



Digital Entomology: From Automated Traps to Real-Time Pest Forecasting

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Timely information about insect pests is essential for effective crop protection. Farmers need to know which pest is present, when it appears, whether its population is increasing and whether intervention is actually required. Traditionally, this information has been obtained through field scouting and manual examination of pheromone, sticky, light or food-baited traps. Although these methods remain valuable, they require regular field visits, trained personnel and considerable time. Manual monitoring may also provide information only at widely spaced intervals, making sudden pest increases difficult to detect. Advances in electronics, sensors, artificial intelligence (AI), wireless communication, cloud computing and remote sensing are gradually changing this situation. Together, these tools are giving rise to what may broadly be called digital entomology, the application of digital technologies to detect, identify, monitor and forecast insect pests. The objective is not to replace entomologists or conventional field scouting. Rather, digital technologies can increase the frequency of observations, analyse large amounts of information and help convert pest records into timely management decisions. Automated monitoring is therefore becoming an important component of precision agriculture and modern Integrated Pest Management (IPM) (Preti et al., 2021).

From Conventional Traps to Smart Traps

Pheromone, sticky and light traps have long been used for monitoring insect pests. In conventional systems, traps must be visited regularly, insects identified manually, and counts entered into field records. This is practical when only a few traps are involved but becomes labour-intensive when monitoring is conducted over large areas. Preti et al. (2021) highlighted that manual trap inspection limits both the spatial and temporal resolution of pest-monitoring programmes. Camera-equipped traps offer an alternative by capturing images of trapped insects and transmitting them remotely. In some systems, images can be examined daily or even several times per day without requiring repeated visits to the field.

Modern smart traps may contain:

- digital cameras,
- infrared or optical sensors,
- microprocessors,
- wireless communication modules,
- GPS,
- solar panels or batteries, and
- software for automatic data processing.

Electronic traps can therefore record the arrival of insects and communicate those observations to a remote database. Welsh et al. (2022), for example, demonstrated the use of optoelectronic sensor traps for automated surveillance of lepidopteran pests. Similarly, Lello et al. (2023) reviewed automatic fruit-fly monitoring technologies and showed that image, optical and acoustic sensors can be incorporated into trap networks for remote surveillance.

These systems are particularly attractive for orchards, invasive-pest surveillance and area-wide monitoring programmes where trap networks may contain hundreds of individual monitoring points.

Artificial Intelligence for Insect Recognition

Collecting images automatically solves only part of the problem. The insects still need to be identified and counted. Artificial intelligence, especially machine learning and deep learning, can help automate this step. Computer-vision systems are trained using labelled photographs of target insects. Once sufficient training data are available, the model learns visual patterns associated with a species and can attempt to recognize insects in new images. Deep-learning algorithms such as convolutional neural networks and modern object-detection architectures can identify and count objects directly from photographs. Their use in agricultural pest monitoring has expanded rapidly during the last decade. A systematic review of deep-learning approaches for insect detection concluded that automated image recognition has considerable potential for smart pest monitoring, while emphasizing challenges related to image quality, insect size and field variability. More recent reviews similarly identify computer vision as an important component of precision pest management (Ariza-Sentís et al., 2024; Mittal et al., 2024). Kariyanna and Sowjanya (2024) also highlighted the growing role of AI in insect identification, pest monitoring, forecasting and decision support. AI can process data originating from cameras and sensors much faster than manual observation, making it particularly useful where large numbers of images must be examined. A practical example was provided by Ahmed et al. (2024), who developed an IoT-based intelligent pest-monitoring system for oriental fruit fly in guava orchards. Their smart trap combined insect capture, imaging, machine-learning classification and cloud-based communication, demonstrating how field monitoring can be partially automated. However, automated recognition is not error-free. Overlapping insects, dust, poor illumination, damaged specimens and morphologically similar species can reduce accuracy. Models trained using insects from one region may also perform poorly when applied to different geographical populations or field environments.

Internet of Things: Connecting Traps and Sensors

The Internet of Things (IoT) refers to networks of connected devices capable of collecting and exchanging information. In agriculture, these devices may include weather sensors, cameras, soil-moisture probes, smart traps and automated irrigation systems.

For pest monitoring, an IoT system may follow a simple sequence:

Insect captured → image recorded → insect detected → data transmitted → information stored in the cloud → farmer or extension worker receives an alert

The major advantage is connectivity. Instead of waiting several days for trap observations to be manually collected and reported, information may become available almost immediately.

Kiobia et al. (2023) reviewed IoT-based insect-detection systems in cotton and reported growing use of cameras, acoustic sensors and deep-learning algorithms for detecting both pests and beneficial insects. At the same time, they emphasized that relatively few insect species have been incorporated into reliable automated systems and that species similarity remains an important challenge. More broadly, IoT-based agriculture allows information from traps to be combined with temperature, relative humidity, rainfall and crop-condition data, creating a more complete picture of the field environment (Prakash et al., 2023).

Drones and Remote Sensing

Smart traps provide information about insect activity at specific points, but pest outbreaks often vary across a field. Remote sensing helps add this spatial dimension. Unmanned aerial vehicles (UAVs or drones) equipped with red-green-blue (RGB), multispectral, thermal or hyperspectral cameras can rapidly examine large crop areas. Pest injury may alter canopy colour, leaf area, temperature, reflectance or crop vigour, creating patterns that can potentially be detected from aerial imagery. Remote sensing is therefore useful for identifying hotspots of crop stress, although it may not always identify the actual insect responsible for the damage.

For this reason, drone observations should normally be linked with field scouting and trap information. Ariza-Sentís et al. (2024), after reviewing object detection and tracking in precision farming, emphasized the increasing importance of computer vision for real-time agricultural monitoring. UAV technologies have similarly become important platforms for precision crop surveillance because they can provide spatially detailed information much faster than conventional field surveys.

In practice, smart traps and remote sensing provide complementary information:

Smart traps tell us which insect is active, and drones or satellites show where crop stress is occurring. Thus, combining both may improve pest surveillance.

From Pest Monitoring to Pest Forecasting

The real advantage of digital entomology emerges when monitoring is combined with forecasting. Insect development is strongly influenced by temperature and other environmental factors. Traditional forecasting systems have long used degree-day accumulation, phenology models and weather observations to estimate events such as egg hatch, adult emergence and generation development. Damos (2015) described how web-based decision-support systems can integrate weather observations and pest-development models to guide IPM decisions. Such systems move pest management beyond simply recording current population levels and towards predicting future risk. Digital monitoring provides a much larger and more continuous stream of data for these forecasting systems. For example, a model may analyse:

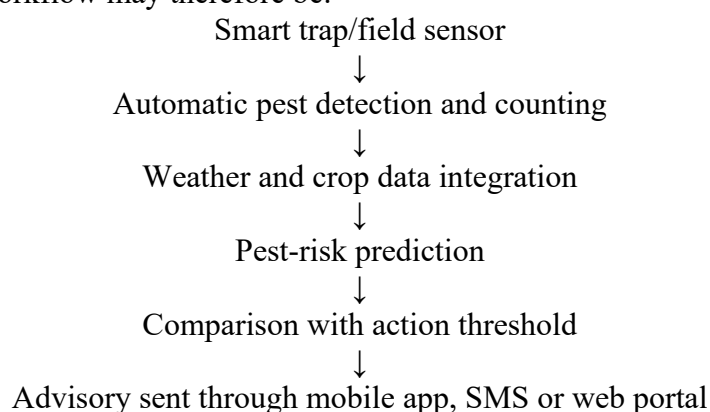
- previous trap catches,
- current insect abundance,
- temperature,
- rainfall,
- relative humidity,
- crop growth stage,
- historical outbreak patterns, and
- geographical information.

Machine-learning algorithms can search these datasets for relationships associated with pest population increases. Mittal et al. (2024) reviewed approaches including regression, classification and time-series forecasting for predicting pest infestation and emphasized the importance of data quality and model validation. Thus, digital tools can help predict pest outbreaks before populations become high, allowing earlier and better-timed IPM action.

Decision-Support Systems and Farmer Advisories

Forecast information becomes valuable only when it reaches the person who must make a management decision. A Decision-Support System (DSS) converts data into practical information. Pest counts, weather records and prediction models may be combined with action thresholds to provide recommendations.

A typical digital workflow may therefore be:



Digital decision-support systems have been explored for IPM for many years. Singh and Gupta (2016) reviewed information and communication technology-based decision-support

approaches for pest management in India, while Damos (2015) described web-based systems integrating pest models with management decisions. The increasing availability of mobile phones, cloud platforms and low-cost sensors makes such systems much more practical today than when early forecasting models were developed.

Table 1: Major Digital Tools for Pest Management

Technology	Use in entomology	Main benefit
Smart camera traps	Photograph captured insects	Remote trap inspection
Optical sensors	Detect insect entry or movement	Continuous pest counts
AI/computer vision	Identify and count insects	Reduces manual image examination
IoT networks	Connect traps and sensors	Near real-time data transmission
Weather sensors	Measure temperature, rainfall and humidity	Inputs for pest forecasting
Drones/UAVs	Survey crop canopy	Locate pest-damage hotspots
Remote sensing	Detect crop-stress patterns	Large-area monitoring
Machine learning	Analyse historical and current data	Predict pest outbreaks
Decision-support systems	Convert data into recommendations	Support timely IPM action

Challenges

Despite its potential, digital entomology still faces important limitations.

1. Cost

High-quality cameras, sensors and communication systems can be expensive, particularly for small and marginal farmers.

2. Power and Connectivity

Remote monitoring devices need reliable batteries, solar power and network coverage. Poor connectivity can restrict real-time communication.

3. Image and Data Quality

Dust, rain, changing light conditions and insect overlap may interfere with automated detection. AI models are only as good as the data used to train them.

4. Closely Related Species

Computer-vision systems may struggle to separate morphologically similar species. This can be especially problematic when one species is a pest and another is beneficial.

5. Limited Reference Datasets

Kiobia et al. (2023) noted that many existing systems have been developed for only a small number of pests. Large, accurately labelled datasets representing different life stages, seasons and regions are needed.

6. Transferability

A forecasting model developed for one location may not work equally well elsewhere because climate, cropping systems and pest biology differ.

7. Farmer Usability

The final output must be simple. Farmers need information such as “high pest risk-inspect the crop”, rather than complicated AI scores or technical graphs. Preti et al. (2021) similarly identified cost, power autonomy, image quality and incomplete automation as important limitations of camera-based traps.

Future Prospects

The future of digital entomology will probably involve increasing integration of technologies rather than isolated tools. A future pest-monitoring platform could combine:

smart traps + weather stations + satellite/UAV imagery + AI + pest models + mobile advisories
Edge computing may allow pest identification to occur directly inside the trap instead of sending every photograph to a remote server. This can reduce internet requirements and

provide faster responses. Automated detection systems may also be linked to precision-management equipment so that control measures are applied only where they are needed. However, trained entomologists will remain essential. AI may recognize patterns, but pest biology, economic thresholds, natural enemies and ecological context still require expert interpretation.

Conclusion

Digital entomology represents an important shift from periodic manual monitoring towards continuous and data-driven pest surveillance. Camera-equipped traps can monitor insect activity remotely, AI can assist identification and counting, IoT networks can connect field devices, and forecasting systems can transform pest and weather data into early warnings. Its greatest value lies not in replacing conventional entomology but in improving the speed, frequency and usefulness of pest information. When integrated with field scouting, economic thresholds and IPM principles, these technologies can support more timely interventions and may help reduce unnecessary pesticide applications. Digital entomology therefore represents a transition from simply detecting pests after they appear towards anticipating pest risk before serious crop damage occurs.

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