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Precision Entomology: Integrating IoT, Remote Sensing, AI and Decision-Support Systems

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Precision entomology represents the integration of entomological knowledge with digital sensing, connectivity, spatial observation, artificial intelligence and decision-support technologies to improve the detection, forecasting and management of agricultural insect pests. Conventional pest scouting is often periodic, labour-intensive and spatially limited, whereas IoT-enabled traps and sensors can provide continuous observations, remote sensing can characterize crop condition across large areas, and artificial intelligence can transform heterogeneous observations into pest detections, population estimates and risk predictions. Decision-support systems can then translate these outputs into practical recommendations for field scouting, biological control, pheromone deployment or selective chemical intervention. Recent reviews show increasing integration of IoT, AI, drones, remote sensing and automated pest detection, while also emphasizing limitations related to dataset quality, field variability, cost, connectivity and external validation. This review discusses the conceptual basis of precision entomology, IoT-enabled pest monitoring, remote sensing, AI-based identification and forecasting, data fusion, spatial risk mapping, decision-support systems, precision intervention, benefits, challenges, data governance and future directions. Particular emphasis is placed on moving from isolated technology demonstrations toward end-to-end systems in which sensing, analytics, expert validation and management decisions form a continuous feedback loop.

Introduction

Agricultural insect pests are dynamic biological populations whose abundance and distribution change with crop stage, weather, landscape structure, natural enemies and management practices. Effective pest management therefore depends not only on knowing which pest is present but also on understanding where it occurs, how rapidly populations are changing and whether abundance is approaching an economically important level. Traditional scouting provides valuable field knowledge, but manual inspection can be difficult to scale across large and heterogeneous production areas. Precision entomology can be viewed as a technology-enabled extension of IPM in which pest observations are collected at higher spatial and temporal resolution and integrated with environmental and crop information. IoT sensors can provide continuous data, remote sensing can provide spatial coverage, AI can automate image interpretation and prediction, and decision-support systems can convert data into management recommendations. Recent reviews describe this convergence as a pathway toward real-time or near-real-time pest monitoring and more targeted interventions. The objective is not simply to replace field entomologists with automated systems. Instead, precision entomology should strengthen human decision-making by expanding observation capacity, identifying patterns that may be difficult to detect manually and delivering timely alerts. Expert knowledge remains important for confirming unusual detections, interpreting ecological context and deciding whether an intervention is justified.

Current research is increasingly organized around complete operational workflows rather than individual technologies. Recent work on AI-driven IPM emphasizes the sequence of monitoring, pest-pressure estimation, thresholds, decision support, intervention and feedback, while systematic reviews of remote sensing and AI identify data availability, cost, field variability and insufficient external validation as important barriers to adoption.

Conceptual Framework of Precision Entomology

Precision entomology brings together multiple data streams. These may include smart traps, camera systems, weather stations, soil and crop sensors, satellite imagery, UAV observations, pheromone trap counts, manual scouting and historical pest records. AI and statistical models can integrate these observations with crop phenology and environmental information to estimate pest pressure and spatial risk.

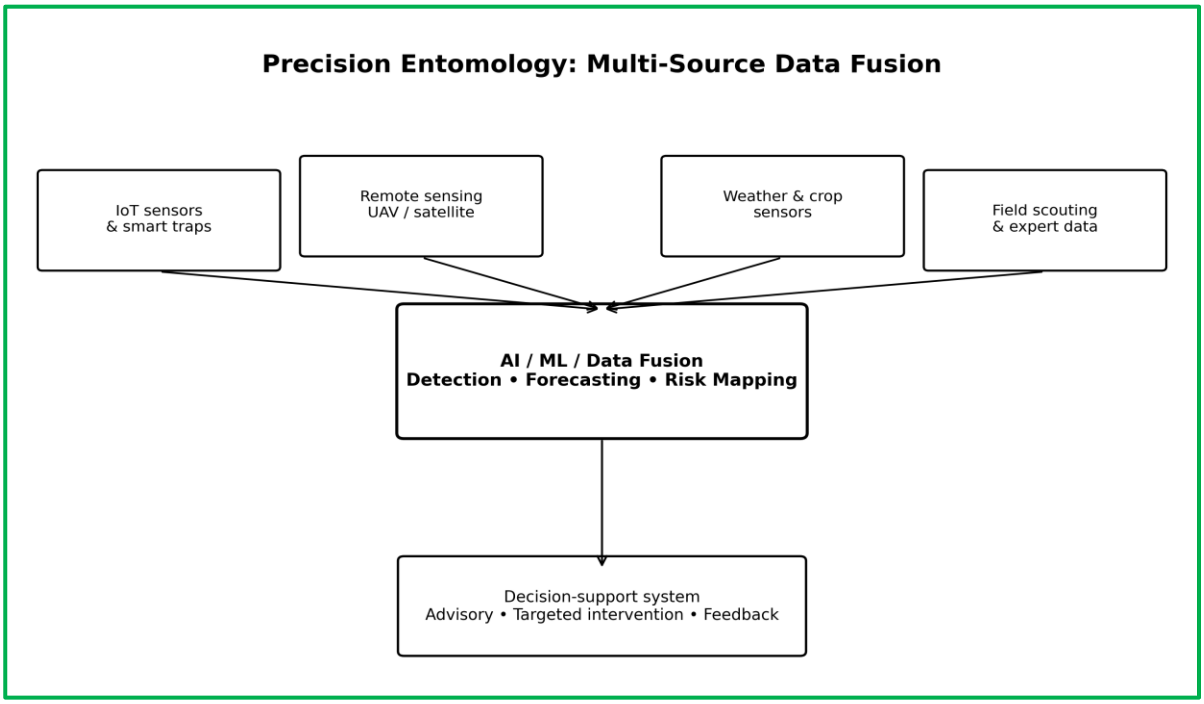

Figure 1. Conceptual framework for precision entomology showing integration of IoT, remote sensing, field observations and environmental data through AI-based analytics into decision-support outputs.

The value of integration lies in complementary strengths. IoT systems provide temporal continuity, remote sensing provides spatial context, field observations provide biological confirmation, and AI can process large datasets. A decision-support system provides the final interface between data and action. This structure helps prevent a common weakness of technology-focused projects in which accurate detection is demonstrated but no clear pathway exists from detection to an agronomically justified management decision.

IoT-Enabled Insect Pest Monitoring

The Internet of Things connects sensors and devices that collect and transmit data. In entomology, IoT systems can include pheromone traps with cameras, sticky traps with imaging units, acoustic sensors, environmental sensors, light traps and field gateways. These systems can collect observations at regular intervals without requiring a person to visit every monitoring point. Camera-equipped traps can provide images of captured insects, while machine-learning models can classify or count target species. Environmental sensors can simultaneously record temperature, humidity, rainfall and other variables relevant to pest development. A review focused on cotton insect monitoring reported that AI and IoT systems have been applied to detection, classification and counting of pests and beneficial insects, while noting that only a limited number of species have been addressed relative to the diversity of agricultural insects.

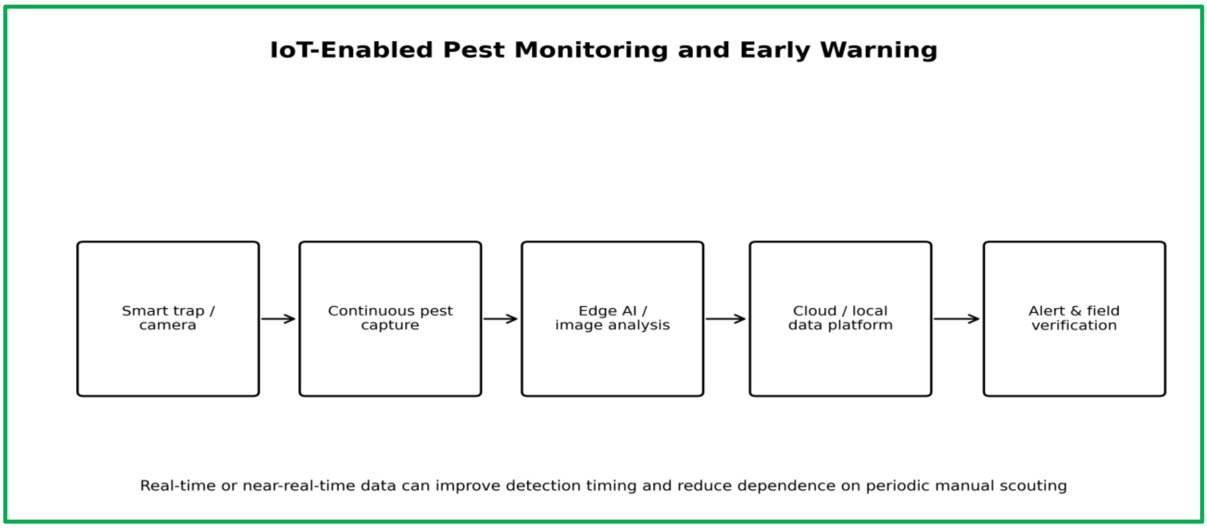

Figure 2. General IoT-based workflow for automated pest monitoring, image analysis, data transmission and field-level early warning

Continuous monitoring can improve the timing of intervention because pest activity can be detected between conventional scouting visits. However, sensor placement, power supply, network connectivity, weather resistance, maintenance and calibration are important practical considerations. Low-power edge devices and solar-powered systems may improve suitability for remote fields.

Remote Sensing for Pest and Crop Monitoring

Remote sensing provides a means of observing agricultural landscapes without inspecting every plant manually. Satellite platforms, UAVs and proximal sensors can collect RGB, multispectral, hyperspectral and thermal observations. These data are often more effective at detecting crop condition or stress than directly identifying individual insects, particularly when insects are too small to resolve from aerial imagery. Pest infestation can produce changes in plant physiology, canopy structure, water status or spectral characteristics. Remote sensing can therefore contribute to indirect pest detection by identifying spatial patterns of crop stress that can then be investigated through field scouting. A recent systematic review of remote sensing and AI for crop pest and disease monitoring reported increasing use of UAV and satellite observations, including RGB, multispectral, hyperspectral and thermal configurations, with AI methods such as CNNs, random forests, support vector machines, segmentation, object detection and multimodal data fusion. □cite□turn0search11□

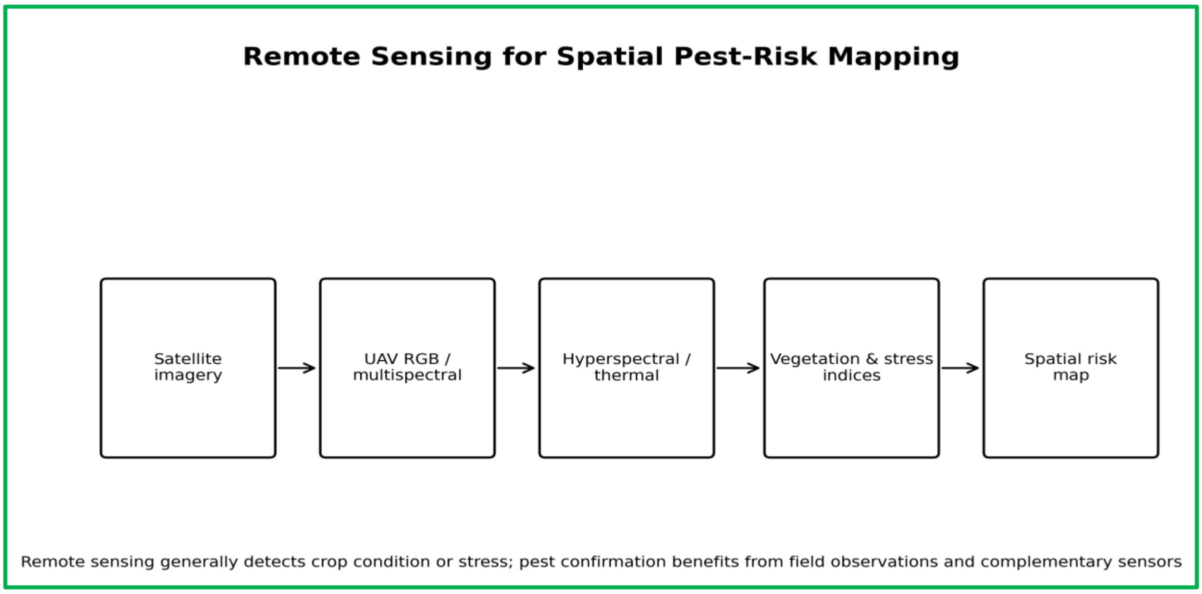

Figure 3. Conceptual remote-sensing workflow for spatial pest-risk mapping using satellite, UAV and proximal spectral observations

The distinction between pest detection and crop-stress detection is important. A spectral anomaly may be caused by insects, pathogens, nutrient deficiencies, drought or other stresses. Remote sensing should therefore be combined with ground observations and contextual information before a pest diagnosis is made.

UAVs and Proximal Sensing

Unmanned aerial vehicles provide flexible high-resolution observation of crop fields and can be equipped with RGB, multispectral, hyperspectral or thermal sensors. UAVs can revisit selected fields at relatively short intervals and generate spatial maps that identify areas requiring ground inspection. Proximal sensing platforms mounted on tractors, robots or handheld devices can provide even higher-resolution observations. These systems may be useful for detecting visible insect damage, insect presence or crop responses at plant level. Autonomous platforms could eventually combine navigation, imaging and pest recognition to survey selected areas according to a risk-based sampling plan. The principal limitation of UAV and proximal sensing is that higher resolution usually reduces the area covered per flight or increases acquisition and processing costs. Flight regulations, battery life, weather and image-processing requirements also influence operational feasibility.

AI for Automated Pest Identification

Artificial intelligence can convert images and sensor signals into biological information. Computer-vision models can classify pest species, detect individual insects, count populations and identify symptoms or damage patterns. Convolutional neural networks, object-detection architectures and vision transformers are increasingly used for image-based pest recognition. A 2025 systematic review of AI-driven pest detection in Indian agriculture reported increasing use of computer vision, deep learning and machine learning to automate pest identification and support more targeted crop protection. □cite□turn0search5□ Recent global reviews similarly describe AI applications spanning insect identification, ecological monitoring and predictive pest management, with integration of IoT and remote sensing enabling broader decision-support systems. However, model performance can decline when field conditions differ from training data. Lighting, insect orientation, crop background, life stage, pest density and camera type can create domain shifts. Therefore, field validation, representative datasets and uncertainty estimation are essential for responsible deployment.

AI-Based Pest Forecasting

Detection answers the question of what is present, while forecasting attempts to estimate what may happen next. Pest forecasting can use historical pest counts, temperature, humidity, rainfall, crop stage, degree-day accumulation, landscape information and management history. Machine-learning algorithms can identify nonlinear relationships that may improve short-term prediction when sufficient data are available. Recent research on adaptive high-precision IPM highlights the combination of IoT monitoring and machine learning for feedback-driven pest management. The key opportunity is to use continuous observations to update predictions rather than relying solely on static seasonal calendars. Forecasts should be expressed with uncertainty rather than as deterministic predictions. A risk probability or confidence interval can help users decide whether additional scouting is needed. Models should also be recalibrated when pest populations, climate conditions or production systems change.

Data Fusion and Multimodal Intelligence

No single sensor provides complete information about an agroecosystem. Data fusion combines complementary observations to improve reliability. For example, a pheromone trap can indicate adult pest activity, a weather station can describe conditions affecting development, and satellite or UAV data can identify areas of crop stress. Combining these observations can provide a stronger basis for risk assessment than any individual data stream.
Multimodal AI can integrate images, time-series sensor data, weather observations, spatial coordinates and historical records. The challenge is to ensure that data streams are

synchronized, calibrated and biologically meaningful. Missing data, sensor failures and differences in spatial resolution can introduce errors into the fused model. Data fusion should also distinguish correlation from causation. A strong association between spectral stress and pest abundance may be useful for prediction but does not prove that the pest caused the stress. Field validation and entomological interpretation remain necessary.

Decision-Support Systems for Pest Management

Decision-support systems (DSS) are the operational layer that converts observations and model outputs into recommendations. A DSS may display pest abundance, forecast risk, economic thresholds, weather conditions, crop stage and recommended actions through a web or mobile interface. Recent reviews describe AI-enabled DSS as an important mechanism for translating complex analytics into accessible advisories. A responsible pest DSS should not automatically recommend pesticide application solely because a model detects an insect. The recommendation should consider pest identity, abundance, crop stage, economic threshold, natural-enemy activity, resistance status, weather and available non-chemical options. Human verification can be required when confidence is low or when an unfamiliar pest is detected.
DSS platforms can also record intervention outcomes. After a management action, subsequent pest observations can be compared with predictions to evaluate whether the intervention achieved the intended result. This feedback loop supports continuous improvement of both the model and the management strategy.

Precision Intervention

Once a pest hotspot has been identified, management can potentially be localized rather than applied uniformly across an entire field. Precision intervention may involve targeted scouting, localized pheromone deployment, biological-control releases, spot spraying or variable-rate application. The choice depends on the pest, crop, equipment and economic threshold. Targeted intervention can reduce the area and quantity of pesticide applied, but the ecological behaviour of the pest must be considered. Highly mobile insects can move between treated and untreated zones, and some infestations may require area-wide management. Spatially precise technology should therefore be integrated with knowledge of pest dispersal and landscape structure. Post-treatment monitoring is essential. A precision system should evaluate whether pest pressure declined, whether crop damage stabilized and whether beneficial organisms were affected. This turns precision agriculture into a feedback-driven management process rather than a one-time application.

Integration with IPM

Precision entomology should strengthen rather than replace established IPM principles. Economic thresholds, resistant cultivars, crop rotation, sanitation, biological control, pheromone technologies, habitat management and selective insecticides remain important. Digital technologies improve the observation and timing of these practices. For example, IoT pheromone traps can provide early warning, remote sensing can identify spatially stressed zones, AI can estimate risk and a DSS can recommend field scouting. If intervention is justified, biological or selective chemical control can be targeted to the appropriate area and pest stage. This integrated approach can reduce unnecessary pesticide exposure while maintaining crop protection. The same principle applies to insecticide resistance management. Precision monitoring can identify changes in pest abundance and field performance, while decision-support systems can incorporate mode-of-action rotation and other resistance-management rules. Technology should therefore support sustainable agronomic decisions rather than simply automate spraying.

Current Applications and Emerging Examples

IoT-based insect monitoring has been studied extensively in cotton and other cropping systems, where automated sensors can detect, classify and count insects. Reviews indicate promising performance but also emphasize that relatively few pest species have been addressed compared with the diversity of agricultural pests. In India, recent systematic-review evidence highlights rapid growth in AI-based pest detection research, particularly computer vision and deep learning, while identifying field-scale implementation, dataset limitations and practical deployment as important challenges. Recent field-oriented developments also illustrate the movement toward integrated systems. For example, an AI-IoT pest-control device reported in India combines field cameras with local computing, environmental sensing and farmer-facing alerts. Such examples demonstrate the direction of travel toward systems that connect sensing, interpretation and advisory functions, although independent field validation and long-term agronomic evaluation are still essential before broad conclusions about effectiveness can be made.

Challenges and Limitations

Data quality is one of the greatest limitations. AI systems require large, representative and accurately labelled datasets. Agricultural images are highly variable, and rare pest species may be underrepresented. Dataset bias can cause models to perform well under controlled conditions but poorly in new regions or seasons. Remote sensing introduces another limitation: many pest infestations are detected indirectly through crop response rather than by observing insects themselves. Confounding stresses can generate similar spectral or thermal patterns. Ground-truth observations are therefore essential for model development and validation. IoT systems face practical challenges including power supply, connectivity, sensor fouling, environmental exposure, maintenance and data transmission costs. Rural connectivity can be intermittent, making edge computing and offline functionality valuable. AI models may also lack interpretability. Farmers and extension personnel need to understand why a system generated an alert, especially when management decisions have economic or environmental consequences. Explainable AI, confidence scores and human-in-the-loop verification can improve trust. Economic viability is another major issue. Hardware, installation, data plans, cloud services, software maintenance and technical support can be expensive. Technology should therefore be evaluated using whole-system cost-benefit analysis rather than model accuracy alone.

Data Governance, Privacy and Interoperability

Precision entomology produces spatial and temporal datasets that may reveal information about farm operations, crop distribution and management practices. Data ownership, access control, storage and responsible sharing should therefore be considered during system design. Interoperability is also important because farms may use sensors, weather stations, drones and software from different providers. Standardized data formats and open interfaces can reduce dependence on a single platform and make it easier to integrate new technologies. Research datasets should include metadata describing location, time, crop stage, sensor type and sampling protocol when appropriate. Clear metadata improve reproducibility and help researchers determine whether a model is being evaluated under conditions similar to its intended deployment.

Future Perspectives

The future of precision entomology will likely move from isolated AI models toward integrated, continuously learning agroecosystem intelligence. Digital twins and biology-informed simulation models may combine pest biology, weather, crop development and spatial information to simulate invasion and infestation scenarios. Recent research has proposed such digital-twin approaches for precision farming and pest forecasting. Multimodal foundation models may eventually combine image, text, weather, spatial and sensor information. However, agricultural deployment will require careful validation because general-purpose models may not understand species-specific biological distinctions or local management rules without specialized training. Autonomous scouting is another promising direction. Robots and UAVs could adapt their sampling routes according to pest-risk maps, allowing more intensive observation in high-risk zones and reducing unnecessary coverage of low-risk areas. Edge AI could perform preliminary analysis locally, transmitting only relevant events to a central platform. Climate-aware precision entomology will become increasingly important as temperature and rainfall patterns change pest phenology and distribution. Forecasting systems should therefore integrate climate scenarios and uncertainty rather than relying solely on historical relationships.

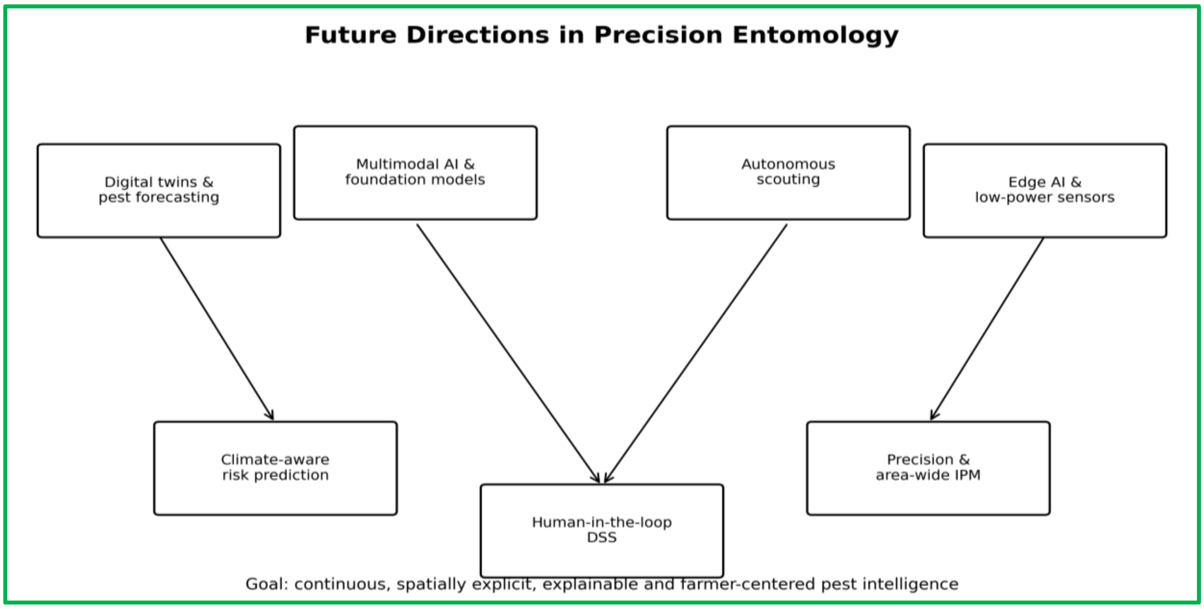

Figure 4. Emerging directions in precision entomology, including multimodal AI, autonomous scouting, edge computing, climate-aware forecasting and human-in-the-loop decision support.

The most useful future systems will remain human-centered. Farmers, extension personnel and entomologists should be involved in defining thresholds, interpreting alerts and evaluating recommendations. The goal should be a decision-support partnership in which technology expands observation and analytical capacity while biological expertise guides action.

Conclusion

Precision entomology represents a promising evolution of agricultural pest management in which IoT, remote sensing, artificial intelligence and decision-support systems are integrated into an end-to-end monitoring and intervention framework. IoT devices can provide continuous pest and environmental observations, remote sensing can extend spatial coverage, AI can automate identification and forecasting, and DSS platforms can convert analytical outputs into actionable recommendations. The greatest opportunity is not any single technology but the integration of complementary data streams. A smart trap may detect an emerging pest population, remote sensing may identify crop-stress hotspots, weather data may explain population development and AI may estimate future risk. A decision-support system can then prioritize field verification and recommend an appropriate IPM response. Nevertheless, precision entomology must overcome limitations related to dataset quality, field generalization, sensor reliability, connectivity, cost, explainability and data governance. Future research should emphasize independent field validation, human-in-the-loop decision-making, climate-aware forecasting, interoperable systems and farmer-centered design. When developed around sound entomological principles and integrated with IPM, precision technologies can improve the timing, spatial targeting and efficiency of pest management. Their long-term value will depend on whether they deliver reliable biological information and economically meaningful decisions under real agricultural conditions.

References

1. Kiobia, D.O., Mwitta, C.J., Fue, K.G., Schmidt, J.M. and Rains, G.C. (2023). A review of successes and impeding challenges of IoT-based insect pest detection systems for estimating agroecosystem health and productivity of cotton. Sensors, 23: 4127. https://doi.org/10.3390/s23084127

2. Sugas, N., Elaiyabharathi, T., Murugan, M., Balaji, K., Srinivasan, T. and Thangamani, C. (2025). Accelerating AI-driven solutions for insect pest detection in Indian agriculture: A systematic review.
3. Panotra, N., Boruah, A., Singh, A., Sharma, D. and Tripathi, P. (2025). Precision Agriculture and Smart Technologies for Insect Pest Management. Uttar Pradesh Journal of Zoology.
4. Ejaz, M.H., Bilal, M. and Habib, U. (2025). Crop Pest Classification Using Deep Learning Techniques: A Review. arXiv:2507.01494.
5. Li, Y., Zha, L., Liu, W., Luo, F. and Xu, C. (2026). From detection to action: artificial intelligence in integrated pest and invasive plant management. Advanced Biotechnology, 4: 25.
6. De Antoni, A., Rucco, M., Cattaneo, A.M., Gezer, E., Sulis, G., Draicchio, P., Iacca, G., Pugliese, A. and Mancini, M.V. (2026). PesTwin: A biology-informed Digital Twin for enabling precision farming. arXiv:2603.12294.
7. FAO (2026). Integrated Pest Management. Food and Agriculture Organization of the United Nations.
8. World Bank (2025). Digital Agriculture and Smart Farming approaches for sustainable agricultural transformation.
9. Ma, C.-S., et al. (2025). Crop pest responses to global changes in climate and land management. Nature Reviews Earth & Environment, 6: 264–283.