11. The use of artificial intelligence and automatic remote monitoring for mosquito surveillance

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Abstract

Mosquito surveillance consists in the routine monitoring of mosquito populations: to determine the presence/absence of certain mosquito species; to identify changes in the abundance and/or composition of mosquito populations; to detect the presence of invasive species; to screen for mosquito-borne pathogens; and, finally, to evaluate the effectiveness of control measures. This kind of surveillance is typically performed by means of traps, which are regularly collected and manually inspected by expert entomologists for the taxonomical identification of the samples. The main problems with traditional surveillance systems are the cost in terms of time and human resources and the lag that is created between the time the trap is placed and collected. This lag can be crucial for the accurate time monitoring of mosquito population dynamics in the field, which is determinant for the precise design and implementation of risk assessment programs. New perspectives in this field include the use of smart traps and remote monitoring systems, which generate data completely interoperable and thus available for the automatic running of prediction models; the performance of risk assessments; the issuing of warnings; and the undertaking of historical analyses of infested areas. In this way, entomological surveillance could be done automatically with unprecedented accuracy and responsiveness, overcoming the problem of manual inspection labour costs. As a result, disease vector species could be detected earlier and with greater precision, enabling an improved control of outbreaks and a greater protection from diseases, thereby saving lives and millions of Euros in health costs.

Keywords: mosquito monitoring, remote surveillance, acoustic sensor, optical sensor, intelligent sensor, smart trap, machine learning, Internet of Things (IoT)

Mosquito surveillance and traditional monitoring methods

Mosquitoes (*Diptera, Culicidae*) are responsible for the transmission of diverse medically and veterinary important disease agents (viruses, protozoans and other parasites) which cause serious diseases in humans and animals, such as malaria, dengue, Zika, yellow fever, chikungunya, West Nile virus, Eastern equine encephalitis or avian malaria. Entomological surveillance plays a key role in human and veterinary disease surveillance within the framework of the 'One Health' concept, where interdisciplinary collaboration and communication in healthcare is crucial (ECDC 2012, 2014, WHO 2017). A paradigmatic example of this 'One Health' approach would be the West Nile Virus (WNV) surveillance. This implies a coordinated strategy of Public Health actors that carry out the diagnoses of possible infected horses and humans that are dead end hosts of the pathogen; the monitoring of *Culex* mosquitoes that may act as vectors in the areas with WNV cases; and the detection of possible infected birds which may act as reservoirs of the virus.

Mosquito surveillance methods should provide clear and meaningful information for program managers and policy-makers for the purpose of: (1) determining and quantifying the composition of mosquito populations which are present in a specific area; (2) monitoring changes in mosquito populations; (3) identifying the presence of new invasive mosquito species which can act as disease vectors; (4) detecting mosquito-borne diseases; (5) determining which control measures need to be conducted; (6) performing the quality assessment of control measures; and (7) designing accurate risk assessment programs in order to prevent and manage potential disease outbreaks (Flores 2015, Schaffner *et al.* 2014).

Mosquito surveillance can be understood as a task involving the routine monitoring of immature stages and adult mosquito populations over the course of an entire mosquito season (Flores 2015, Silver 2008). Several methodologies have been developed to sample and analyse different stages of the biological cycle of mosquitoes (egg, larvae and adults), although most of them mainly target adults since only adult female mosquitoes are responsible for disease transmission (Focks 2003, Sivagnaname and Gunasekaran 2012). Thus, with the exception of pathogen monitoring in immature stages to investigate vertical transmission, adult mosquito surveillance is probably the most precise approach to properly monitor mosquito populations for vector-borne disease (VBD) risk assessment. While some methodologies focus on resting mosquitoes, such as aspiration in vegetation that is performed with entomological aspirators, most have been developed to catch flying mosquito females when seeking hosts for blood feeding or gravid females when seeking oviposition sites (Becker *et al.* 2010, Service 1993).

To allow standardised monitoring of adult mosquito populations, many types of traps have been developed to attract different target species. Some rely solely on a conventional incandescent filament light bulb as the main source of attraction or use an ultra-violet light source while others add CO2 or chemical attractants to the light source. Various models are commercially available. The most popular are adapted models of CDC mosquito light-traps, EVS trap (Figure 1) and in the last decade, BG sentinel traps (Figure 2) with different combinations of light, CO_2 and chemical lure (EMCA 2020). Other traps include the Reiter trap for gravid females, and even types developed not just for mosquito sampling but for mosquito control as well, such as the Mosquito Magnet™, among others. Despite these methodologies, during the first decade of the 21st century the need became evident for a much greater effort to develop, manufacture and market new tools that would be effective for different species and environmental conditions and that could be standardised in different countries in order to obtain more significant and comparable data (Qiu *et al.* 2007).

Several studies have compared the efficacy of different commercial trapping devices, reporting differences in both performance and efficacy depending on the target mosquito species, the type of attractant and other environmental factors (Brown *et al.* 2008, Li *et al.* 2016, Lühken *et al.* 2014, Roiz *et al.* 2012). Generally, BG-traps have shown better, or at least a similar performance, compared to CDC, EVS or MM traps (Li *et al.* 2016, Lühken *et al.* 2014), but the results have been dependent on multiple factors and varied from one study to other. It is important to consider, as pointed out by Brown *et al.* (2008), that differences between traps could affect the estimations of species abundance and composition.

Figure 1. Classic EVS mosquito trap baited with a container with CO_2 pellets.

Figure 2. BG sentinel trap.

Traditional surveillance methods have two main limitations. The first is the cost in terms of time and professionals involved in the surveillance (trap placement, sample collection and transport of the sample to the laboratory for the counting and identification of captured mosquitoes). The second limitation is the inevitable time lag between the moment that the trap is placed in the field and the moment the sample is collected. This lag can be crucial, potentially resulting in the dynamics of mosquito populations in the field not being accurately and timely monitored (Focks 2003).

In this scenario, artificial intelligence (AI) is forging a path in improving traditional entomological surveillance methods by generating new techniques for the automated remote monitoring of mosquito populations. These new approaches include the emergence of automated electronic devices which remotely classify mosquitoes based on the analysis of their flight pattern (Potamitis 2014, Santos *et al.* 2019).

In addition, the use of the 'Internet of Things' (IoT) is enabling that the information collected remotely in the field could be sent wirelessly to a cloud server in real time (Eliopoulus *et al.* 2018, Geier *et al.* 2016, Potamitis *et al.* 2017). Thus, eliminating the gap between trap installation and collection, representing mosquito population dynamics much more accurately.

New technological approaches for remote mosquito surveillance through the perspective of artificial intelligence

Acoustic sensing technology

Mosquito flight tones have been extensively studied since the first half of the 20th century, mainly through the use of acoustic methods such as microphones (Kahn and Offenhauser 1949). Mosquito flights produce a tone as a side effect of wing movement. This tone is also a communication signal that is frequency-modulated during courtship and can be detected by other mosquitoes thanks to certain properties of their antennae including Johnston's organ at the base of each antenna (Cator *et al.* 2009, Gibson *et al.* 2010). Rapid frequency modulation flight in males occurs as a response to female wing beat frequency and is likely to represent a pre-copulatory controlled flight to maintain a close-range position while attempting to seize and engage terminalia with the female (Simões *et al.* 2016). Females have the ability to reject or accept the male mating attempt. In the event that the interaction between male-female pairs is successful, copulation will take place preceded by an acoustic harmonic convergence (Aldersley and Cator 2019, Aldersley *et al.* 2016).

With these acoustic properties in mind, entomologists have been pursuing the control of mosquitoes by means of sound traps for many decades (Kahn and Offenhauser 1949) and continue to do so (Diabate and Tripet 2015, Rohde *et al.* 2019). Sound traps, such as the Sound Gravid Aedes Trap (SGAT), the Male Aedes Sound Trap (MAST) (Staunton *et al.* 2020a), or other modified commercial traps with an acoustic basis, are nowadays being used as cost-effective alternatives for field use in areas with sterile male mosquito rear-and-release programs (Johnson and Ritchie 2016, Rohde *et al.* 2019, Staunton *et al.* 2020b).

The acoustic detection of insects is a highly active research field, especially in its application to food crops and stored grain pests (Eliopoulos *et al.* 2016, Hagstrum *et al.* 2012, Potamitis *et al.* 2009) but also with respect to pests of medical importance, such as mosquitoes (Salim *et al.* 2017, Vasconcelos *et al.* 2019). In recent years, so-called deep learning techniques have become widely used in bioacoustic classification tasks based on the analysis of mosquito wing beat frequency. However, since mosquitoes from different species can actually have overlapping frequency distributions, it seems insufficient to use the fundamental wing beat frequency as the sole distinguishing characteristic between species (Chen *et al.* 2014). To improve the classification method, metadata such as time or place of recording can be used as additional features to differentiate between mosquitoes with varying circadian activity or geographic distribution.

Current approaches for mosquito wing-beat analysis and classification through acoustic sensors include the use of mobile phones as an easily available tool for entomological surveillance (Fernandes *et al.* 2020, Li *et al.* 2017, Mukundarajan *et al.* 2017). Mobile phones offer the advantage of automatically registering time and location stamps for acoustic data and allow the collection of other metadata such as photographs which can support identification. Studies based on mobile phone-based bioacoustics demonstrate that even low-cost smartphones are capable of accurately recording mosquito wing-beat frequencies, enabling continuous and large-scale data mapping which can be particularly useful in resource-constrained areas (Mukundarajan *et al.* 2017). In this sense, there are some open data platforms that rely on the participation of non-expert volunteers to record the wing-beat sound of the mosquitoes. Two of the most popular ones are 'ABUZZ' (Mukandarajan *et al.* 2019) and 'Humbug Zooniverse' (Kiskin *et al.* 2020).

The inconvenience of acoustic methods is the limitation to the quality of the microphone recordings of the insects in field conditions. Many mosquito bioacoustics experiments are undertaken in unnatural conditions with tethered individuals or in acoustically isolated spaces, thus leading to difficulties to apply these models in in field conditions (Arthur *et al.* 2014). Given this difficulty in microphone-sourced field recordings, classification models based on machine learning algorithms commonly suffer from scarce and poor-quality data.

Chen *et al.* (2014) reported a 'lack of progress' in acoustic technology applied to the automatic classification of insects. This can be attributed to limitations of the microphones themselves. One such limitation is microphone sensitivity. The sound attenuates with the distance from the microphone according to an inverse squared law, which means that if an insect is flying three times more distant from the microphone, the sound intensity will drop to one ninth. When increasing the microphone sensitivity to mitigate this effect, any surrounding noise will saturate the signal. Filtering insect detection can then become a complex task, as well as requiring more system processing power. Besides, systems based on a microphone and recorder set spend the entire experiment running time making recordings, thus increasing power consumption.

The foremost challenges for acoustic sensing approaches are related to dealing with the problem of the signal-to-noise ratio of recorded audio and power consumption. As a result, optical approaches for remote sensing and automatic classification have gained in popularity as they offer significant performance advantages (Potamitis and Rigakis 2015, Santos *et al.* 2018, 2019).

Optical sensing technology

Optical technology for mosquito wing beat analyses dates back to the second half of the 20^{th} century when the first photoelectric cell was discovered to detect the light modulation of a flying insect crossing its field of detection (Richards 1955). This was the starting point for the implementation of numerous studies on the use of optical sensors to monitor mosquito flight patterns which continue to the present day (Gibson *et al.* 2010, Kirkeby *et al.* 2016, Ouyang *et al.* 2015, Potamitis 2014, Potamitis and Rigakis 2016a).

The diverse light source options for optical sensing include laser and LED (light emitting diodes). Potamitis and Rigakis (2015) developed a novel noise-robust optical sensor to record insect wing beats and analysed the recording performance of both types of light sources, comparing them to the recordings of an acoustic sensor. The results showed that both performed as well or even better than the acoustical sensing approach in any ambient light condition. Unlike acoustic sensors, optoelectronic sensors only record when triggered by flying insects, allowing large savings in power consumption. In addition, optoelectronic sensors are capable of modulating the optical signal at high frequencies, thus eliminating major optical interference sources and increasing sensor efficiency without further data processing requirements (Santos *et al.* 2018).

Optical sensors basically comprise an optical emitter (a laser beam or a LED array) and an optical receiver (a phototransistor, mainly photodiodes) creating a FOV (field of view). When an insect crosses the FOV, fluctuations in light intensity (caused by the partial occlusion of the light from the wing's movement) are perceived by the optical receiver. The signal containing information on the detected insect's wing beat frequency is then amplified, filtered, and demodulated in an audio signal (Batista *et al.* 2011, Potamitis and Rigakis 2016b). The conversion of the optical signal into audio data allows comparison of the results obtained with those available in the literature for acoustic systems.

The practical applications of these new findings involve extending the use of optical sensors from laboratory tests to the production of massive datasets and the creation of smart insect traps that can count, recognise, and alert for the presence of insects of economic and public health importance (Potamitis *et al.* 2018). Novel optoelectronic sensor prototypes are being trained with several machine learning algorithms, mainly Bayesian classifiers, to learn how to distinguish between mosquito species and mosquito gender (male and female) based on their wing beat frequency (Batista *et al.* 2011, Genoud *et al.* 2018, 2019; Ouyang 2015; Potamitis and Rigakis 2016b). While high accuracy values in gender discrimination are now commonly obtained, classification to species level is still challenging (Genoud *et al.* 2018), although the use of deep learning techniques has shown promising levels of precision (Fanioudakis *et al.* 2018).

The biggest difficulty appears when trying to distinguish two different mosquito species from the same genus as they may have overlapping frequency spectrums. This suggests that the fundamental wing beat frequency alone, although it may be sufficient to distinguish the mosquito genus or gender, it may be insufficient on its own to properly classify mosquito species. This inefficacy will be even more apparent in the context of field measurements, where plenty of mosquito species, Diptera and other insects may be present. A common way to improve identification accuracy is to add other predictor variables in addition to fundamental wing beat frequency (Batista *et al.* 2011, Chen *et al.* 2014, Genoud *et al.* 2019). For instance, Genoud *et al.* (2019) proposed the use of the depolarisation ratio of the mosquito body together with the wing-beat frequency to distinguish gravid from non-gravid females, which reported high accuracy results.

Another option to increase the accuracy of automated taxonomical classification of mosquitoes in field studies may be the use metadata (Chen *et al.* 2014): meteorological features (temperature, humidity, and air pressure), spatiotemporal features (distance from freshwater, land cover type, human/livestock population density, local agricultural type, time of year, time of day, etc.) and circadian rhythms. Certain species are more adapted to survive in particular environmental conditions, e.g. many mosquitoes are native to tropical and subtropical regions, where the climate is typically warm and wet. The ambient temperature can be determinant in insect classification since it influences insect metabolism, leading to an increase in the wing beat frequency. Villarreal *et al.* (2017) reported an increase of 8-13 Hz per degree Celsius (°C) in females of *Aedes aegypti*, revealing a highly dependent relationship between these factors. Circadian rhythm is also an important feature to be considered since mosquitoes have different peaks of activity throughout the day which can be of help to distinguish between species. However, circadian rhythm cannot be used without at least a rough estimate of the population of each considered species (Genoud *et al.* 2019). If a species with a small population has an activity peak at the same time as another with a much larger population but with lower activity, although their probability of interaction with the sensing instrument may be equal, the classification system will consider the former to be much more likely, thus inducing a bias in the results.

New optoelectronic devices for remote sensing include, in addition to insect counts and classification, the use of IoT technology. This allows that the entire information that is being registered remotely in the field, is also being transmitted wirelessly to a central monitoring agency in real time for risk assessment analysis. In this way, novel optoelectronic sensors can be self-organised in networks that collectively report data at local, regional, country, continental, and global scales. The emergence of so-called e-traps has the potential to profoundly impact entomological surveillance and pest control (Potamitis *et al.* 2017).

Smart trap technology

Novel smart traps entail the possibility of automating everything that is still presently done manually (collecting insect information in the field, processing that information, and sending it to vector control technicians) thanks to the use of IoT technology. The development of IoT solutions using conventional approaches is complex and time consuming due to the lack of common architectures and languages, and the widespread use of non-standard, proprietary interfaces and sensor data formats. Numerous developers, companies and R&D groups have been using state-of-the art commercial platforms like Arduino (Italy), Raspberry Pi (UK) or BeagleBone (USA), which are capable of prototyping straightforward sensor applications with low technology readiness levels (TRL) of between 1 and 4. However, such platforms may be insufficient if advances are to be made to TRL 5 prototyping and above, especially if dealing with sensors that are not off-the-shelf. This implies that off-the-shelf platforms offer limitations to reach TRL 9 (go-to-market), where manufacturers will be fighting issues of functionality, cost, power consumption, scalability, margin, manufacturability, testability, packaging, mechanical robustness and working conditions (e.g. temperature, humidity), etc.

To address this, IRIDEON (Spain) has developed SENSCAPE®, a disruptive, modular, standards-based framework for the development of fast IoT time-to-market solutions. There are several advantages to developing an IoT application with SENSCAPE: (1) ready-made hardware platforms – static and mobile; (2) standards based, (3) interoperability; (4) scalability; (5) low power consumption; (6) reduced costs; (7) smartphone integration; (8) customisation and (9) cloud-ready. The general idea is to use SENSCAPE® as the platform to combine a sensor capable of capturing physical information from flying insect, with two emerging disruptive technologies: IoT and AI.

The IoT refers to systems of physical devices that receive and transfer data through wireless networks without human intervention, while AI refers to the combination of algorithms developed to have machines reasoning like human beings. The combination of these various elements could lead to a solution where each trap acts as an interconnected device that can remotely analyse each captured flying insect, just as a professional entomologist would do.

For the moment, only one optical sensor product designed for the remote monitoring of mosquito populations is commercially available, the Biogents BG-Counter (Germany) (Geier *et al.* 2016). This device is able to distinguish between mosquitoes and other different insects, and to count mosquitoes, but does not provide further information on mosquito species, sex or other attributes. In parallel, there is another optoelectronic sensor prototype that has been created by IRIDEON (Spain), which is already capable of distinguishing between species, sex and age of mosquitoes in laboratory conditions (Brosa 2018). The mosquito sensor is an optoelectronic device comprising an emitter, an array of LEDs, and an array of phototransistors acting as photoreceptors connected in parallel. This optical setup generates a light field. The sensor constantly captures the input from the sensor but only processes the samples when a triggering event occurs, i.e. when there is a perturbation of the light field. Optical sensor, microprocessor, and wireless communications are integrated into the electronics module.

Smart trap stations can be deployed as a wireless sensor network (WSN) with bidirectional management of data between sensors and a cloud application framework. When an insect is drawn into the trap equipped with a sensor, its characteristic wing flapping modulates the light field. Captured signals are sampled at a rate sufficient to resolve the fundamental frequency of the wing-flap as well as several overtones. The light field is also perturbed by other physical elements associated to the flying insect: the kinetics of flight (speed, direction, and trajectory) and morphology (body/wing size and shape). Each of these physical elements of flying insects that cause a perturbation of the light field leads to a species-specific signature. The signal of this signature is filtered, amplified, acquired and processed using a combination of AI methods (e.g. rule-based systems, genetic algorithms, artificial neural networks and fuzzy models). Depending on the tests performed, these methods can be used to count each event that perturbs the light volume, determine if the event is caused by a flying insect, analyse if the flying insect is a mosquito or not, classify the genus of the insect, identify the species, identify the sex and estimate the age in days (Figures 3 and 4).

These assets have been benchmarked by experts and judged to be at TRL 7 for genus (accuracy 90-92%), species (accuracy 75-80%) and sex classification (accuracy 93-99%) of *Aedes albopictus*, *Ae. aegypti* and *Culex pipiens*. The sensor also achieved TRL 5 for age classification of each of these species (accuracy 61-95%), giving an overall TRL 6 (Brosa, 2018). Further work is being done to improve the overall accuracy of the solution to reach TRL 9 by 2022.

How intelligent traps can improve mosquito monitoring and arbovirus control programs

Integrated pest management (IPM) relies on the accuracy of pest population monitoring (Freier and Boller 2009). Without gathering information of population dynamics, and related ecological factors, it is almost impossible to execute an appropriate control at the right place and time. Mosquitoes are usually spread across large areas and boundaries, and the use of traditional surveillance methods which are strongly dependent on human labour is unsuitable for efficient large-scale monitoring (BIPRO 2009). Fully automated remote monitoring could be the key in this context.

Earth observation service for preventive control of insect disease vectors – the VECTRACK project

Obtaining high quality field information is notoriously costly and time consuming. The amount of money required can significantly be reduced by combining cost-efficient sampling strategies,

Figure 3. Vector control technician installing a trap with IRIDEON's smart mosquito sensor.

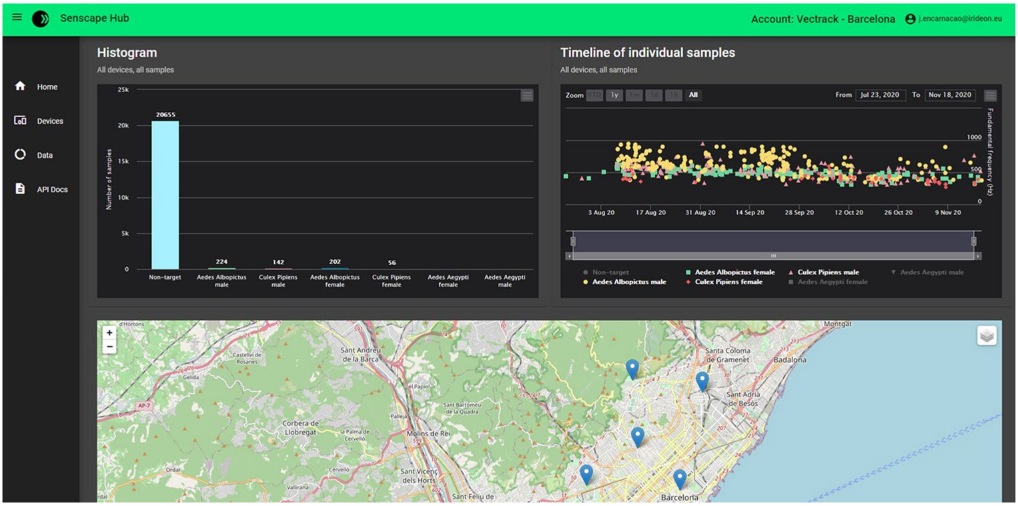

Figure 4. Dashboard of the software cloud application of the smart mosquito sensor.

remote sensing, and spatial modelling techniques to compute risk maps of vector presence and abundance, as well as maps indicating high-risk zones for the establishment of exotic species at local or regional level. Such maps could then serve as a basis for targeted surveillance and VBD risk assessments. To address this, IRIDEON is heading a Horizon 2020 (H2020) project called VECTRACK, in collaboration with AVIA-GIS (Belgium), the IRTA-CReSA research institute (Spain) and the public health institute CEVDI/INSA (Portugal). VECTRACK constitutes a novel and unique opportunity, integrating the added value of Earth observation (EO), spatial-positioning and information and communications technology (ICT) technologies: Copernicus data + operational vector mapping with spatial modelling + IoT ground sensors + IoT smart mosquito traps + IoT interoperable disease vector data cloud application. The proposed innovation is a service platform for which Copernicus is a critical part of the solution. The main objective is to develop and validate a new Copernicus-based EO service to monitor disease vectors, associated to a novel ground wireless sensor network comprising miniaturised nodes measuring micro-environmental data (T °C, %RH, etc.), together with a smart trap station acting as a gateway.

Earth observation platform can measure land surface temperature and vegetation, which act as the main drivers of vector population (C3S 2020). Given the importance of the evolution of the meteorological parameters, the technical requirements for these satellites are: (1) high temporal resolution (1 day); (2) medium spatial resolution (1 km); and (3) measurement in the visible/near infrared part of the electromagnetic spectrum for derivation of vegetation indices and in thermal infrared for temperature.

In this context, it is important to mention the contribution of AVIA-GIS in their development of VECMAP, a seamless system and service that integrates the entire process of producing risk maps into a single package that supports all the steps required to map and model, at various scales, the distribution of vectors and to plan surveillance and control programs. This system provides all the satellite data required to obtain the risk maps, however is limited by the fact that it uses data from periodical manual trap inspections. This value proposition is strengthened by IRIDEON's smart IoT ground sensors, deployed in the field integrated with standard commercial mosquito traps. With the combination of all approaches, it is finally possible to remotely and automatically acquire near real-time ground data on mosquito counts, sex, species, age and local micro-environmental parameters. This data is invaluable as an automatic and direct input to feed mosquito-borne epidemic models.

Future approaches

With the use of novel smart traps, new challenges will appear; the automated identification of different mosquito species should be improved to the same level as when it is performed by a skilled entomologist and should be supervised until this degree of accuracy is reached. New maintenance and logistic protocols will need to be developed, as traps will go from being mobile and temporary to fixed and permanent.

With new methodologies, surveillance and control programs can be significantly affected as they require important scientific and logistic efforts for the management of large amounts of mosquito traps and collected samples. With the use of remote monitoring systems, once the system has been developed, these efforts can be redirected to other areas and most of the classification work would be done in an automatic way, but always with an accurate quality control system. The data will be completely interoperable and thus available for the automatic running of prediction models, the performance of risk assessments, the issuing of warnings and the undertaking of historical analyses of infested areas. In this way, vector control professionals could establish automatic surveillance programs with unprecedented accuracy and responsiveness, overcoming the labour costs of manual inspections. As a result, disease vector species will be detected earlier with greater precision, enabling improved control of outbreaks and a lower risk of disease transmission.

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