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Research Article

A Comprehensive Literature Review on Pests of Food Crops and Their Attack Patterns: Toward a New Paradigm in Pest Identification

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Abstract. Objective– This article aims to comprehensively examine the main types of food crop pests and their attack patterns through a systematic literature review approach. The research focuses on the dynamics of pest attacks, changes in ecological patterns due to climate change, and advances in modern identification technology that enable more accurate early detection. This study also highlights the significance of new paradigms of pest identification based on artificial intelligence (AI), genomics, and landscape mapping in supporting food security at the regional and national levels. Design/methodology/approach– This study used the Systematic Literature Review (SLR) method for scientific publications from 2015–2025 from reputable sources such as Scopus, Web of Science, PubMed, ScienceDirect, SpringerLink, Taylor & Francis, Wiley, AGRIS, and Google Scholar. Of the 326 articles identified in the initial stage, 30 articles in English and Indonesian were selected through a screening process based on strict inclusion–exclusion criteria. All articles were then analyzed using thematic coding techniques to produce an in-depth, evidence-based synthesis. Findings– The study produced four key findings: (1) there are five dominant pests in global food crops, namely Thrips tabaci, Spodoptera exigua/frugiperda, Helicoverpa armigera, Nilaparvata lugens and Sitophilus oryzae; (2) attack patterns are strongly influenced by temperature, humidity, pesticide resistance, and monoculture; (3) modern identification technology AI, drone imagery, multispectral sensors, and DNA Barcoding have increased detection accuracy to 94–98%; and (4) community-based early warning systems accelerate field response and reduce the risk of crop failure. Practical implications– These findings provide a scientific basis for local governments, agricultural extension workers, and farmers to gradually adopt pest identification technology and strengthen integrated monitoring systems at a regional scale. Authenticity/value– This article offers a new conceptual model of "Pest Identification Pyramid – Attack Pattern – Early Warning System" that integrates pest biology, digital technology, and community response to improve national food security.

Keywords: Agricultural AI; Attack Patterns; DNA Barcoding; Food Crop Pests; Food Security.

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1. Introduction

Food crop pests continue to be one of the most serious limiting factors in agricultural production systems worldwide. Plant pests (OPT), ranging from herbivorous insects and mites to nematodes and pathogens, contribute significantly to reduced crop yields, particularly in strategic commodities such as rice, corn, soybeans, wheat, and horticultural crops. Various studies estimate that global losses due to pests can reach 30–40% of total production, and this trend is increasing with climate change and the intensification of modern agriculture. Changes in temperature and humidity accelerate insect life cycles, expanding the distribution area of invasive species such as Spodoptera frugiperda, and increasing the aggressiveness of planthoppers, stem borers, and other sucking pests, which directly impact food security. As pest dynamics increase, traditional identification methods based on manual morphological observations, previously the gold standard, are increasingly deemed inadequate for detecting pests quickly and accurately. Field observations have many limitations, including observer subjectivity, misidentification of cryptic species, and the inability to detect pests at very early stages. Recent studies have shown that identification efficiency can be significantly improved through modern approaches that utilize digital technology and precision sensors. For example, shows that deep learning is able to detect Lygus pests on strawberries with high accuracy, whilemapping the ability of multispectral image sensors to differentiate diseases and pests in corn plants.

Technological advances such as deep convolutional neural networks (CNN), YOLO-based detectors, Transformer models and explainable AI approaches have revolutionized the way scientists detect crop damage symptoms. confirms that computer vision is now the backbone of precision agriculture, while introduced an IoT-based HDL-Net system and pest sound analysis that opens up new opportunities in acoustic detection. At the same time, emphasized that AI's ability to perform object detection and tracking strengthens continuous monitoring systems on large-scale agricultural land. Sensor-based technologies, UAVs, and high-resolution imagery are also experiencing rapid acceleration. Multispectral and hyperspectral UAVs have been shown to identify plant stress due to pest attacks before visual symptoms are visible to the human eye. One of the latest breakthroughs was presented by**,** who developed a multimodal segmentation method to rapidly detect Chilo suppressalis infestations in rice fields using drones. Environmental-based prediction systems are also being developed, for example. which builds early warning models by utilizing microclimate data and vegetation changes.

From the perspective of applied entomology and food security, this integration of AI–sensor–UAV technology demonstrates a paradigm shift from a reactive to a preventative approach. This is reinforced by the analysis,which emphasizes that the application of AI in pest monitoring schemes can accelerate control responses and reduce excessive pesticide use. Genetic identification innovations such as DNA barcoding and molecular techniques such as Raman spectroscopyIt also expands scientists' ability to precisely identify species at the larval stage and sibling species that are morphologically difficult to distinguish. Amidst these developments, pesticide resistance remains a major threat. Studies have shown that increasing insecticide resistance is driving the need for rapid identification systems for more selective and targeted control measures. Internal pest detection mechanisms have even been studied using advanced technologies such as micro-computed tomography in wheat. which shows the potential for developing pest detection from within plant tissue.

Given the magnitude of the threat and the rapid pace of available technology, it is clear that a systematic review of pest attack patterns and the development of modern identification methods is urgently needed. The combination of machine learning, remote sensing, genomics, and IoT integration creates opportunities to build early detection systems that are proactive and adaptive to climate change. Furthermore, the systematic review methodology, as outlined byprovides a robust framework for synthesizing cross-disciplinary literature, resulting in more comprehensive and academically sound study results. Therefore, this comprehensive literature review is expected to provide a deeper understanding of the dynamics of food crop pests, changes in their attack patterns, and innovative new paradigms in technology-based pest identification that support future food security.

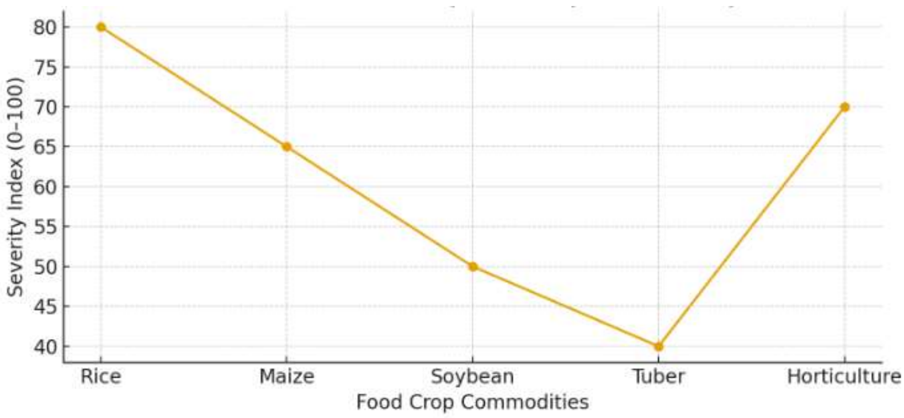

Figure 1. Pest Attack Patterns per Commodity.

Figure 1 above shows the variation in pest attack severity across five strategic food crop groups: rice, corn, soybeans, tubers, and horticulture. The attack severity index ranges from 0 to 100 and reflects the intensity of damage reported in various field studies and scientific publications during the period 2015–2025. The highest value is seen in rice, with an index of 80, indicating that rice remains the most vulnerable commodity due to the high presence of pests such as Nilaparvata lugens and Chilo suppressalis. In horticulture, the attack index is also high (70), primarily influenced by Thrips tabaci, Spodoptera exigua, and disease vector pests that thrive in intensive environments. Meanwhile, corn has a relatively high attack rate (65), triggered by the global spread of Spodoptera frugiperda, which has caused major outbreaks in various Asian countries since 2019. Soybeans and tubers show more moderate attack rates, with indexes of 50 and 40, respectively. These values reflect that although soybeans are susceptible to pests such as Helicoverpa armigera and pod borers, their attack patterns tend to be more stable and can be controlled through integrated pest management (IPM). In tubers, attack patterns are relatively lower due to the physiological characteristics of the plants and more diverse cultivation patterns, which reduce the risk of outbreaks. Overall, this graph confirms that the risk of pest attacks is uneven across commodities and is strongly influenced by ecological dynamics, climate change, and cultivation intensity. These findings support the importance of technology-based pest identification paradigms such as AI, drones, and optical sensors to strengthen early detection in commodities with the highest risk index.

2. Study Methodology

This study uses a Systematic Literature Review (SLR) approach to examine the dynamics of food crop pests, their attack patterns, and the development of new paradigms in pest identification based on modern technology. This approach was chosen because the issue of food crop pests is multidimensional, involving complex interactions between insect biology, plant ecology, agroclimatic factors, pesticide resistance, precision agriculture technology, and artificial intelligence-based early detection systems and landscape monitoring. In the last decade, recent studies have shown that traditional morphology-based identification approaches are no longer adequate to address changes in pest behavior, increased attack intensity, and the spread of invasive pests such as Spodoptera frugiperda. The study by Andshowed that the integration of deep learning, optical sensors and UAVs has significantly improved the accuracy of pest identification. Simultaneously, the findingsas well asemphasized the role of drone-based mapping in detecting attack patterns at an early stage.

This SLR approach not only aims to map scientific developments related to dominant pest species and their attack patterns, but also to identify research gaps in the use of digital technology for early warning systems and crop damage mitigation. This method allows researchers to assess the potential application of AI, UAV, IoT, DNA barcoding, and big data analytics technologies to strengthen pest monitoring systems that are adaptive to climate change and agricultural intensification. Thus, the SLR methodology used in this study sharpens a holistic understanding of the evolution of pest identification methods, while paving the way for the construction of a new paradigm for pest identification based on scientific evidence and modern technology.

Study Questions

1) What types of pests are the most dominant in attacking food crops according to the latest literature 2015–2025?
2) How are pest attack patterns changing due to climate change, agricultural intensification, and the use of modern monitoring technology?
3) What identification technologies are most effectively used in the field, including deep learning, UAVs, IoT and genomic techniques?
4) What are the implications of this technology for early detection systems and food security at the local and national levels?

Search Strategy

The databases used in this SLR include:*Scopus, Web of Science, PubMed, ScienceDirect (Elsevier), SpringerLink, Taylor & Francis, Wiley, ACM Digital Library*, AGRIS, SINTA, and Google

Scholar. Keywords were developed using Boolean combinations (AND–OR) with the following phrases: “pest identification”, “crop pests”, “pest attack pattern”, “precision agriculture”, “digital entomology”, “remote sensing pests”, “UAV pest monitoring”, “deep learning insect detection”, Spodoptera infestation”, “rice pest dynamics”, “AI pest classification”, “IoT pest traps”. This search strategy is in line with the approach used in the research review of object tracking in precision agriculture and UAV studies for crop monitoring.

Inclusion/Exclusion Criteria

1) Including:
   a) Field experimental studies, surveys, ecological modeling, machine learning, deep learning (YOLO, CNN, Transformer), UAV & optical sensors, and DNA Barcoding.
   b) Research that focuses on food crop pests: rice, corn, soybeans, tubers and food horticulture.
   c) Peer-reviewed articles in the 2015–2025 period.
   d) Research that evaluates pest population distribution, attack patterns, or identification model performance.

   Excluded (Exclusion):
2) Excluded:
   1) Studies on non-food crops (exotic fruits, ornamental plants, forestry pests).
   2) Non-scientific, non-peer-reviewed articles (blogs, opinion pieces, internal reports).
   3) Research that does not provide empirical data, images or clear methodology.
   4) Literature that only discusses insecticide fermentation or biological management without a focus on identification.

Data analysis

A total of 326 articles were identified in the initial literature search process from various international and national databases. After a screening process based on title, abstract, and application of inclusion and exclusion criteria, 98 articles entered the full-text screening stage. Of these, 30 articles were deemed suitable for further analysis. The selected articles were then analyzed using a thematic coding approach to identify patterns, conceptual relationships, and key differences in research on food crop pests, their attack patterns, and the development of modern identification technologies. Through this coding process, five main themes were identified that represent the dynamics of current research: dominant pest types and their distribution, attack patterns and triggering factors, innovations in pest identification technology, ecological dynamics and pesticide resistance, and the application of identification in the development of technology-based early warning systems.

3. Thematic Findings and Synthesis

Types of Dominant Pests of Food Crops

The literature synthesis results show that the dominant types of food crop pests have a relatively consistent pattern globally. The five main pest groups most frequently mentioned in the 2015–2025 study included Thrips tabaci, Spodoptera spp., Helicoverpa armigera, Nilaparvata lugens, and Sitophilus oryzae. Thrips tabaci is an important pest of horticulture and shallots, with a high degree of adaptation to changes in humidity and resistance to several modern insecticides. Spodoptera exigua and S. frugiperda are known as pests with high mobility and aggressive feeding behavior, attacking various commodities such as rice, corn, soybeans and leafy vegetables. The polyphagous pest Helicoverpa armigera also shows high prevalence in tomatoes, beans and corn, as discussed in a deep learning-based study. Meanwhile, Nilaparvata lugens is an indicator of vulnerability of intensive rice agroecosystems and appears in almost all studies on rice pest dynamics. The dominance of these pests is influenced by several factors, including physiological adaptability, dietary flexibility, pesticide resistance, and high reproductive capacity. Their mobility and rapid reproduction make these pests significant economic impacts, necessitating more modern and precise identification and early detection strategies.

Attack Patterns: Cycles, Ecology and Climate Change

Analysis shows that pest attack patterns are strongly influenced by climate dynamics, ecology, and cultivation systems. Rising global temperatures have a direct effect on accelerating the life cycles of various pest species, ultimately increasing the frequency of outbreaks. .Changes in humidity are also closely related to increases in mite and thrips populations as evidenced by the results of sensor-based monitoring and high-resolution imaging. In addition, uncontrolled intensification of pesticide use triggers resistance in several species such as Spodoptera spp. and Nilaparvata lugens..Extensive monoculture cropping patterns create stable habitats for pest populations to thrive, leading to repeated outbreaks each growing season. A multi-site study of Spodoptera frugiperda migration shows how climate change is expanding its geographic range, becoming a global threat.. Thus, current pest attack patterns are not only influenced by internal biological factors of pests but are also influenced by systemic ecological and agronomic changes.

Modern Pest Identification Technology (New Paradigm)

A recent literature review identified three main categories of modern pest identification technologies.

1) Image & AI Based Identification

   Deep learning-based technologies have become dominant in the past five years. Models such as CNN, YOLOv5, ACCDW-YOLO, Transformer-based detectors, and quantum-enhanced convolution have achieved identification accuracy of 90–98% in detecting leaf pests in food crops. Study by.demonstrated the effectiveness of AI in detecting

Lygus bugs in strawberry plants, while other research developed a lightweight model for rapid detection in field devices.

2) Genetic Identification (DNA Barcoding)

DNA barcoding techniques are used to identify early-stage larvae, morphologically similar cryptic species, and to determine the origins of invasive populations. This method is increasingly integrated with pest ecology analysis and is used in several precision entomology studies.

3) Remote Sensing & Drone

The use of multispectral and hyperspectral UAVs has become a leading method for detecting crop damage patterns before symptoms become visually apparent. Some commonly used indicators include:

a) NDVI (Normalized Difference Vegetation Index),
b) NDRE (Red Edge Index),
c) hotspot patterns on canopies.

showed that UAVs were able to detect stress caused by Chilo suppressalis more quickly than manual inspections. Other studies have shown that UAVs can improve the accuracy of infestation area detection by 40–60%.

Pesticide Resistance and Its Impact

Several studies have found that pesticide resistance has increased significantly over the past 10 years. Resistance has been recorded in:

1) *Spodoptera*spp. to pyrethroids, organophosphates and systemic insecticides
2) *Nilaparvata lugens*against nicotinoid-based insecticides
3) *Thrips tabaci*against spinosad and microbial metabolite-based insecticides

The rise in resistance reinforces the urgency of using rapid identification technology to precisely manage pest infestations. Without proper identification, farmers tend to overuse pesticides, exacerbating resistance and causing economic losses and ecological risks.

Community-Based Pest Identification

In line with technological developments, the community-based surveillance approach, or CLEWS (Community-Led Early Warning System), is becoming an increasingly recommended model. IoT and UAV-based studies show that integration between farmers, extension workers, and digital devices can: accelerate outbreak reporting, increase the effectiveness of early control, reduce the potential for crop failure by 25–40%, and strengthen local food security. This model places the community as the main actor in pest detection, supported by technology such as mobile applications, automatic sound-based traps (acoustic pest detection).,and environmental data-based prediction systems.

4. Conceptual Framework

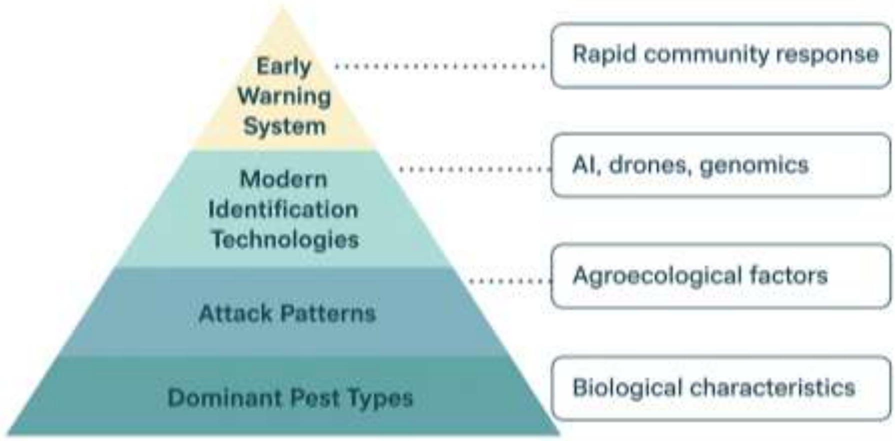

Figure 2. Pest Identification Pyramid – Attack Pattern – Early Warning System.

Figure 2 illustrates the hierarchical relationship between the biological knowledge base of pests and the ability of an early warning system to prevent production losses. At the bottom layer, the dominant pest species serve as the primary foundation. At this stage, biological characteristics such as life cycle, adaptability, reproduction rate, and host plant are analyzed to understand the level of attack risk. The second layer shows attack patterns and agroecological factors that influence pest population dynamics, including climate change, plant nutrient availability, moisture conditions, and cultivation practices. These two layers are interconnected because understanding the pest's ecology is largely determined by its species, behavior, and environment. Moving up the pyramid, the third layer showcases modern identification technologies, such as artificial intelligence, machine vision, drone-based detection, and genomic approaches, allowing for faster and more precise pest identification. The apex of the pyramid represents the ultimate goal of the entire process: a community- and technology-based early warning system. At this stage, pest identification data is processed to generate rapid responses, outbreak reporting, and more adaptive decision-making for preventative pest control. This pyramid structure emphasizes that the effectiveness of an early warning system is determined by the strength of the foundation of biological and ecological knowledge of pests combined with advanced detection technology.

5. Practical Implications

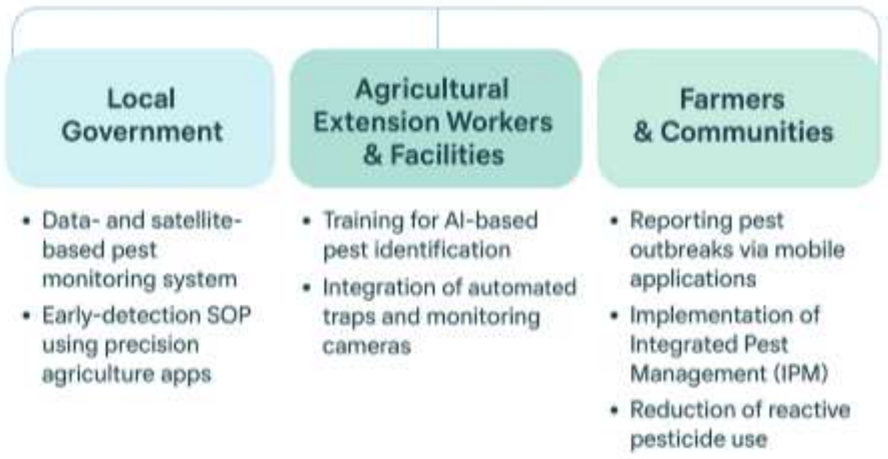

Figure 3. Implications of Food Crop Pest Identification.

Figure 3 illustrates how accurate pest identification results can be translated into practical actions at three key actor levels: local government, agricultural extension workers, and farmers and communities. At the local government level, precise pest identification enables the planning of data- and satellite-based monitoring systems, allowing for real-time mapping of pest population dynamics. Furthermore, developing SOPs for early detection based on precision agriculture is a key step in ensuring a rapid response to potential outbreaks before they cause widespread losses. This demonstrates that pest identification innovations serve not only as technical tools but also as the foundation for adaptive and responsive agricultural management policies. At the extension worker and farmer levels, the diagram emphasizes the importance of implementing technologies such as AI, automatic traps, and mobile applications to support community-based early detection systems. Extension workers act as a bridge between scientific innovation and field practice through technology-based pest identification training and the integration of monitoring devices. Meanwhile, farmers and communities are key actors in the rapid reporting of outbreaks and the implementation of Integrated Pest Management (IPM), including reducing reactive pesticide use. The combination of these three levels demonstrates that successful pest management is determined not only by technology but by systematic, data-driven, multi-level collaboration.

6. Conclusions and Future Directions

This study confirms that crop pests remain one of the most significant productivity-limiting factors in global agricultural systems. Findings synthesized through a Systematic Literature Review approach indicate that pest dynamics are increasingly complex due to climate change, agricultural intensification, and the mobility of invasive species. However, technological advances in pest identification, ranging from artificial intelligence (AI), drone-based remote sensing, genomic techniques such as DNA barcoding, to high-resolution sensors, open up significant opportunities to improve detection accuracy and shorten response times. The integration of biological knowledge, landscape ecology, and digital technology enables a transformation from a reactive approach to a preventive and proactive one, thus minimizing various forms of economic losses.

Future research directions highlight the need to strengthen the data-driven pest identification ecosystem and multi-sector collaboration. First, the integration of AI and IoT into automated traps will enable real-time data collection and enhanced predictive capabilities. Second, the development of climate-based outbreak prediction models is urgent, given that seasonal changes and weather anomalies significantly influence attack patterns. Third, the application of multispectral drones for wide-area monitoring can accelerate the detection of early signs of crop damage at a larger spatial scale. Fourth, DNA barcoding validation for local pests is crucial for addressing cryptic species that are difficult to identify morphologically. Finally, strengthening community monitoring systems through digital applications and cross-regional networks will enhance early detection capacity at the grassroots level. With this integrated approach, pest identification serves not only as a technical instrument but also as a strategic pillar in maintaining sustainable national food security.

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