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Chapter · September 2025

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# Health Protection, Including Environmental and Food Safety (EPHO 3)



Anna Förster, Gibson Kimutai, Myat Su Yin, Peter Haddawy and Urte Klink

**Abstract** Health protection encompasses measures and practices that protect individuals, groups, or populations in order to prevent and mitigate the effects of infectious disease, environmental, chemical, or other threats. Digital tools and approaches increasingly shape the field covered by this essential public health operation, namely infectious disease control, as experienced during the COVID-19 pandemic. Here, we provide various perspectives and two specific examples of digitalization: infectious disease vector monitoring as an environmental health topic and food safety. These examples exemplify the broad range of topics the EPHO covers. We highlight the potential as well as limitations of digital tools to support these areas.

**Keywords** Environmental monitoring · Internet of things · Machine learning · Workplace protection · Mosquito counting · Mosquito identification

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# 1 Introduction

Health protection is a rather generic term encompassing measures and practices that protect individuals, groups, or populations to prevent and mitigate the effects of infectious disease, environmental, chemical, or other threats (Ghebrehewet et al. 2016). Health protection is one of the key fields of public health and an essential public health operation (EPHO3), with environmental and occupational health protection and food safety being key drivers of implementing health-related regulatory policies historically and in current times. Digital technologies have increasingly shaped the field of health protection, and there are numerous examples of new applications and technological solutions to support health protection functions in all domains. This chapter highlights the potential of digital technologies for this public health function using examples of infectious disease prevention through environmental mosquito monitoring, and digital tools for food safety.

## 1.1 *ICT-Supported Mosquito Identification and Counting*

One prominent example of using modern ICT technologies for health protection is the automatic detection and classification of mosquitoes. The goal is to be able to produce counts of mosquitoes of different species since different species serve as vectors of different diseases. This is a very important health protection issue, associated mainly with Sustainable Development Goal 3 (Good Health and Well Being), and could significantly contribute to better control of some widely spread diseases, such as malaria, dengue, zika, and West Nile virus. These diseases are currently mainly encountered in tropical countries, but with climate change, they are expected to propagate to other areas too, and have already been discovered in parts of Europe (Madeira and south of Italy). Currently, state-of-the-art research focuses on the automatic detection and classification of specific species of mosquitoes. Practical, large-scale use in the field is very rare and very challenging. In the next few paragraphs, we will first discuss the algorithms to detect and classify mosquitoes before discussing the challenges associated with deployments and some examples of their potential usage.

Obtaining accurate counts of mosquitoes by species is important for estimating risk, focusing disease control efforts (e.g., dissemination of bed nets, installation of screens, elimination of mosquito breeding sites), and monitoring results of mosquito vector control efforts. Different ways exist to classify mosquitoes automatically (Spitzen and Takken 2018; Joshi and Miller 2021). The first and most coarse approach is to detect actual or potential breeding sites. The next level is to detect mosquitoes without identifying their precise species. The highest precision level is achieved when the exact species can be identified.

The second problem is counting the mosquitoes. Again, several levels of detail are possible: from fuzzy and approximate, like “high number” or “low number,” to exact counts. Different algorithms enable different levels of detail for each of the

two problems (identification and counting). In the next paragraphs, we will step through the available techniques of how to identify mosquitoes and will discuss the levels of detail of each of the techniques and other properties of digital technologies, such as the cost and their real-world applicability.

## 1.2 Identification of Breeding Sites

Apart from manual surveys, breeding sites are usually identified via images. Two possible sources of images have been proposed: street view images (as taken from a normal human perspective) and aerial images.

Street view images are easy to take, and even some open sources can be used, like Google Street View Images (Haddawy et al. 2019). The technical approach is to train a machine learning model to identify various types of water containers, such as pots, vases, old tires, and trash bins. A drawback of using street view images is that they only cover areas along roads and thus miss containers in yards, fields, and indoors. In addition, containers may be occluded by other objects. One should also consider their timeliness when using image sources like Google Street View, as those sources are updated only very irregularly. This can be partially addressed using crowd-sourced images like those from Mapillary or Open Street Cam. This approach can be used with citizen science to acquire data from end users and their smartphones. Despite the limitations of using street view images, the generated container counts have been shown to have a good correlation with larval counts and to improve the accuracy of predictive models of dengue in studies conducted in Thailand (Yin et al. 2021) (Fig. 1).

Aerial images are typically taken by drones—autonomously or remotely (Passos et al. 2022; Bravo et al. 2021; Amarasinghe 2017; Carrasco-Escobar et al. 2022). Drones are able to survey very large areas in a very short time and “see” also

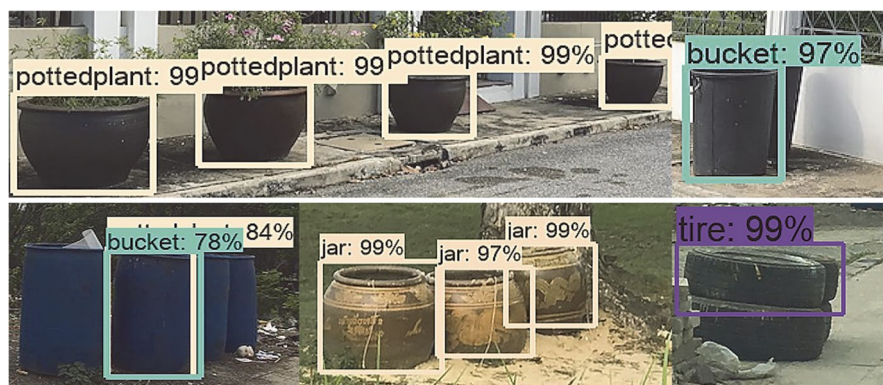


**Fig. 1** Street view images of containers with an accuracy of breeding site predictions (Image reproduced with permission from Haddawy et al. (2019))

otherwise hidden areas like gardens or fields. However, this approach also has some disadvantages. First, data privacy is an issue when taking images of private properties. Second, trees and bushes can largely obstruct the view. Last but not least, one needs drones, which are expensive, especially for developing countries. Satellite images can also be used but are usually not timely (Knoblauch et al. 2023) and may not have sufficient resolution to detect many relevant containers.

Both methods also suffer from usual machine learning-related problems. First, only a priori known types of containers can be identified, and new, unexpected ones cannot be easily integrated into the machine learning model on the fly, although they can be added with additional training data. Second, the accuracy is usually high, but false negatives and positives also exist. For example, one problem with street view images is that tires attached to cars are also recognized as tires but are not, in fact, water reservoirs. This can be solved with sufficient training data or by detecting the car's presence (Haddaway et al. 2019).

One possible extension to these methods is to identify larvae in the water directly (instead of identifying only water container tanks). For example (Arista-Jalife et al. 2020), work uses deep learning methods to analyze pictures of water tanks and identify mosquito larvae. The authors achieved a very good classification accuracy of over 90%. However, the images of each tank need to be of high enough resolution to detect the larva, which is, for example, typically not the case for street-view images.

In summary, identifying breeding sites via ICT is a very promising and relatively cheap (even with drones) alternative to manual surveys. One big advantage is that citizens can be involved, which also increases the knowledge about the problem and thus also its possible counteractions.

### **1.3 Image Processing for Mosquito Identification**

Image processing can be used to identify mosquitoes and differentiate them from other insects or even to identify different species of mosquitoes. For example, in (Okayasu et al. 2019) the authors collected images of three different species of mosquitoes (*Aedes albopictus*, *Anopheles stephensi*, and *Culex pipiens pallens*) in a lab environment and implemented various machine learning methods to classify them. They managed to achieve 95% accuracy with a deep learning model. However, one should consider that the results are based on high-quality images clearly showing the mosquito. This is different when working in a realistic environment. Moreover, the deep learning model developed by the authors is quite processing-intensive and requires the images to be processed in a rich environment, such as a powerful desktop or cloud service.

This approach has been further developed by (Semwal et al. 2022), where the authors use a mobile robot to attract, trap and classify mosquitoes. The robot attracts the mosquitoes towards an isolated chamber with good lighting conditions and a camera. The cues used include Ultra Violet (UV) Light-Emitting Diode (LED) at

368 nm, octanol, and lactic acid, and the robot's motion mimics the movement of a living creature. Additionally, a fan pulls the mosquitoes towards the isolated chamber with a yellow glue surface. There, a camera takes pictures of an area of many mosquitoes at once, and image preprocessing is applied to cut out individual mosquitoes. Then, a similar approach with deep learning is developed and applied to differentiate between *Aedes Aegypti*, *Aedes Albopictus*, and *Culex*. Even in an outdoor real environment, the authors achieve more than 80% accuracy, which is sufficient for coarse and large-scale surveys. However, the authors do not discuss the issue of attracting other, potentially protected insects into the trap. Another practical drawback is that mobile robots need a flat surface on which to move around. One immediate idea would be to use drones instead of mobile robot, but it is still being determined whether the air fluctuations around the drone will allow trapping the mosquitoes at all. Of course, the approach can also be used without any robots or other moving elements and attract mosquitoes, similar to any conventional mosquito trap.

#### ***1.4 Acoustic and Optoacoustic Identification of Mosquitoes***

Mosquito wingbeats possess distinct and recognizable flight tones, making them an effective tool for monitoring and surveilling mosquito populations. This includes detecting the presence of mosquitoes, accurately counting their numbers, and identifying the species and sex of individual mosquitoes (Joshi and Miller 2021). Mosquito species and sex classification using wingbeat frequency data can be divided into two groups: those using microphones to collect audio recordings of sound pressure waves and those using opto-acoustics obtained through audification of mosquito wingbeats interacting with a light source (Hermann et al. 2011). Audio input data can be presented as a raw signal, a power spectral distribution, or a spectrogram image (Fanioudakis et al. 2018; Yin et al. 2021), to name a few. Chen et al. (2014) applied the Discrete Fourier Transform to an audio recording snippet/segments corresponding to a flying mosquito and fitted a Gaussian distribution for each wingbeat frequency histogram to achieve 95.23% accuracy in classifying six insect sounds (including mosquitoes) which were equally distributed. Ouyang et al. (2015) employed the EM algorithm to create Gaussian mixture models for mosquito species and gender classification, achieving 87.9% accuracy. Vasconcelos et al. (Vasconcelos et al. 2019; 2024) presented various signal features to detect mosquitoes in the field and controlled lab environments. Meanwhile, Ziemer and colleagues (2022) have suggested extracting features from the mosquito sound to mimic the sound processing in the mosquito antenna.

Low-cost automated devices and machine-learning techniques have also been used for mosquito species detection based on acoustic signals (Genoud et al. 2018 ; Kimutai and Förster 2023). Potamitis (2014) constructed a codebook of power spectral density patterns for each mosquito species using the sonification of a signal from a sensor device embedded in an insect trap. Deep learning models for image classification have been used to extract features from spectrogram representations

of wingbeat recordings for species and sex identification. Luna-Gonzalez et al. (2020) extracted audio features, transformed them into a color image and applied a CNN to achieve 90.75% accuracy in classifying mosquito species from optical sensor samples. Yin and colleagues (Yin 2021–2) built a 1D-CNN model and a 1D-CNN with LSTM model for mosquito classification based on raw audio waveforms and achieved an accuracy of over 93% on a dataset of pure audio recordings of males and females of five mosquito species. Fanioudakis et al. (2018) experimented with several deep-learning network architectures, XgBoost, and lightGBM, to classify mosquito species. They found that DenseNet121, trained with spectrograms, achieved the highest accuracy of 96%. Kiskin et al. (2021) presented a Bayesian Convolutional Neural Network (BCNN) pipeline to automatically record, detect, and archive mosquito sounds from recordings made with mobile phones.

Similarly, Yin et al. (2023) developed a deep learning-based pipeline for detecting and classifying four mosquito species in Thailand based on acoustic signals. Recently, there have been quite successful attempts to compress the models to be run on low-cost microcontrollers, for example, with the help of TinyML (Altayeb et al. 2022). Smartphones can also be sensors (Mukundarajan et al. 2017; Sinka et al. 2021). This makes these solutions low-cost and thus usable in resource countries where mosquitoes breed more because of the unhygienic environments.

## ***1.5 Potential Applications of Mosquito Identification and Counting***

There are only very few real-world applications of ICT-supported mosquito identification or counting. Most of the work presented so far has been only tested in lab or testbed environments, and many challenges remain before they can be used in real applications. However, the first results are highly promising, and thus in this section, we discuss the potential applications.

The most often discussed application is to estimate mosquito vector counts and to estimate the proportions of species. Such an application can be a real game changer for pest control, with much lower costs than manual surveys and much bigger precision (time and area) of the acquired data. Once fully developed, such applications have the potential for low-cost implementation in areas at the highest risk for mosquito-vector disease, as they can be realized at low cost, low required training, and scalable dissemination. It is also possible to immediately eliminate mosquitoes when using a trap. This is, for example, very useful for private gardens, schools, sporting facilities, etc.

Another currently discussed application is the automatic distribution of mosquito repellants. Repellants are usually distributed automatically, but in a simple way, by releasing them in regular intervals. However, the repellants are also a health risk by themselves and are costly. Thus, a more intelligent release based on really present mosquitoes of the dangerous species will be very beneficial. The information about the repellent usage can also be easily provided to the end users, e.g., for re-fill or general information.

## ***1.6 Challenges of Real-World Applications***

For image-based methods, one of the challenges is the quality of the images, especially when taken by end users and their smartphones. They often need to be clearer, of low resolution, with bad lighting conditions, the area of interest is not in focus, and many more. Another problem is their availability, for example, from private grounds. Yet another problem is their timeliness (e.g. when using satellite images or sources like Google Streetview) and the obstruction from foliage. What is needed is a high-resolution, regular screening of areas of interest, including private grounds and badly accessible areas. One of the simplest and cost-efficient ways of acquiring such data is currently citizen science and empowering all citizens to contribute. This will require developing very user-friendly services adapted for children, handicapped persons, and illiterate persons. Citizen science also requires extensive information campaigns and incentives to participate, which need to be developed and run by the authorities.

When using traps with acoustic methods, the main challenge remains the noisy environment. Here, more data from real environments must be gathered to improve the algorithms and make them more robust against background noise. The cost of the systems will remain high as long as only a few traps are used. However, if the traps prove practical and accurate enough, the cost savings will still be significant compared to manual work, which will also push the costs of the individual sensors down.

However, there is another challenge with counting mosquitoes with traps. The so-called sensor range is very limited, i.e., the mosquito needs to be very close to the trap, and thus a very small area can be monitored. Installing more traps will not necessarily improve the situation, at least not much. Thus, research must focus more on attracting mosquitoes into the traps and avoiding attracting other insects. Current methods include the use of heat, odors, and CO<sub>2</sub>. The method used must be cost-efficient and must only require a refill sometimes.

The last challenge comes from the used ICT methods themselves. The most accurate current models for mosquito detection and classification are deep learning models. But these require large amounts of training data, which is labor intensive to gather in the case of mosquito wingbeat data. Deep learning models also require large amounts of memory and processing power. Thus, it is not trivial to deploy them in a cost-efficient and power-efficient way.

## **2 Digital Approaches for Food Safety Measures**

Food safety is a major concern worldwide as harmful substances in food can pose significant health risks and negatively impact economies. Digital applications can potentially improve food safety testing and keep food provision chains safe. The World Health Organization states that foodborne diseases account for 420,000

deaths yearly (WHO 2015). Despite strict legislation and standard methods for chemical and microbiological/pathogen food safety testing, food-related scandals still occur, posing threats to consumer health and the food economy (Tsagkaris et al. 2019). Food scandals, such as dioxins in eggs (Kupferschmidt 2011) and aflatoxins in dairy (Popovic et al. 2017), have highlighted the need for improved and innovative methods for monitoring contaminants. Typically, high-performance liquid or gas chromatography coupled with mass spectrometry is used for chemical food safety testing, while culture plate analysis is often used for microbiological/pathogen testing. Despite their high reliability, these methods are expensive, time-consuming, and require trained personnel (Jafari et al. 2021). Therefore, cheaper, portable, fast analytical tools are needed to ensure consumer safety and minimize health risks and economic losses.

New mobile sensing approaches are being developed to address the limitations of traditional food safety testing methods. These devices offer faster testing, lower costs, ease of use, and minimal equipment requirements. Sensing technologies can be integrated with smartphones to create platforms for food safety analysis that function as lab-on-smartphones (Rateni et al. 2017). Smartphones have various components such as a processor, camera, wireless connectivity, and display, making them useful for measurement and detection. However, they need to be augmented by other accessories to function as laboratory instruments. Many external sensor modules have been designed and integrated with smartphones, extending their capabilities for extracting more sophisticated diagnostic information (Zhang and Liu 2016). These comparatively inexpensive devices can run routine tests rapidly and on-site, provide personalized diagnostic options and enable rapid inspection of suspected contamination. For instance, smartphones can help allergic individuals by providing personalized health information capability or allowing quick detection of contamination from foodborne pathogens or other harmful substances (Rateni et al. 2017; Zhang and Liu 2016).

Smartphone-based methods for food analysis can be classified as either lab-on-smartphone biosensors or smartphone optical and spectroscopy methods (Zhang and Liu 2016).

Smartphone-based biosensors benefit from the optical capabilities of smartphones, such as the camera acting as a photodetector and the light source (Jafari et al. 2021). Biosensors integrate bio-receptors and a transduction method to detect target analytes. The analyte and receptor interaction produces a measurable signal, allowing for direct detection and high selectivity. However, prior sample treatment is necessary for transduction. Biosensors offer affordable and fast analysis in a portable and miniaturized format. Combining smartphone technology with adapted biochemical assays can create biosensor-based analytical systems for on-site detection of various analytes, including contaminants, drugs, pesticide residues, and foodborne pathogens (Rateni et al. 2017).

Various methodologies are used for lab-on-smartphone biosensors, including fluorescence imaging, colorimetric assay, and electroanalytical methods (Rateni et al. 2017). An example of smartphone-based colorimetric readers includes the development by Levin et al., who created a smartphone-based colorimeter to screen

groundwater for excess fluoride that can be used in areas affected by fluorosis, an ongoing challenge in India. The colorimeter used a commercially available reagent and an easy-fit, compact sample chamber adapter but required each phone's calibration due to color sensing variation. A software program was developed to analyze the red-green-blue color of the image, resulting in fluoride estimation comparable to expensive laboratory methods without technical expertise (Levin et al. 2016).

Spectroscopy involves analyzing the different wavelengths of light absorbed, emitted, or scattered by a material to gather information about its properties, such as composition, structure, and physical state. As such, spectroscopy is a valuable tool for non-invasive analysis in various industries, such as food quality assessment, but most setups are expensive and cumbersome, limiting their use in laboratory settings. Recent advancements in micro-technologies have allowed the development of portable spectrometers that are cost-effective and small in size. However, miniaturized systems must provide reliable results without intervention from trained technicians. The goal is to integrate spectrometers into smartphones to provide real-time sensitive and specific spectroscopic information (Bouyé et al. 2016; Rateni et al. 2017).

An example of smartphone-based spectroscopy includes a handheld fluorescence-based imaging device developed by Oh et al. to enhance visual detection of fecal contamination on red meat, fat, and bone surfaces of beef under varying luminous intensities. This device comprises four 405-nm 10 W LEDs for fluorescence excitation, a charge-coupled device camera, an optical filter at 670 nm, and a Wi-Fi transmitter for sending real-time data to a smartphone or tablet. The system successfully identified the localization of most fecal contamination spots on beef surfaces by detecting chlorophyll metabolites discharging fluorescence near 670 nm, and results suggest that this method can effectively assist in visually inspecting and detecting fecal contamination (Oh et al. 2016).

Although these smartphone-based food diagnostic technologies show potential and new techniques and methodologies are constantly developed, several limitations must be addressed. These technologies often require peripherals for analysis, which limit their practicality in field conditions. The analytical procedures required for obtaining meaningful results may involve instruments and materials typically found only in laboratories. Time-consuming and multi-stage sample preparation procedures can discourage potential end-users, particularly those without training. The repeatability, selectivity, and limit of detection of proposed methods must be thoroughly tested and confirmed while considering the complexity of food matrices. It is important to note that smartphone cameras may have default settings optimized for photography, and color readouts may not be transferable across different smartphone models (Kalinowska et al. 2021). Despite technological advancements, some of these devices are still at the proof-of-concept stage and require more testing before being introduced (Jafari et al. 2021). Additionally, legal challenges may arise in implementing such devices, as analytical methods must meet regulatory requirements (Tsagkaris et al. 2019). Societal and ethical impacts also need to be considered (see Chap. "Ethical Implications of User Autonomy in Digital Public Health", Dassow et al. in this handbook).

Nevertheless, smartphones and other digital devices can change the current food testing concept by allowing farmers and consumers to conduct food safety analysis with a simple sample preparation protocol and smartphone application. Users can receive a fast answer directly from their phone, and the online connectivity of smartphones can be used as a quality assurance feature. If a sample is contaminated, the user could alert an expert group responsible for confirmatory analysis (Tsagkaris et al. 2019). Due to the complexity of the food matrix and recent developments in the field, particularly biosensors utilizing microfluidics and bioassays may be used for smartphone-based food analysis in the future. Such solutions of on-site analytical techniques will make food quality assessment more accessible, convenient, and readily available (Kalinowska et al. 2021). Ultimately, these innovative technologies can help reduce the risk of foodborne diseases.

### 3 Concluding Remarks

The examples provided in this chapter only offer a first insight into the broad range of digital applications and systems increasingly shaping the field of health protection from environmental, occupational, nutritional, and other risks. Many of these applications are still in their infancy, and so are the insights into the positive and negative consequences of novel digital and/or AI tools with relevance for health protection. As in many other fields, there is an urgent need to accomplish sound evaluations of new approaches to strengthen those that build up the toolbox of digital technologies in support of the health protection of the population.

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