Remote Sensing and Automated Monitoring Systems for Insect Pest Detection and Surveillance

Abstract

Insect pests pose a significant threat to agricultural production, requiring effective monitoring and management strategies. Recent advancements in remote sensing and automated monitoring technologies offer promising solutions for early detection and surveillance of insect pests in agricultural systems. This review paper explores the current state-of-the-art remote sensing and automated monitoring approaches for insect pest detection, including satellite imagery, unmanned aerial vehicles (UAVs), wireless sensor networks, and machine learning algorithms. We discuss the advantages, limitations, and potential applications of these technologies in precision agriculture and integrated pest management. Case studies highlighting successful implementations of remote sensing and automated monitoring systems for major insect pests are presented. Furthermore, we outline future research directions and challenges in developing cost-effective, scalable, and reliable pest monitoring solutions. The integration of remote sensing and automated monitoring systems with decision support tools and precision pest control strategies holds great promise for improving crop protection and ensuring sustainable food production in the face of increasing pest pressures.

Keywords: remote sensing, automated monitoring, insect pests, precision agriculture, integrated pest management

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- research method
- results obtained
- conclusion

1. **Introduction**

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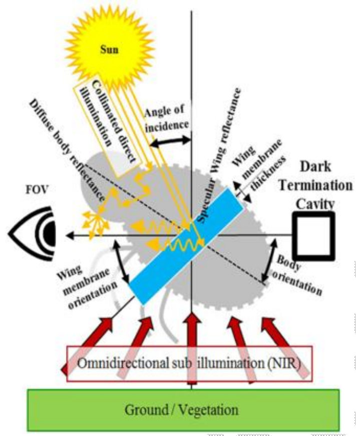

Fig 1 : Insect scattering

Insect pests are a major concern in agricultural production, causing significant yield losses and economic damage worldwide. The global crop losses due to insect pests are estimated to be around 20-30% annually (Oerke, 2006). Effective monitoring and management of insect pests are crucial for minimizing crop damage and ensuring food security. Traditional pest monitoring methods, such as manual scouting and sticky traps, are labor-intensive, time-consuming, and often fail to provide timely and accurate information on pest population dynamics (Pimentel, 2009). Moreover, these methods are limited in their spatial coverage and resolution, making it challenging to detect and monitor pests at a large scale.

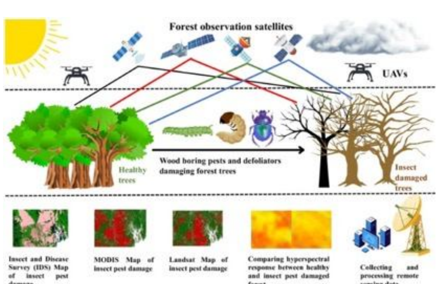

Fig 2 : Use of Satellites for Forest observation

Recent advancements in remote sensing and automated monitoring technologies have opened up new possibilities for early detection and surveillance of insect pests in agricultural systems. Remote sensing techniques, such as satellite imagery, unmanned aerial vehicles (UAVs), and hyperspectral imaging, allow for non-invasive and large-scale monitoring of crop health and pest infestations (Zhang *et al.*, 2019). Automated monitoring systems, including wireless sensor networks, acoustic detection systems, and computer vision techniques, enable continuous and real-time monitoring of pest populations and their behavior (Jiang *et al.*, 2018).

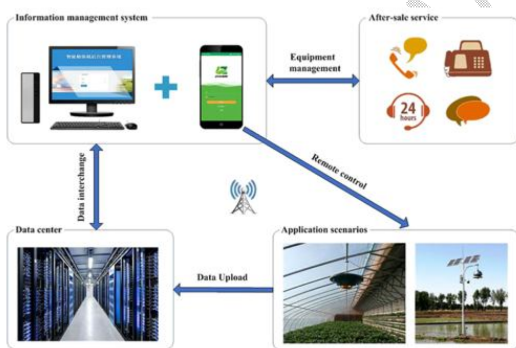

Fig 3 : Integration of remote sensing and automated monitoring systems

The integration of remote sensing and automated monitoring systems with precision agriculture practices and decision support tools has the potential to revolutionize pest management strategies. Precision agriculture involves the use of advanced technologies, such as global positioning systems (GPS), geographic information systems (GIS), and variable rate application (VRA) systems, to optimize crop production and resource utilization (Gebbers&Adamchuk, 2010). By combining remote sensing and automated monitoring data with precision agriculture tools, farmers can make informed decisions on targeted pest control interventions, reducing the reliance on broad-spectrum pesticides and promoting sustainable pest management practices.

This review paper aims to provide a comprehensive overview of the current state-of-the-art remote sensing and automated monitoring technologies for insect pest detection and surveillance. We discuss the principles, applications, advantages, and limitations of various remote sensing and automated monitoring approaches. Case studies highlighting successful implementations of these technologies for major insect pests are presented. Furthermore, we explore the integration of remote sensing and automated monitoring systems with precision agriculture practices and decision support tools for effective pest management. Finally, we outline the challenges and future research directions in developing cost-effective, scalable, and reliable pest monitoring solutions.

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2. **Remote Sensing Techniques for Insect Pest Detection**

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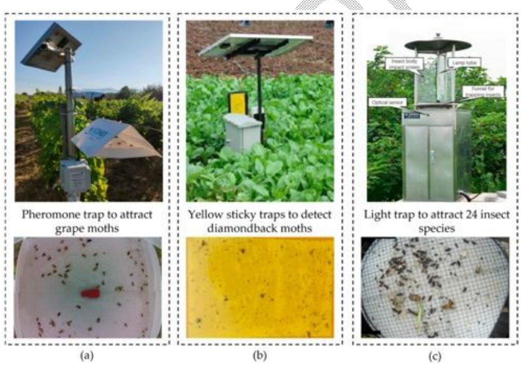
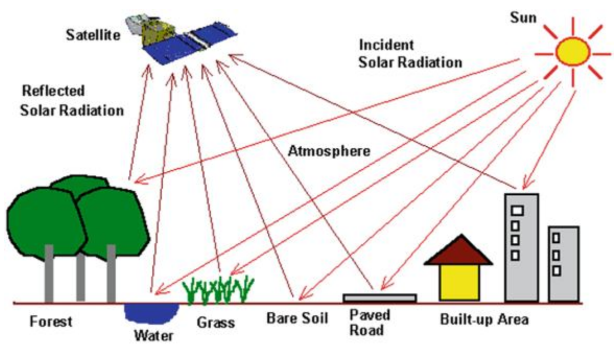


Fig 4 : Remote Sensing Techniques for Insect Pest Detection

Remote sensing techniques have emerged as powerful tools for monitoring crop health and detecting insect pest infestations at various spatial and temporal scales. These techniques involve the acquisition and analysis of data from a distance using sensors mounted on satellites, aircraft, or UAVs. The spectral, spatial, and temporal resolution of remote sensing data allows for the detection of subtle changes in vegetation health and the identification of pest-infested areas (Zhang *et al.*, 2019). In this section, we discuss the principles, applications, advantages, and limitations of satellite imagery, UAVs, and hyperspectral imaging for insect pest detection.



2.1 **Satellite Imagery**

Fig 5 : Satellite imagery for monitoring crop health

Satellite imagery has been widely used for monitoring crop health and detecting insect pest infestations at a regional or global scale. Satellite sensors, such as Landsat, MODIS, and Sentinel, provide multispectral data with varying spatial and temporal resolutions (Zhang *et al.*, 2019). The spectral bands of these sensors, particularly in the visible and near-infrared regions, are sensitive to changes in vegetation health and can be used to derive vegetation indices, such as the Normalized Difference Vegetation Index (NDVI) and the Enhanced Vegetation Index (EVI) (Huang *et al.*, 2018).

The application of satellite imagery for insect pest detection relies on the principle that pest-infested crops exhibit distinct spectral signatures compared to healthy crops. For example, aphid-infested wheat fields have been shown to have lower NDVI values compared to healthy fields due to the reduction in chlorophyll content and leaf area (Mulla *et al.*, 2017). Similarly, the red palm weevil (*Rhynchophorus ferrugineus*) infestation in date palm trees has been detected using satellite imagery based on the changes in the spectral reflectance of infested trees (Javeedalee*et al.*, 2019).

Table 1. Comparison of satellite sensors used for insect pest detection

Sensor	Spatial Resolution	Temporal Resolution	Spectral Bands	Application Examples

Sensor	Spatial Resolution	Temporal Resolution	Spectral Bands	Application Examples
Landsat	30 m	16 days	11	Aphid detection in wheat, Red palm weevil detection in date palm
MODIS	250 m - 1 km	Daily	36	Locust outbreak monitoring, Armyworm detection in maize
Sentinel	10 m - 60 m	5 days	13	Bark beetle detection in forests, Whitefly monitoring in cotton

The main advantage of satellite imagery is its ability to cover large geographic areas and provide repeated observations over time. This allows for the monitoring of pest population dynamics and the identification of hot spots for targeted control measures. However, the spatial resolution of satellite imagery may not be sufficient for detecting small-scale pest infestations or individual insect pests. Moreover, the presence of clouds, atmospheric effects, and vegetation canopy structure can limit the accuracy of pest detection using satellite data (Zhang *et al.*, 2019).

Several case studies have demonstrated the successful use of satellite imagery for insect pest detection. For instance, Mulla *et al.* (2017) used Landsat imagery to detect Russian wheat aphid (*Diuraphisnoxia*) infestations in wheat fields in the United States. They found that the NDVI values of aphid-infested fields were significantly lower than those of healthy fields, indicating the potential of satellite imagery for early detection of aphid infestations. Similarly, Javeedalee*et al*. (2019) used SPOT-6 satellite imagery to detect red palm weevil infestations in date palm plantations in the United Arab Emirates. They developed a spectral index based on the red and near-infrared bands that could accurately differentiate between healthy and infested trees.

2.2 **Unmanned Aerial Vehicles (UAVs)**

UAVs, also known as drones, have emerged as a promising tool for high-resolution and flexible monitoring of insect pests in agricultural systems. UAVs can be equipped with various sensors, such as RGB cameras, multispectral cameras, and thermal cameras, to capture detailed imagery of crop canopies and individual plants (Maes & Steppe, 2019). The high spatial resolution (centimeter-level) and low altitude of UAV imagery allow for the detection of small-scale pest infestations and the identification of individual insect pests.

Fig 6 : Unmanned Aerial Vehicles for pest monitoring

The types of UAVs used for pest monitoring can be broadly classified into fixed-wing and rotary-wing UAVs. Fixed-wing UAVs have longer flight times and can cover larger areas, making them suitable for surveying extensive crop fields. Rotary-wing UAVs, such as quadcopters and hexacopters, have better maneuverability and can hover over specific locations, enabling detailed inspections of individual plants or pest hot spots (Maes & Steppe, 2019).

The sensors and payloads used for pest detection on UAVs vary depending on the target pest and the crop system. RGB cameras are commonly used for visual inspection of pest damage and the identification of pest stages (e.g., eggs, larvae, adults). Multispectral cameras, which capture data in multiple spectral bands, can be used to derive vegetation indices and detect changes in plant health due to pest infestations. Thermal cameras can detect temperature variations in crop canopies, which may indicate pest-induced stress or disease (Maes & Steppe, 2019).

The data processing and analysis techniques for UAV imagery involve a combination of image pre-processing, feature extraction, and machine learning algorithms. Image pre-processing steps, such as orthorectification, mosaicking, and radiometric calibration, are necessary to ensure the spatial and spectral consistency of UAV imagery (Zhang *et al.*, 2019). Feature extraction techniques, such as texture analysis, edge detection, and object-based image analysis (OBIA), are used to identify and delineate pest-infested areas or individual insect pests. Machine learning algorithms, including support vector machines (SVM), random forests (RF), and convolutional neural networks (CNN), are employed for the classification and mapping of pest infestations based on the extracted features (Ghosh, 2021).

Table 2. Sensors used in UAVs for insect pest detection

Sensor	**Spectral Bands**	**Spatial Resolution**	**Application Examples**
RGB Camera	3 (Red, Green, Blue)	Centimeter-level	Visual inspection of pest damage, Identification of pest stages
Multispectral Camera	4-10	Centimeter-level	Vegetation index calculation, Plant health monitoring
Thermal Camera	1 (Infrared)	Centimeter-level	Detection of pest-induced stress, Disease monitoring

Several case studies have demonstrated the successful use of UAVs for insect pest monitoring in various crop systems. For example, Hoffmann *et al.* (2021) used UAV-based RGB imagery to detect and map the infestation of the European corn borer (*Ostrinianubilalis*) in maize fields. They developed a CNN model that could accurately classify healthy and infested plants based on the visual symptoms of pest damage. Similarly, Kalischuk*et al.* (2022) used multispectral UAV imagery to monitor the infestation of the wheat stem sawfly (*Cephus cinctus*) in wheat fields. They found that the vegetation indices derived from the multispectral data, such as the Normalized Difference Red Edge (NDRE) index, could effectively differentiate between healthy and infested wheat plants.

The main advantages of UAVs for insect pest monitoring include their high spatial resolution, flexibility in data acquisition, and the ability to cover large areas quickly. UAVs can provide near real-time information on pest infestations, enabling timely and targeted control measures. However, the operational costs, regulatory requirements, and data processing challenges associated with UAV-based pest monitoring need to be considered (Maes & Steppe, 2019).

2.3 **Hyperspectral and Multispectral Imaging**

Hyperspectral and multispectral imaging techniques have shown great potential for detecting insect pest infestations based on the spectral signatures of infested plants. Hyperspectral imaging involves the acquisition of data in hundreds of narrow spectral bands, providing detailed spectral information about the target objects. Multispectral imaging, on the other hand, captures data in a fewer number of spectral bands (typically 4-10) that are strategically selected to maximize the discrimination between different features (Zhang *et al.*, 2019).

The principles of hyperspectral and multispectral imaging for pest detection rely on the fact that pest-infested plants exhibit distinct spectral signatures compared to healthy plants. The spectral differences can be attributed to changes in leaf pigments, water content, and cellular structure due to pest feeding or disease (Huang *et al.*, 2018). For example, aphid-infested wheat leaves have been shown to have lower reflectance in the near-infrared region and higher reflectance in the visible region compared to healthy leaves (Yuan *et al.*, 2014).

The application of hyperspectral and multispectral imaging for insect pest detection involves the acquisition of high-resolution spectral data from crop canopies using ground-based, UAV-based, or satellite-based platforms. The spectral data is then processed using various techniques, such as spectral vegetation indices, spectral angle mapping, and machine learning algorithms, to identify and map pest-infested areas (Zhang *et al.*, 2019).

One of the challenges in using hyperspectral and multispectral imaging for pest detection is the selection of optimal spectral bands or indices that are sensitive to specific pests or diseases. This requires a good understanding of the spectral characteristics of the target pests and their host plants. Moreover, the high dimensionality of hyperspectral data poses challenges in data storage, processing, and analysis (Huang *et al.*, 2018).

Table 3. Comparison of hyperspectral and multispectral imaging for insect pest detection

Imaging Technique	**Number of Spectral Bands**	**Spectral Resolution**	**Advantages**	**Limitations**
Hyperspectral Imaging	Hundreds	Narrow (2-10 nm)	Detailed spectral information, High	High data dimensionality,

			discrimination power	Complex processing, High cost
Multispectral Imaging	4-10	Wide (20-100 nm)	Simpler data processing, Lower cost	Limited spectral information, Lower discrimination power

Recent studies have shown the potential of hyperspectral and multispectral imaging for insect pest detection in various crop systems. For instance, Yuan *et al.* (2014) used hyperspectral imaging to detect aphid infestation in wheat fields. They identified specific spectral bands and indices that were sensitive to aphid infestation levels and developed a partial least squares regression model for estimating aphid density. Similarly, Ishimwe *et al.* (2014) used multispectral imaging to detect the infestation of the tomato leafminer (*Tutaabsoluta*) in tomato plants. They found that the ratio of the near-infrared to red bands could effectively discriminate between healthy and infested tomato leaves.

Despite the promising results, the operational use of hyperspectral and multispectral imaging for insect pest detection is still limited due to the high cost and complexity of the imaging systems. Future research should focus on the development of cost-effective and user-friendly hyperspectral and multispectral sensors that can be easily integrated into existing pest monitoring workflows. Moreover, the integration of hyperspectral and multispectral data with other data sources, such as weather data and crop growth models, can provide a more comprehensive understanding of pest population dynamics and improve the accuracy of pest risk assessments (Zhang *et al.*, 2019).

3. **Automated Monitoring Systems for Insect Pest Surveillance**

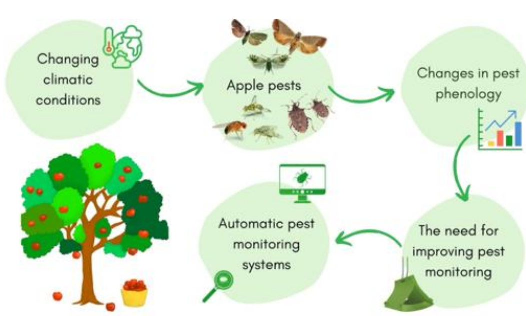


Fig 7 : Automated Monitoring Systems for Insect Pest Surveillance

Automated monitoring systems have emerged as an effective tool for continuous and real-time surveillance of insect pest populations in agricultural systems. These systems involve the deployment of various sensors and devices, such as wireless sensor networks, acoustic sensors, and computer vision systems, to collect data on pest activity, behavior, and environmental conditions. The data collected by these systems can be processed and analyzed using advanced algorithms to provide actionable information for pest management decisions. In this section, we discuss the principles, applications, advantages, and limitations of wireless sensor networks, acoustic detection systems, and computer vision techniques for insect pest surveillance.

3.1 **Wireless Sensor Networks**

Wireless sensor networks (WSNs) consist of a large number of small, low-cost, and low-power sensor nodes that are distributed throughout the crop field to monitor various parameters related to pest activity and environmental conditions (Jiang *et al.*, 2018). The sensor nodes are equipped with various sensors, such as temperature, humidity, light, and CO_2 sensors, which can detect changes in the microclimate that are conducive to pest development. The sensor nodes communicate with each other and with a base station using wireless protocols, such as ZigBee or LoRa, forming a multi-hop network (Chisimba*et al.*, 2022).

The architecture of WSNs for pest monitoring typically consists of three main components: sensor nodes, gateway nodes, and a central server. The sensor nodes are responsible for data collection and local processing, while the gateway nodes facilitate the communication between the sensor nodes and the central server. The central server receives the data from the gateway nodes and performs advanced processing, analysis, and visualization (Jiang *et al.*, 2018).

The sensor types used in WSNs for pest monitoring can be broadly classified into two categories: direct and indirect sensors. Direct sensors, such as camera traps and acoustic sensors, directly detect the presence or activity of insect pests. Indirect sensors, such as temperature, humidity, and light sensors, measure environmental parameters that are related to pest development and behavior (Shah *et al.*, 2022).

Table 4. Sensors used in wireless sensor networks for insect pest monitoring

Sensor Type	Parameters Measured	Application Examples
Temperature Sensor	Air and soil temperature	Monitoring of pest development rates, Prediction of pest outbreaks
Humidity Sensor	Relative humidity	Monitoring of pest habitat suitability, Prediction of fungal disease outbreaks
Light Sensor	Light intensity, Photoperiod	Detection of pest activity patterns, Monitoring of crop growth stages
CO_2 Sensor	CO_2 concentration	Monitoring of plant stress, Detection of pest respiration
Camera Trap	Insect images, Videos	Identification of pest species, Monitoring of pest activity and behavior
Acoustic Sensor	Insect sounds, Vibrations	Detection of pest feeding and mating activities, Estimation of pest population density

Data transmission and power management are critical aspects of WSNs for pest monitoring. The sensor nodes typically operate on battery power and have limited computational and storage capabilities. To prolong the network lifetime and ensure reliable data transmission, various power management strategies, such as duty cycling and data aggregation, are employed (Jiang *et al.*, 2018). Duty cycling involves alternating between active and sleep modes to conserve energy, while data aggregation reduces the amount of data transmitted by combining and compressing sensor readings (Chisimba*et al.*, 2022).

Several case studies have demonstrated the successful implementation of WSNs for insect pest monitoring in different crop systems. For example, Jiang *et al.* (2018) developed a WSN system for monitoring the population dynamics of the rice brown planthopper (*Nilaparvatalugens*) in rice fields. The system consisted of temperature, humidity, and light sensors, as well as camera traps for capturing insect images. The sensor data were transmitted to a cloud server for analysis and visualization, enabling real-time monitoring of pest population levels and early warning of pest outbreaks. Similarly, Shah *et al.* (2022) used a WSN with acoustic sensors to monitor the activity of the red palm weevil (*Rhynchophorus* *ferrugineus*) in date palm plantations. The system could detect the feeding and mating sounds of the weevil, providing an estimate of the pest population density and facilitating targeted control measures.

The main advantages of WSNs for insect pest monitoring include their ability to provide continuous and real-time data on pest activity and environmental conditions, their scalability and flexibility in deployment, and their potential for integration with other precision agriculture technologies, such as variable rate application systems (Jiang *et al.*, 2018). However, the deployment and maintenance of WSNs can be challenging due to the harsh environmental conditions in agricultural fields, the need for regular battery replacements, and the potential for sensor failures or communication disruptions (Chisimba*et al.*, 2022).

3.2 **Acoustic Detection Systems**

Acoustic detection systems have emerged as a promising tool for monitoring insect pest populations based on their species-specific sounds and vibrations. Many insect species produce distinctive sounds during their feeding, mating, or communication activities, which can be detected and analyzed using acoustic sensors (Mankin *et al.*, 2011). The principles of acoustic detection involve the capture of insect sounds using microphones or piezoelectric sensors, followed by signal processing and pattern recognition algorithms to identify the target pest species and estimate their population density (Koubaa *et al.*, 2021).

The application of acoustic detection systems for insect pest monitoring has been demonstrated in various crop systems, such as grain storage facilities, orchards, and vineyards. For example, the detection of insect pests in stored grain, such as the rice weevil (*Sitophilus oryzae*) and the red flour beetle (*Triboliumcastaneum*), has been achieved using acoustic sensors that capture the feeding and movement sounds of the insects (Mankin *et al.*, 2011). Similarly, the detection of the Asian citrus psyllid (*Diaphorina citri*), a vector of the citrus greening disease, has been demonstrated using acoustic sensors in citrus orchards (Mankin *et al.*, 2019).

The development of insect sound recognition algorithms is a critical component of acoustic detection systems. These algorithms involve the extraction of relevant features from the acoustic signals, such as the temporal and spectral characteristics, followed by the classification of the signals into different pest species or activity patterns (Koubaa *et al.*, 2021). Machine learning approaches, such as support vector machines (SVM), hidden

Markov models (HMM), and deep learning neural networks, have been employed for insect sound recognition with high accuracy (Potamitis*et al.*, 2022).

The main advantage of acoustic detection systems is their ability to provide non-invasive and real-time monitoring of insect pest populations without the need for visual inspection or physical contact with the insects. Acoustic detection can be used for early warning of pest infestations, estimation of pest population densities, and evaluation of the effectiveness of control measures (Mankin *et al.*, 2019). However, the performance of acoustic detection systems can be affected by environmental noise, the presence of non-target insect species, and the variability in insect sound production (Koubaa *et al.*, 2021).

3.3 **Computer Vision and Machine Learning Techniques** Computer vision and machine learning techniques have gained significant attention for automated insect pest monitoring in recent years. These techniques involve the acquisition of digital images or videos of insect pests using cameras or smartphones, followed by image processing and analysis using advanced algorithms (Biswas *et al.*, 2022). The principles of computer vision for pest detection rely on the extraction of visual features, such as color, shape, texture, and motion, from the images or videos, which are then used to identify and classify the insect pests (Kour *et al.*, 2022).

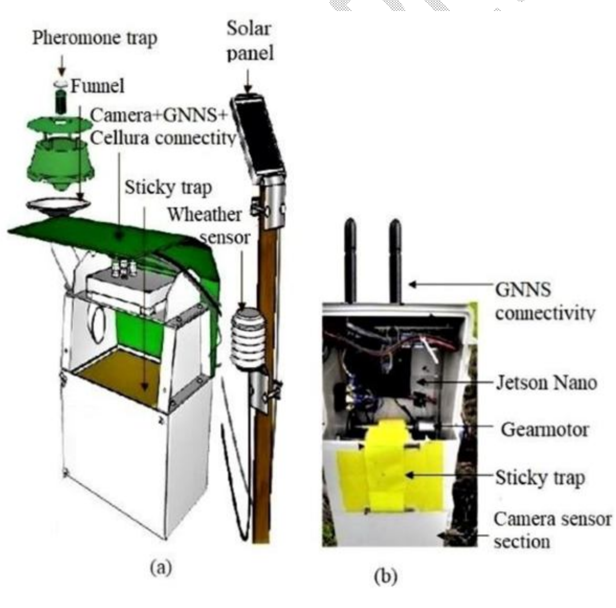


Fig 8 : Remote monitoring devices

Image processing algorithms for pest detection typically involve a series of steps, including image pre-processing, segmentation, feature extraction, and classification. Image pre-processing techniques, such as noise reduction, contrast enhancement, and color space transformation, are applied to improve the quality and consistency of the images (Biswas *et al.*, 2022). Image segmentation algorithms, such as thresholding, edge detection, and region growing, are used to separate the regions of interest (i.e., insect pests) from the background (Kour *et al.*, 2022). Feature extraction techniques, such as scale-invariant feature transform (SIFT), histogram of oriented gradients (HOG), and local binary patterns (LBP), are employed to extract distinctive features from the segmented regions (Biswas *et al.*, 2022).

Machine learning algorithms, such as support vector machines (SVM), random forests (RF), and convolutional neural networks (CNN), are widely used for automated insect pest classification based on the extracted features. These algorithms learn from labeled training data and build models that can classify new images or videos into different pest species or damage levels (Kour *et al.*, 2022). Deep learning architectures, particularly CNNs, have shown remarkable performance in insect pest classification tasks due to their ability to automatically learn hierarchical features from large datasets (Nath *et al.*, 2021).

Table 5. Machine learning algorithms for automated insect pest classification

Algorithm	**Principle**	**Advantages**	**Limitations**
Support Vector Machines (SVM)	Finds optimal hyperplane to separate classes	Works well with small datasets, Handles high-dimensional data	Sensitive to noisy data, Difficult to interpret
Random Forests (RF)	Ensemble of decision trees, Majority voting	Handles large datasets, Robust to overfitting	Computationally expensive, Prone to bias
Convolutional Neural Networks (CNN)	Learns hierarchical features from images	High accuracy, Automatic feature extraction	Requires large labeled datasets, Computationally intensive

Several case studies have demonstrated the successful application of computer vision and machine learning techniques for insect pest monitoring in various crop systems. For instance, Nath *et al*. (2021) developed a CNN-based system for the detection and classification of the rice brown planthopper (*Nilaparvatalugens*) in rice fields. The system achieved an accuracy of 98.7% in classifying the planthopper from field-captured images, outperforming traditional machine learning algorithms such as SVM and RF. Similarly, Kour *et al.* (2022) used a combination of image processing and machine learning techniques to detect and classify the damage caused by the tomato leafminer (*Tutaabsoluta*) in tomato plants. The system achieved an accuracy of 96.3% in classifying the damage levels based on the extracted color and texture features.

The main advantages of computer vision and machine learning techniques for insect pest monitoring include their high accuracy, automation potential, and scalability. These techniques can process large volumes of image data and provide real-time information on pest infestations, enabling timely and targeted control measures (Biswas *et al.*, 2022). However, the performance of these techniques depends on the quality and diversity of the training data, the selection of appropriate features and algorithms, and the computational resources available (Kour *et al.*, 2022).

4. **Integration of Remote Sensing and Automated Monitoring Systems**

The integration of remote sensing and automated monitoring systems offers a comprehensive and multi-scale approach for insect pest detection and surveillance. By combining data from satellite imagery, UAVs, wireless sensor networks, and computer vision systems, a more complete picture of pest population dynamics and crop health can be obtained (Zhang *et al.*, 2019). Data fusion and multi-sensor approaches are key to leveraging the strengths of different monitoring technologies and overcoming their individual limitations (Yao *et al.*, 2022).

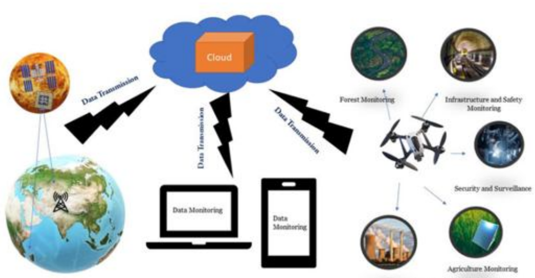


Fig 9 : Integration of remote sensing and automated monitoring systemsfor insect pest detection

Data fusion involves the integration of data from multiple sources to provide a more accurate and reliable estimate of pest infestation levels and crop damage. For example, the combination of satellite imagery and UAV data can provide both large-scale and high-resolution information on pest-infested areas, enabling precision targeting of control measures (Yao *et al.*, 2022). Similarly, the integration of wireless sensor network data with computer vision systems can provide real-time information on pest activity and behavior, facilitating early detection and rapid response to pest outbreaks (Jiang *et al.*, 2018).

Decision support systems (DSS) play a crucial role in translating the data from remote sensing and automated monitoring systems into actionable information for pest management. DSS are computer-based tools that integrate data from various sources, such as weather stations, crop models, and pest monitoring systems, to provide risk assessments, economic thresholds, and management recommendations (Magarey *et al.*, 2018). For example, the integration of remote sensing data with weather-based pest models can provide early warning of pest outbreaks and guide the timing and location of control measures (Fleisher *et al.*, 2020).

Precision pest control strategies, such as site-specific pesticide application and biological control, can be greatly enhanced by the integration of remote sensing and automated monitoring systems. By identifying the spatial and temporal distribution of pest infestations, precision pest control techniques can target the application of control measures to the infested areas, reducing the overall pesticide use and minimizing the impact on non-target organisms (Yao *et al.*, 2022). For instance, the use of UAV-based remote sensing data to guide the release of natural enemies, such as parasitoids or predators, can improve the efficiency and effectiveness of biological control programs (Giles *et al.*, 2021).

The economic and environmental benefits of integrating remote sensing and automated monitoring systems for insect pest management are substantial. By enabling early detection, precision targeting, and optimized control strategies, these technologies can reduce the economic losses caused by pest infestations, improve crop yields and quality, and minimize the environmental impact of pesticide use (Zhang *et al.*, 2019). Moreover, the adoption of these technologies can enhance the sustainability and resilience of agricultural systems, contributing to food security and environmental conservation (Magarey *et al.*, 2018).

5. **Challenges and Future Directions**

Despite the significant advancements in remote sensing and automated monitoring technologies for insect pest detection and surveillance, several challenges and limitations remain. One of the major technological challenges is the development of cost-effective, reliable, and user-friendly sensors and platforms that can withstand the harsh environmental conditions in agricultural fields (Zhang *et al.*, 2019). The scalability and interoperability of monitoring systems across different crops, regions, and pest species are also important considerations for their widespread adoption (Jiang *et al.*, 2018).

Data management and integration pose significant challenges due to the large volumes and diverse formats of data generated by remote sensing and automated monitoring systems. The development of standardized data protocols, metadata standards, and data sharing platforms is crucial for facilitating the integration and analysis of multi-source data (Yao *et al.*, 2022). Moreover, the need for advanced data analytics, such as machine learning and big data techniques, to extract meaningful insights from the vast amounts of monitoring data is increasingly recognized (Biswas *et al.*, 2022).

The adoption and user acceptance of remote sensing and automated monitoring technologies in pest management are influenced by various factors, such as the perceived usefulness, ease of use, and cost-effectiveness of the technologies (Zhang *et al.*, 2019). The development of user-friendly interfaces, decision support tools, and training programs is essential for promoting the uptake of these technologies by farmers, extension agents, and pest management professionals (Magarey *et al.*, 2018).

Future research directions in remote sensing and automated monitoring for insect pest management should focus on addressing these challenges and advancing the state-of-the-art technologies. The development of low-cost, miniaturized, and energy-efficient sensors and platforms, such as Wireless Sensor Networks (WSN) and Internet of Things (IoT) devices, is a promising avenue for enhancing the scalability and affordability of monitoring systems (Jiang *et al.*, 2018). The integration of emerging technologies, such as Artificial Intelligence (AI), Big Data Analytics, and Cloud Computing, with remote sensing and automated monitoring systems can greatly improve their performance, adaptability, and decision-making capabilities (Biswas *et al.*, 2022).

Another important research direction is the development of multi-scale, multi-sensor, and multi-pest monitoring frameworks that can provide a comprehensive and integrated assessment of pest population dynamics and crop health (Yao *et al.*, 2022). The incorporation of ecological and biological knowledge, such as pest-crop interactions, natural enemy populations, and landscape factors, into monitoring systems can enhance their predictive power and guide sustainable pest management strategies (Fleisher *et al.*, 2020).

Table 6. Advantages and limitations of remote sensing and automated monitoring systems for insect pest management

Advantages	**Limitations**
Early detection of pest infestations	High initial costs and technical expertise required
High spatial and temporal resolution	Dependence on weather conditions and data quality
Non-destructive and non-invasive monitoring	Limited ability to detect low-density pest populations
Scalability and flexibility in deployment	Potential for false positives and false negatives
Integration with precision pest control strategies	Data management and interpretation challenges
Economic and environmental benefits	User acceptance and adoption barriers

Furthermore, the validation and benchmarking of remote sensing and automated monitoring technologies under diverse field conditions and cropping systems are essential for assessing their reliability, robustness, and transferability (Zhang *et al.*, 2019). The establishment of collaborative research networks, data sharing platforms, and public-private partnerships can facilitate the development, testing, and dissemination of these technologies across different regions and stakeholders (Magarey *et al.*, 2018).

6. Conclusion

Comment [MOU5]: Try checking again, is this conclusion in accordance with the research objectives?

Remote sensing and automated monitoring technologies have emerged as powerful tools for insect pest detection and surveillance in agricultural systems. Satellite imagery, unmanned aerial vehicles, wireless sensor networks, and computer vision techniques offer unique opportunities for non-destructive, real-time, and high-resolution monitoring of pest populations and crop health. The integration of these technologies with precision agriculture practices and decision support systems has the potential to revolutionize pest management strategies, reducing economic losses, improving crop yields, and promoting sustainable agriculture.

However, the adoption and widespread use of remote sensing and automated monitoring technologies for insect pest management face several challenges, including technological limitations, data management and integration issues, user acceptance and adoption barriers, and the need for validation and benchmarking under diverse field conditions. Future research should focus on addressing these challenges and advancing the state-of-the-art technologies through the development of low-cost, reliable, and user-friendly sensors and platforms, the integration of emerging technologies such as AI and Big Data Analytics, and the establishment of collaborative research networks and data sharing platforms.

The successful implementation of remote sensing and automated monitoring systems for insect pest detection and surveillance requires a multidisciplinary approach, involving collaboration among entomologists, plant pathologists, agronomists, computer scientists, and engineers. The integration of ecological and biological knowledge with advanced monitoring technologies is crucial for developing sustainable and effective pest management strategies. By harnessing the power of remote sensing and automated monitoring, we can enhance the resilience and productivity of agricultural systems, ensure food security, and protect the environment for future generations.

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Comment [MOU6]: some references do not match between the citations in the body of the article and the reference list. Try checking again so that this reference list really includes what is cited in the body of the article (between the citations and the reference list are matching)

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