving environments. The Mothbox design prioritises low cost, simplicity, and repairability, and all documentation is open-source to maximise potential for scaling and broad use.

The Mothbox is composed of a Raspberry Pi miniature computer that controls a 64 megapixel camera (9248 × 6944 resolution), lights for attracting nocturnal insects, and lights to illuminate the insects for taking photographs (akin to a camera flash). The system is housed in a watertight plastic box and powered by a 156Wh lithium battery (commercially available and legal on most flights). All electronic components are within the watertight housing in the default configuration. Ports in the base of the housing allow for connection to a solar panel, additional batteries, or external light sources as required. The camera faces a 'target' - a piece of 3mm acrylic with felted acrylic fabric on one side that provides a surface diffusely illuminated by the attractant light and with enough texture for insects to land. The default sheet size is 29 cm x 20.5 cm, and is attached to the Mothbox via clear acrylic arms positioned 30cm from the camera. This gives a functional resolution of 25 px/mm per photograph, at this resolution most insects > 3mm in length can be readily identified to family level (Fig. 2). At this distance, the camera field of view can

accommodate a sheet of up to 29 cm x 58 cm, however this leaves less margin for error in positioning the arms and sheet and so we suggest use of the default sheet size. The Mothbox can easily be adapted to using larger target sheets at greater distances to the cameras, although this will result in functionally lower resolution photographs (fewer pixels per insect). Mothbox can also be positioned to focus on any flat surface, without the need for a dedicated target sheet, as the camera auto-focuses. A complete Mothbox weighs 2 - 3 kg , depending on the model and configuration, and is 28 x 18 x 12 cm.

We have prioritised ease of Do-It-Yourself construction and repair in the Mothbox 4.5 design. Minimal tools are required for construction, and most repairs can be accomplished with a screwdriver, knife, and hot glue stick. We opted for using lever nuts for electrical connections to avoid soldering and enable ease of modification and repair. The internal framework as well as the arms and sheet backing are made with laser-cut 3mm acrylic, and all components can be cut from a single 50 x 60 cm sheet of acrylic. While still 3D-printable, this flat pack design choice enables easy field servicing, as replacement components can be cut and drilled by hand from acrylic or wood of the appropriate thickness. In terms of programming, setting up a Mothbox in default configuration requires simply loading a ready to go operating system image onto an SD card. No coding expertise is needed. The main customization required is changing the sampling schedule, which can be achieved by editing a scheduling CSV file placed in the data storage drive. Mothbox 5.0 combines many of the electronic components of Mothbox 4.5 into one printed circuit board (PCB), decreasing construction time, number of components, and cost per unit. Mothbox 5.0 includes physical switches for setting the sampling schedule, which increases ease of

use in field conditions. Mothbox 5.0 electronics are housed in a custom 3D-printed box, while 4.5 are in a commonly available clear acrylic box.

Motion-activated photo saving was the default on the original automated light trap prototype (Bjerge et al., 2021). We use timelapse (photos taken at regular intervals) instead to conserve battery life and to reduce costs. Motion-activated functions are computationally heavy. Keeping on-board computational requirements to a minimum decreases energy consumption and enables use of less expensive Raspberry Pi models. Furthermore, we have observed that the increase in richness of insect assemblages attracted to the sheet tends to be cumulative if the attractant lights remain on. If an insect moves off of the sheet while the attractant lights are on, it still typically remains in the area of the Mothbox until the lights turn off, flying around it or landing on different surfaces. Mothboxes can be programmed for any sampling schedule. In Panama, where daylength is consistently between 11.35 and 12.40 hours with sunset at 18:20 ($\pm$ 20 mins annually) and sunrise at 6:20 ($\pm$ 20 mins), we programmed the following default schedule: Five one-hour sampling intervals spaced throughout the night (at 19:00, 21:00, 23:00, 2:00 and 4:00) with photographs taken every minute. Each Mothbox produces 300 photos (approximately 5.2GB of data) per night on this schedule. We chose this as the default schedule over continuous recording to save battery life while still sampling insect assemblages at different times of night. This approach has the added advantage of clearing the sheet of insects between sampling sessions, which anecdotally decreases the abundance of predators (geckoes, mantids, and ants) on the sheet and allows for insect turnover throughout the night. The Mothbox lasts for approximately 12 hours of run time per battery, or two nights with the default schedule.

The single integrated battery can be augmented by attaching an additional box containing up to three more batteries connected in parallel, increasing run time to 48 hours. Portable solar panels ranging from 10-60 watts can be added to extend run time. Larger solar panels will allow more hours of sampling per night or fewer required hours of direct sunlight. We caution that solar panels are of limited usefulness in closed-canopy tropical forests, especially in the wet season. The Mothbox system can run on any schedule with no hardware modification, the only limitation is battery life and so for continuous operation the Mothbox can be connected to mains power.

The hardware for both Mothbox versions is fully open source with a CERN-OHL-W license (Digital Naturalism Laboratories, 2025a), the operating software has an MIT licence, and the documentation is CC BY 4.0. Full specifications, including instructions for construction, programming, use, and adaptation are available on Github (*Mothbox Github*, 2024).

2.1.2 Mothbeam

To complement the Mothbox, we used an open-source printed circuit board (PCB) with light emitting diodes (LEDs) that emit a range of light frequencies designed to specifically attract insects (the Mothbeam). The Mothbeam, originally created and open-sourced by Moritz Buttlar of LabLab (Buttlar, 2024), was designed in collaboration with the Mothbox team as an inexpensive, open-source equivalent of a LepiLED (Brehm, 2017). There are two Mothbeam PCB configurations, each with three LEDs. One configuration targets violet light (365, 395, 405 nm) and the other targets visible light (one full spectrum white LED, 450, 520 nm). By default, each Mothbox 4.5 comes with one of each PCB and

both PCBs are activated when collecting data. Mothbox 5 has three PCB slots that are each individually controllable. The Mothbox can be programmed to only use one PCB, and the PCBs can be modified to deactivate individual LEDs or dim light intensity, to target particular taxonomic groups or reduce battery consumption. We have also designed stand-alone Mothbeams for use with traditional moth sheeting. Either two or four PCBs are mounted to an aluminium heat sink, housed in water-resistant acrylic housing. Material costs for one standalone mothbeam is approximately $30. Just like the Mothbox, the Mothbeam runs on 12V power (it is operable between 9 and 36V). The addition of an inexpensive ($10) step-up converter allows use of the Mothbeam with any standard USB power bank (5V). Like the Mothbox, Mothbeams are fully open source with a CERN-OHL-W licence (Digital Naturalism Laboratories, 2025b).

2.1.3 Mothbot

We developed 'Mothbot', an open-source machine learning tool and user interface for processing data from automated light traps. There are two parts of Mothbot: 'Mothbot Process' and 'Mothbot Classify'. The first detects insects from sourceImages, identifies them, and spatially clusters them, the second is designed for human validation of computer vision identification and manual finer-taxonomy classification, as well as data export. Mothbot Process uses a combination of two open-sourced AI programs: YOLO (Redmon et al., 2016) and BioCLIP (Stevens et al., 2024). A custom YOLO model trained on Mothbox data from 4500 hand-labeled images automatically detects and crops individual insects (down to ~1 mm total length) from novel imagery. These cropped images (called

‘detections’) are then fed to a modified BioCLIP model with filters for taxonomic and geographic limitations to assist detection. The detections are then processed with a custom clustering algorithm. The detections' visual features are extracted with DINOv2 (https://github.com/facebookresearch/dinov2) and then grouped by similarity with HDBSCAN (Hierarchical Density-Based Spatial Clustering of Applications with Noise - https://pypi.org/project/hdbscan/). These visual clusters are further sub-grouped temporally (i.e. by the time the photo they appear on was taken) to create hierarchical groupings of detected organisms that are not only visually similar but exist in temporal ‘tracks’ over a set of sequentially-taken images. The metadata associated with each detection are then added into each detection image via EXIF.

The resulting output is then loaded into the ‘Mothbot Classify’, a user interface that allows for human validation of the BioCLIP identifications. Mothbot Classify includes an easily searchable, hierarchical taxonomic classification system that can be rapidly applied to detections in a dataset. Mothbot Classify facilitates designating morphospecies that can be linked to iNaturalist observations and exports data to a Darwin Core formatted CSV file (Wieczorek et al., 2012). The human-in-the-loop workflow for refining taxonomy is not required for generating an output CSV file, but we believe it is currently an essential step in generating high-quality data from automated insect monitoring devices, as it is for mammal camera trap data (Huebner et al., 2024; Leorna & Brinkman, 2022).

2.2 Field assembly and deployment

When the arms and target sheet are in place and the Mothbox has been switched on, it can be mounted to a tree using a strap through the handle (Fig 1). Straps used for conventional camera traps work well for this. In our case studies we deployed the Mothbox at chest height on trees, which minimises additional installation equipment while still elevating the Mothbox above the ground to increase attractant light range. Mothboxes can be deployed in the canopy with a throw line, on the ground, in open areas, and mounted to tripods or frames with minor modifications. In some areas, for example the tropical forests we used for the case studies, deploying a Mothbox on the ground not only decreases the range of the attractant lights, but also invites predatory ants and spiders to the target sheet, and so elevating the device is advised. An early version of the Mothbox was developed for drone deployment into rainforest canopies during the 2023 Rainforest XPRIZE competition in Singapore. After collection, photos can be retrieved via a USB drive or SD card, and processed with the Mothbot program.

2.3 Data processing

Processing data with the Mothbot user interface (UI) starts with selecting file paths for a folder containing Mothbox photos, a CSV file that contains deployment metadata, and a CSV file containing a species list. The formatting for the metadata CSV file is based on the Camera Trap Metadata Standard (Forrester et al., 2016) and Darwin Core (Wieczorek et al., 2012) (Table S1). The species list CSV file is in the format of Global Biodiversity Information Facility (GBIF) downloads (Table S2). Species lists from GBIF require cleaning to remove synonyms and other errors (SI Script 1). For our case studies, we generated a

CSV file from GBIF for all insects recorded in Panama and Costa Rica. We also tried running Mothbot with a species list that included arachnids as well as insects, because arachnids are also occasionally attracted to Mothboxes. However, we found that model accuracy improved when arachnids are excluded, and the analysis process was more time efficient when manually correcting the identifications of spiders.

After selection of the required filepaths, the photos can be processed using the tabs on the Mothbot Process user interface. The first tab finds detections on the source image, the second identifies them, the third adds metadata to JSON files associated with each sourceImage, the fourth clusters detections perceptually, and the fifth adds EXIF data, including GPS coordinates and identification, to cropped detections. Complete instructions for data analysis using the Mothbot scripts can be found on the Mothbox website (*Mothbox Github*, 2024). The final output of Mothbot is a CSV file with occurrences and identifications of each organism photographed in a given deployment, following Darwin Core formatting (Wieczorek et al., 2012).

2.3.2 Terminology

To standardize terminology in automated insect monitoring research, and align with standards used for other automated biodiversity data collection (Bubnicki et al., 2024; Wieczorek et al., 2012), we propose a set of terms used to describe different parts of the data collection and analysis workflows. For example, *deployment* describes a discrete sampling interval associated with one location and one device; *sourceImage* describes the whole un-cropped image taken by an automated insect monitoring device; and *detection* specific subset of a sourceImage that covers only a portion of the sourceImage that contains

one item / organism (generally an insect). See Table S3 for a more extensive list of terminology. We understand that terminology will continue to evolve alongside developments in the field of automated insect monitoring, and do not intend for this to be a final, definitive list, rather an entry point for cross-platform collaboration and standardization.

2.4 Case Studies

For both case studies we used tree-mounted Mothbox 4.5 devices. For each night sampled, we recorded data for five hour periods starting at 19:00, 21:00, 23:00, 2:00, and 4:00), with timelapse set to capture one photo every minute (defined as sampling schedule 'scheduleA' in our metadata). After collecting the Mothboxes from the field we processed the data using the Mothbot system set to order level automatic identification, we then manually identified each insect detected to the finest taxonomic level possible and assigned morphospecies to all insects that were not identified to species level.

2.4.1 Case study 1: Insect activity and time of night

The Mothbox is well suited to answer questions about insect behaviour as it is unsupervised and collects standardised data. Most flying insects use light to maintain flight altitude and control, via the dorsal-light-response (Fabian et al., 2024). Because of this, it has been suggested that insects are only trapped by lights in passing, rather than being attracted to them from farther away. Based on the assumption that insects attracted to light

traps, like the Mothbox, are active only in the immediate sampling area, then the Mothbox can assess activity patterns of nocturnal insects and shifts in composition at different times of night. Understanding how the activity patterns of different insects vary throughout the night can help describe ecological relationships that are otherwise difficult to study, such as overlapping activity patterns of different insect groups and species of specialist insectivorous bats (Rydell et al., 1996).

This case study aimed to assess how insect activity patterns changed over the night. A single Mothbox was deployed with an extra battery for four continuous nights 10 - 13 April 2025. The sampling site (7.49388, -80.31782) was located on a ridgetop in a remote part of the Azuero Peninsula of Panama accessed by offroad driving and hiking.

2.4.3 Case study 2: Land use in fragmented landscape

This study demonstrates that the Mothbox has significant potential as a tool for conservation and restoration monitoring. As tropical ecosystem restoration accelerates in response to the twin crises of climate change and biodiversity loss, the need for effective, scalable biodiversity monitoring has never been greater (Collen et al., 2008; Schmeller et al., 2017). While carbon sequestration is relatively straightforward to quantify, assessing biodiversity - particularly insect diversity - remains a major challenge (Wauchope et al., 2024). Traditional survey methods are often labor-intensive, taxonomically limited, and spatially constrained, making it difficult to capture the full complexity of ecological recovery. As a result, large-scale reforestation projects tend to be evaluated and funded based on carbon outcomes, while biodiversity gains remain poorly documented and

undervalued (Cole et al., 2024; Ermgassen & Löfqvist, 2024). Panama currently recognizes monoculture plantations of introduced timber species as a type of reforestation (*DECRETO LEY No. 1*, 1994), while ecological restoration success tends to be higher for natural regeneration than for active restoration in tropical forests (Crouzeilles et al., 2017). To assess the effect of different reforestation systems on insect diversity, we deployed four Mothboxes simultaneously on the Azuero Peninsula of Panama at four sampling points for two consecutive nights 11 - 13 April 2025. The Mothboxes were deployed in two stands of teak plantation, a young secondary forest planted with native species, and a mature secondary forest. All sampling points were separated by at least 250m.

3 Results and Discussion

3.1 Deployments

During the insect activity and time of night case study Mothbot generated a total of 6,271 detections, with nine orders and 43 families represented across all nights of the deployment. A total of 219 unique species were recognised but only 36 of the species could be readily identified to species level by a general entomologist (not an expert taxonomist), the remaining 183 (84%) were assigned morphospecies names. A total of 1046 images were collected during this deployment, less than the expected 1200 due to early battery discharge on the last night of the deployment (consequently, there is no data for the final session of night 4). The target sheet was clean of insects at the beginning of each hour-long session (Fig. 3 c and d), indicating that when the Mothbeam attractant lights were off all insects left the sheet. During each session, both number of detections per photo (Fig. 3 c)

and morphospecies richness (Fig. 3 d) increased with time since attractant lights turned on. The first session (19:00 - 20:00) had the greatest number of cumulative detections and the greatest morphospecies richness (Fig. 3 a and b) (P = .0002 and .0021, respectively, ANOVA).

During the land use case study Mothbot generated a total of 2,755 detections across all four sampling sites and both nights of the deployments. Eight orders and 40 families were represented, and a total of 158 species were recorded (though 94% were designated morphospecies). Both mature and native restoration forests had greater species richness and number of detections than the teak plantations. The mature forest site had greater richness than the native restoration forest, while the converse was true for the total number of detections (Fig. 4).

Some limitations encountered during the deployments included the limited battery life restricting the monitoring time, and the potential for insects to land outside the camera frame (e.g. on the bark of the deployment tree). Battery life could be extended with use of additional batteries or a solar panel positioned in the canopy or forest clearings. However such logistical difficulties may not be required for obtaining ecologically significant results, given that it is possible to differentiate forest types from collecting moth data for just one night (Duran et al., 2022b). Both case studies occurred towards the end of the dry season, when the moon was close to full and above the horizon during all sampling intervals. Both of these variables suggest that total richness and activity were underestimated for these sample sites (Janzen, 1987; McGeachie, 1989). It did not rain during our chosen case studies as it was the dry season in Panama, however Mothboxes withstood daily downpours during wet season testing in Panama for several weeks at a time. Due to the

remoteness and rugged terrain of the field sites used for our case studies, we deployed the Mothboxes on trees using camera trap straps. This is the fastest, lightest, and easiest system, short of putting them on the ground, however it does mean that some moths attracted to the Mothboxes likely landed on the trunk of the tree instead of on the target sheet.

3.2 Data processing

The Mothbot system allows users to choose the taxonomic level at which the AI identifies detections. Model accuracy depends largely on the quality and quantity of reference data, as well as the presence of cryptic species. Finer taxonomic resolution introduces accuracy trade-offs and increases the time required for manual validation. We found the model sufficiently accurate at the Order level for rapid human validation. In highly diverse regions with limited reference data, such as the tropical forests used in our case studies, the model performs poorly at species level. With more manual identification of automated insect detections, we expect that future AI models will achieve finer resolution, with reliable family-level identification for most groups and genus- or species-level identification for selected taxa.

Our data analysis system is based on the assumption that automated monitoring systems for insects empower experts and do not replace them. Expert taxonomists will be invaluable in the training and refinement of AI models. Consequently, we prioritized accuracy and ease of human verification over fine taxonomic identification at this stage. When expert taxonomists are not available to aid in data validation and refinement, we

recommend uploading one example of each morphospecies (unique-looking insect that is distinct from others but cannot be identified to species level) from each deployment to iNaturalist for verification (Campbell et al., 2023). Because BioCLIP uses GBIF data, these iNaturalist uploads will eventually feed back into improving the accuracy of Mothbot identifications.

4 Future Directions

4.1 Hardware

Mothbox can be adapted for specific use cases beyond those showcased in the case studies. For example, Mothbox hardware includes extra relays that can be used for adding additional functions such as triggering a release of pheromones at programmed times to attract targeted species, or to control nectar release from a synthetic flower. The main limiting factor for deployment length is battery life. If deployed in a location with continuous power, Mothboxes could operate for entire field seasons rather than just short deployments in remote locations. While we have focused on nocturnal insects and have only conducted tests at night, the additions described above could expand the range of operation into daytime. The Mothbox is designed as a standalone sensor, but it is ideally suited for use in multi-sensor monitoring arrangements, for example with simultaneous acoustic monitoring with Audiomoths (Hill et al., 2017), and conventional camera traps. In addition, synchronizing Mothbox data collection with environmental variables, including ambient light, wind speed, humidity, precipitation, and temperature, would help identify

the drivers of changes in insect activity throughout the night and shifts in insect richness across seasons.

While Mothbox development has focused on deployment in remote tropical locations, the system can be applied in any regions or ecosystem where there is an interest in monitoring nocturnal insects. Inclusion of Mothboxes in large-scale ecological monitoring networks like the Long Term Ecological Research (LTER) network and the National Ecological Observatory Network (NEON) would yield an additional valuable dataset for insect population trends (*LTER*, n.d.; *NSF NEON*, n.d.). Mothbox would also be well suited to monitor pollinator activity and diversity in agriculture, or the spread of invasive species.

4.2 Data processing

The accuracy of computer vision models improves when the training data closely matches the data being classified, and Mothbox raw images provide ideal conditions: insects are captured against a flat white background, with consistent lighting and a fixed distance from the camera. The same cannot be said for the massive and visually diverse datasets like those on GBIF, which include many dead, pinned insects, and insect *in-situ* in their environments. In time, with larger Mothbox datasets, we will augment the BioCLIP model with human-validated data identified to finer taxonomic resolution data, producing a region-specific improved version of the Mothbot that can accurately identify taxa below family level. We believe that this tiered regional approach will result in the highest quality and efficient data collection, whereby an initial round of monitoring and identification to a coarse taxonomic resolution using the default Mothbot is followed by human validation to

create a regional reference library. Future collections in the region can then be run through an augmented Mothbot system at finer-scale resolution. We believe that broad use of this approach will rapidly change our ability to classify species so that all insects photographed with automated insect monitors can be confidently identified to Genus or Family level by Mothbot. In the meantime, higher taxonomic levels can be used as surrogates of species-level data (Báldi, 2003; Zou et al., 2020), an approach that is key to current large-scale insect monitoring in the tropics while taxonomic expertise, genetic reference libraries, and photographic reference libraries catch up with monitoring needs.

Future success of automated insect monitoring will require greater investment in traditional taxonomy and ecological research. The accuracy of the computer vision models employed by automated insect monitors like the Mothbox are limited by training data. Improving training datasets will require manual validation and refinement of existing images and ongoing data collection. Automated insect monitors are likely to document undescribed species, presenting exciting opportunities for prioritising sampling sites and taxa for identification and description of novel species.

Perhaps the most important need for automated insect monitoring is a centralised repository for human-validated image storage and model development. Such repositories exist for mammal camera trapping (Vélez et al., 2023). A comparable platform for insect light-trap data would allow projects worldwide to upload their observations, with human-validated records feeding into regionally refined machine-learning models. In return, users would receive AI-based identifications and organised datasets. As participation grows, the expanding volume of training data would further improve identification accuracy. To reduce cloud storage requirements for such a repository only cropped images that have

undergone an initial on-board processing step could be accepted, rather than bulk raw data which is often largely composed of blank sheet space.

5 Conclusion

Mothbox will offer for insect monitoring what low-cost camera trapping offers for mammals. By decreasing the time, cost, and specialised knowledge required for monitoring insects, Mothbox enables standardised insect monitoring at the landscape scale. This technology increases scientific capacity for monitoring global trends in insect populations, and acts as a tool for exploring new ecological relationships and behavioural patterns. Importantly, Mothbox will make biodiversity monitoring more accessible to community conservation groups, empowering restoration and conservation.

Figures

Figure 1 Mothbox 4.5 deployed in a tropical forest in Panama.

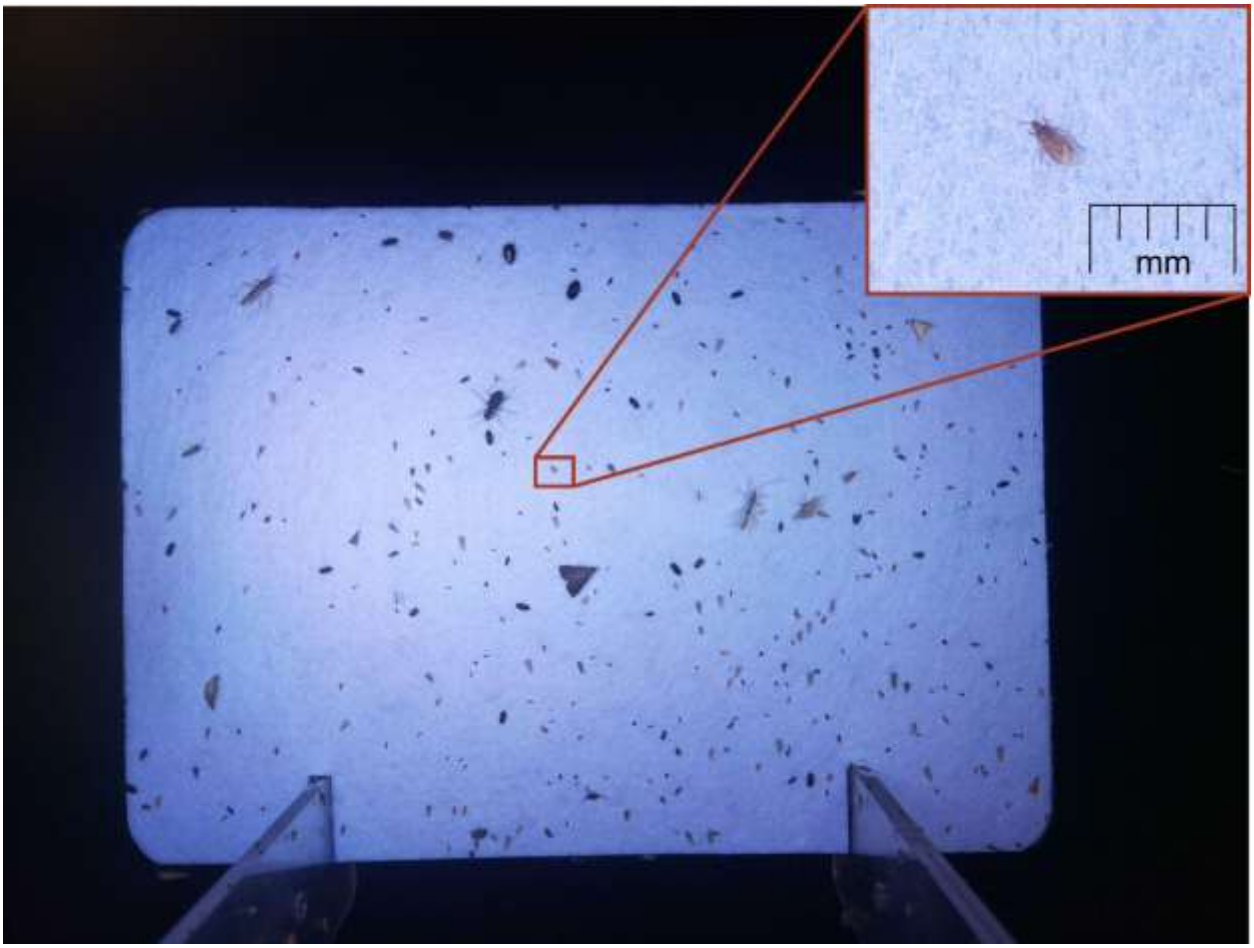
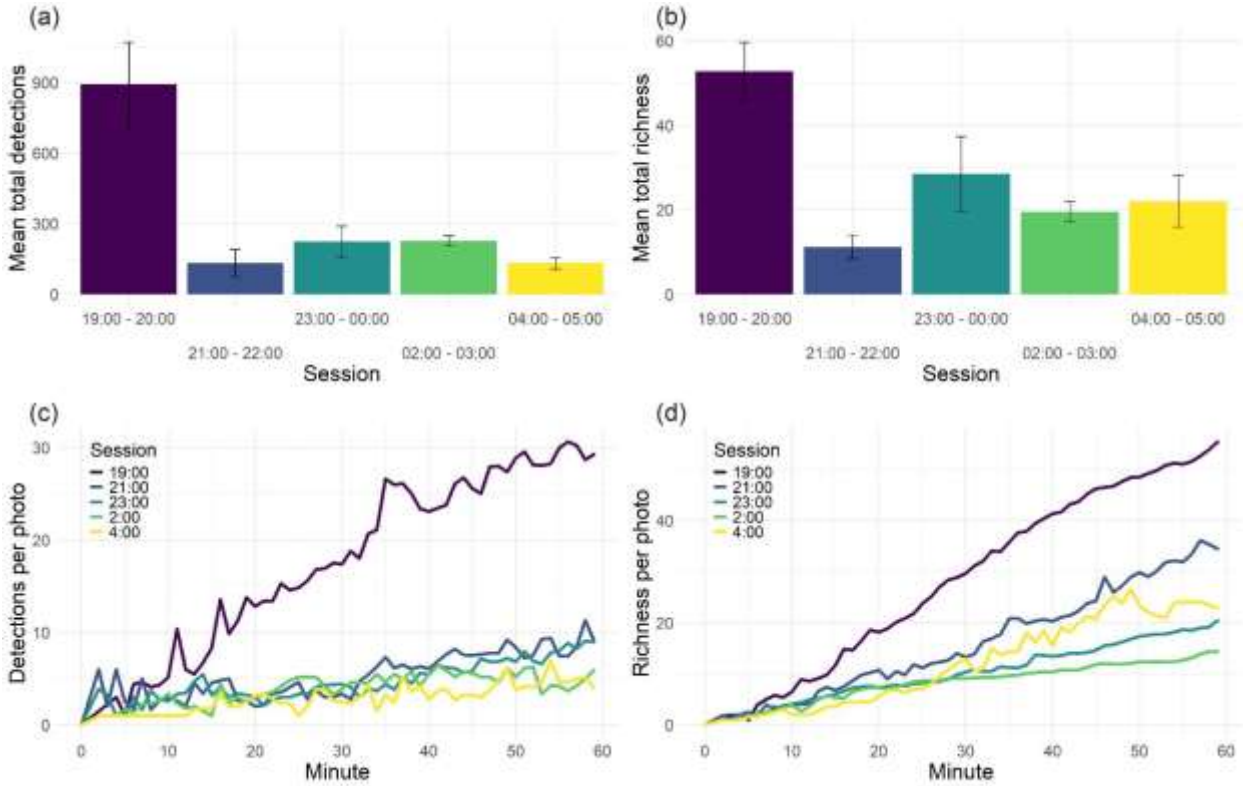


Figure 2 Unedited photo taken by a Mothbox in Panama, with an inset to demonstrate the capacity for documenting small insects like this 1.5 mm long minute pirate bug (Anthocoridae). The resolution of the full photo is 9248 x 6944 pixels. The scale provided in the inset photo is in millimeters.



(c)

Figure 3 data from insect activity case study: (a) total number of detections (individual organisms in each photo, for all photos) for five discontinuous one-hour sampling sessions; (b) total species richness within five discontinuous one-hour sampling sessions; (c) total number of insect detections in each photo by minute from start of sampling, for the five sampling sessions; (d) species richness per photo across the five sampling sessions. All four panels represent data averaged across the four nights of the deployment. The effect of session on cumulative detections and richness was significant (P = .0002 and .0021, respectively). Error bars in (a) and (b) represent standard error.

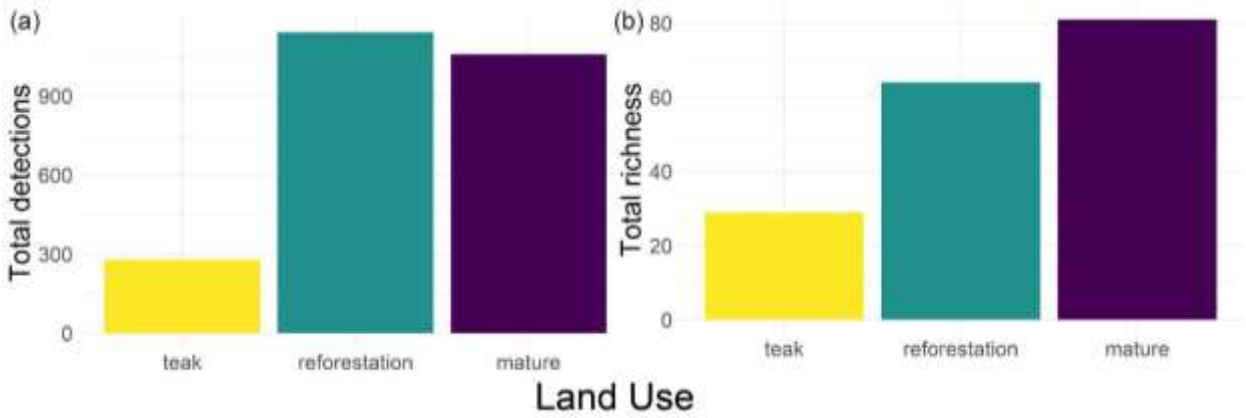


Figure 4 Insect detections and richness for different land uses. Four Mothboxes were deployed simultaneously for two nights at points with different land use histories. Two points were in non-native teak (*Tectona grandis*) plantations, one point was in an area planted with native tree species and undergoing natural regeneration, and one point in mature native forest. Data from both nights was pooled for each point, and teak plantation data was averaged. (a) shows the total number of detections for each land use type, and (b) shows the total species richness for each land use type.

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