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SMART PEST MANAGEMENT IN MAIZE: THE ROLE OF VISUAL DIAGNOSTICS IN CROP DECISION-MAKING

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Abstract

Smart pest management is a key component of resilient maize production systems, particularly under increasing pest pressure and climatic variability. Effective crop management relies on early detection and correct diagnosis of insect pests, yet not all species and developmental stages are equally detectable under field conditions. This study proposes a decision-oriented diagnostic framework for maize pest management, combining visual scouting, high-resolution imaging, digital tools and targeted verification methods, applied across crop phenological stages from emergence to maturity. All maize pests relevant to Western Romania (Ostrinia nubilalis, Helicoverpa armigera, Diabrotica virgifera virgifera, Oulema melanopus, Rhopalosiphum padi, Agriotes spp., Opatrum spp. and Tanymecus spp.) were evaluated in terms of detectability, diagnostic complexity and management relevance. Species and stages were classified into easy, moderate or difficult to detect categories, based on visibility, symptom expression and habitat. Original high-resolution images were used to illustrate decision-relevant diagnostic features and frequent confusion cases. The proposed approach supports integrated pest management by improving diagnostic accuracy, reducing unnecessary interventions and enhancing smart, field-based decision-making in maize crop management.

Key words*: smart pest management, maize, pest diagnostics, IPM, early detection.*

INTRODUCTION

Maize (*Zea mays* L.) is one of the most important cereal crops worldwide and represents a key component of global food security, animal feed production and bio-based industries (Shiferaw et al., 2011; Pretty et al., 2018). In Europe, maize cultivation occupies extensive agricultural areas, particularly in Central and Eastern European regions where pedoclimatic conditions are favorable for high productivity (Eurostat, 2023). Romania is among the leading maize-producing countries in the European Union, and the western region of the country represents an important agricultural area due to its fertile soils and favorable climatic conditions (Popov et al., 2016; Bujora et al., 2023).

Despite its high yield potential, maize production is strongly affected by numerous insect pests that can cause considerable economic losses if not properly monitored and controlled (Oerke, 2006; Savary et al., 2019). Among the most economically important pests affecting maize crops in Europe are the European corn borer (*Ostrinia nubilalis* Hübner), the cotton bollworm (Helicoverpa armigera Hübner), the western corn rootworm (*Diabrotica virgifera virgifera* LeConte) and the cereal leaf beetle (*Oulema melanopus* L.) (Gray et al., 2009; Bažok et al., 2021; EPPO, 2025; CABI, 2021; Grozea, 2015). These species differ considerably in their biology, feeding behavior and damage patterns, affecting different plant organs and crop phenological stages. Their biology and damage symptoms have been extensively documented in previous studies and pest compendia (Pălăgeșiu et al., 2000; Grozea, 2015; CABI, 2021).

In recent decades, climate variability (Mosneang et al, 2015) and changes in agricultural practices have influenced pest population dynamics, increasing the risk of pest outbreaks in many cropping systems (Bebber et al., 2013; Juroszek and von Tiedemann, 2013; Deutsch et al., 2018). In Western Romania, several studies have reported an increasing pressure of maize pests, particularly *Diabrotica virgifera virgifera* and *Ostrinia nubilalis*, whose populations are influenced by climatic conditions and cropping systems (Costea and

Grozea, 2022; Bujora et al., 2023). Previous research conducted in the region has also highlighted the ecological adaptability and population variability of *Diabrotica virgifera virgifera* in maize agroecosystems (Horgoș and Grozea, 2020).

Integrated Pest Management (IPM) has been widely recognized as an effective and sustainable strategy for managing agricultural pests while minimizing environmental and economic impacts (Dhawan and Peshin, 2009; Barzman et al., 2015; Deguine et al., 2021). A key component of IPM is the accurate identification of pest species and the timely detection of infestation levels, which enables targeted interventions and reduces unnecessary pesticide applications (Kogan, 1998; Wearing, 1988). However, pest identification in field conditions may be challenging due to the presence of cryptic developmental stages, concealed feeding habits or morphological similarities among species.

Recent developments in digital agriculture have introduced new opportunities for improving pest monitoring and diagnostics. Image-based insect recognition systems and artificial intelligence tools are increasingly used in agricultural monitoring, enabling rapid pest detection and improving decision-support systems for crop protection (Martineau et al., 2017; Dawei et al., 2019; Li et al., 2021; Chen et al., 2022). Such technologies contribute to the development of smart pest management systems that integrate field observations, digital tools and data-based decision-making (Liu et al., 2016; Ding and Taylor, 2016).

Nevertheless, visual diagnostics supported by high-resolution photography and portable microscopy remains a practical and accessible approach for pest identification under field conditions. These methods allow crop protection specialists to recognize pest species and developmental stages more accurately, detect early infestation symptoms and avoid misidentification that could lead to ineffective control measures (Pălăgeșiu et al., 2000; Grozea, 2015; Bažok et al., 2021).

The present study aims to highlight the role of visual diagnostics and morphological identification as essential components of smart pest management in maize. Using original photographic documentation of several key maize pests collected from Western Romania, the study focuses on diagnostic morphological traits and symptom patterns relevant for early detection and informed pest management decisions. By integrating field observations, digital imaging and targeted diagnostic approaches, this work contributes to the development of a practical framework for smart pest detection and monitoring in maize agroecosystems.

MATERIALS AND METHODS

Study area and crop establishment

The study was conducted during the 2025 maize growing season in agricultural fields located in Western Romania (Berechiu and Petid localities from Bihor County), a region characterized by favorable pedoclimatic conditions for maize cultivation and the recurrent presence of economically important insect pests.

Maize was sown on 5 May 2025, and pest monitoring was carried out throughout the vegetation period, from early crop emergence to grain development stages. Crop development was recorded using the BBCH phenological scale for maize (*Zea mays* L.), allowing the association of pest occurrence and detectability with specific crop growth stages.

Field observations covered several phenological phases, ranging approximately from BBCH 12 (early vegetative stage) to BBCH 78 (grain filling stage).

Field monitoring design

Field observations were conducted in two maize fields (no insecticides applied), using a standardized scouting protocol designed to capture both pest occurrence and diagnostic detectability.

At each monitoring date, three independent readings (replicates) were performed within each field. Each observation consisted of visual inspection of maize plants in order to record: presence of pest species, pest developmental stage (egg, larva, pupa or adult), visible damage symptoms and damage severity.

Damage intensity was evaluated using a semi-quantitative scale (0-3): (0) no visible damage, (1) minor damage symptoms, (2) moderate damage affecting plant tissues and (3) severe damage affecting plant development.

Additionally, the number of inspected plants and the number of affected plants were recorded in order to estimate pest infestation levels.
The monitoring focused on the main maize pests reported in the region, including: *Ostrinia nubilalis, Helicoverpa armigera, Diabrotica virgifera virgifera, Oulema melanopus, Rhopalosiphum padi, Agriotes* spp. and *Tanymecus* spp.
These species represent key pest groups affecting maize during different crop developmental stages.

Smart pest detection framework
The study applied a smart pest detection framework integrating field observation, symptom recognition, targeted sampling, digital imaging and laboratory confirmation.
Pest detection was based on two complementary diagnostic components:
1. Recognition of pest developmental stages (eggs, larvae, pupae and adults).
2. Identification of characteristic damage symptoms.

This combined approach allowed the detection of both active stages (larvae and adults) and inactive or cryptic stages (eggs and pupae), which are often overlooked in routine field scouting.
Symptoms recorded during field inspections included leaf feeding damage, window feeding, stem perforations, silk damage, frass deposits, irregular plant stands, and root-associated injury. These symptoms were used as diagnostic indicators for guiding targeted pest verification.
Photographic documentation and imaging equipment
High-resolution photographic documentation was performed in order to record diagnostic morphological traits and characteristic damage symptoms. Images were captured both in field conditions and during laboratory examination of collected specimens.
For photographic documentation, the following imaging systems was used Canon EOS 80D digital camera equipped with a Sigma 105 mm macro lens (1× magnification) and flash units Yongnuo YN14EX II or Yongnuo YN685, with light diffusion accessories.
These configurations allowed the capture of high-resolution macro images of insect morphological structures and plant damage symptoms, providing detailed visual documentation of diagnostic traits relevant for pest identification.

Laboratory examination of specimens
Selected specimens representing different pest developmental stages were collected during field inspections and transported to the Laboratory of Entomology, University of Life Sciences "King Mihai I" from Timișoara (USVT).
In the laboratory, specimens were examined using a digital binocular microscope with HD touchscreen display, which allowed detailed visualization and documentation of morphological characteristics. Microscopic examination was particularly important for confirming: egg stages, pupal stages, early larval stages and morphologically similar species. Digital microscopic images were used as reference material for documenting developmental stages and supporting the diagnostic process.

Classification of pest detectability
In order to evaluate the practical complexity of pest diagnosis, pest species and developmental stages were classified according to field detectability.
Three diagnostic categories were defined: easy detection-stages easily identifiable through routine visual scouting due to visible insects or highly characteristic damage symptoms; moderate detection-stages detectable through careful plant inspection or targeted scouting of specific plant organs and difficult detection-cryptic stages requiring additional procedures such as soil inspection, plant dissection or laboratory confirmation. This classification allowed the development of a pest detectability matrix, linking pest species, developmental stage and diagnostic complexity.
The diagnostic approach applied in this study integrates field scouting, symptom recognition, detection of pest developmental stages, high-resolution macro imaging and laboratory confirmation. This workflow provides a structured framework for improving pest detection accuracy and supporting decision-oriented pest management in maize cropping systems (Figure 1).

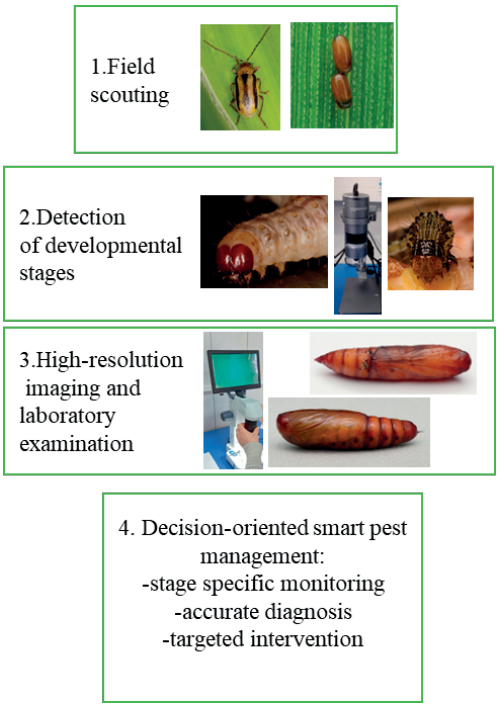

Figure 1. Smart pest detection framework applied for maize pest diagnostics.The framework integrates field scouting preliminary pest identification, detection of pest developmental stages (egg, larva, pupa and adult), high-resolution macro imaging, and laboratory confirmation using a portable digital microscope. All photographs represent original documentation obtained during field monitoring and laboratory examination (made by Veres) and were used as diagnostic references within the smart pest detection approach

Statistical analysis

Descriptive statistics were calculated for pest occurrence and damage intensity.

Differences among pest species were analyzed using one-way analysis of variance (ANOVA) for both damage score and infestation percentage. When significant differences were detected, Tukey's HSD post-hoc test was applied to identify statistically significant pairwise differences.

The relationship between pest occurrence and maize phenological stage was also evaluated using ANOVA, while the association between developmental status (active vs inactive stages) and detection difficulty was analyzed using a Chi-square test.

All statistical analyses were performed using standard statistical procedures commonly applied in agricultural and ecological research.

RESULTS AND DISCUSSIONS

A total of seven major pest taxa were recorded in the two monitored maize fields during the 2025 growing season. Their occurrence differed significantly in terms of infestation rate, damage severity, timing of occurrence, and diagnostic detectability, confirming that maize pest monitoring requires a stage-specific and decision-oriented approach.

Pest occurrence and damage intensity

The summary of pest occurrence and damage intensity is presented in Table 1, while the corresponding graphical representation of mean infestation rate is shown in Figure 2 and mean damage severity in Figure 3. Among the monitored pests, the highest mean infestation levels were recorded for *Ostrinia nubilalis* (52.3%) and *Helicoverpa armigera* (49.7%), followed by *Diabrotica virgifera virgifera* (47.0%) and *Rhopalosiphum padi* (37.3%) (Table 1, Figure 2). Lower infestation values were observed for *Oulema melanopus* (32.8%), while the lowest levels were associated with *Tanymecus* spp. (17.3%) and *Agriotes* spp. (9.3%).

Table 1. Occurrence and damage severity of the monitored maize pest species in the study fields

Pest	n	Mean BBCH	Mean infestation ± SD (%)	Mean damage ± SD
Agriotes	6	28,7	7.0 ± 2.8	0.50 ± 0.00
Diabrotica	6	75,3	47.0 ± 3.3	1.83 ± 0.26
Helicoverpa	6	71	49.7 ± 12.0	2.33 ± 0.52
Ostrinia	6	63,3	52.3 ± 5.3	3.00 ± 0.00
Oulema	6	23,3	31.3 ± 8.1	1.25 ± 0.27
Rhopalosiphum	6	36,3	37.3 ± 6.5	1.83 ± 0.26
Tanymecus	6	15	17.3 ± 5.8	0.92 ± 0.20

A similar trend was observed for damage severity. The highest mean damage scores were recorded for *O. nubilalis* and *H. armigera* (3.00), whereas intermediate values characterized *D. virgifera virgifera* (1.83), *R. padi* (1.75), and *O. melanopus* (1.35). The lowest damage values were associated with *Tanymecus* spp. (0.92) *and Agriotes* spp. (0.58) (Table 1, Figure 3). These results indicate that the most destructive pest species in the present dataset were also those associated with more

specific and diagnostically informative damage symptoms.

The statistical comparison among pest species confirmed that these differences were highly significant. One-way ANOVA showed a strong species effect both for damage score, $F(6.35) = 59.27$, $p<0.001$, and for infestation percentage, $F(6.35) = 37.42$, $p<0.001$ (Table 3).

Table 2. Post-hoc comparison of mean damage severity among pest species according to Tukey HSD test

Pest species	n	Mean damage	SD damage	Mean infestation (%)	SD infes-tation	Tukey group	
Agriotes	6	0.5	0	7	2.75	e*	c**
Diabrotica	6	1.83	0.25	47	3.28	C	a
Helicoverpa	6	2.33	0.51	49.66	12.02	B	a
Ostrinia	6	3	0	52.33	5.27	A	a
Oulema	6	1.25	0.27	31.33	8.06	D	b
Rhopalosiphum	6	1.83	0.25	37.33	6.53	C	b
Tanymecus	6	0.91	0.20	17.33	5.75	De	c

*damage group; **infestation group

ost-hoc comparisons using Tukey's HSD test grouped *O. nubilalis* and *H. armigera* in the highest damage category, while *Agriotes* spp. and *Tanymecus* spp. formed the lowest group (Table 2, Figure 3). This pattern suggests that pests attacking stems, ears, or reproductive organs produce more visible and agronomically severe symptoms than early-season or soil-associated pests.

Field effect and consistency of observations

The comparison between the two monitored fields showed no significant field effect for either damage score or infestation rate (Table 3). This indicates that the variation observed in the study was determined mainly by pest species and crop phenology rather than by field-specific conditions. From a methodological perspective, this result is important because it supports the consistency of the monitoring framework across the two sites and suggests that the diagnostic approach is reproducible under comparable maize-growing conditions.

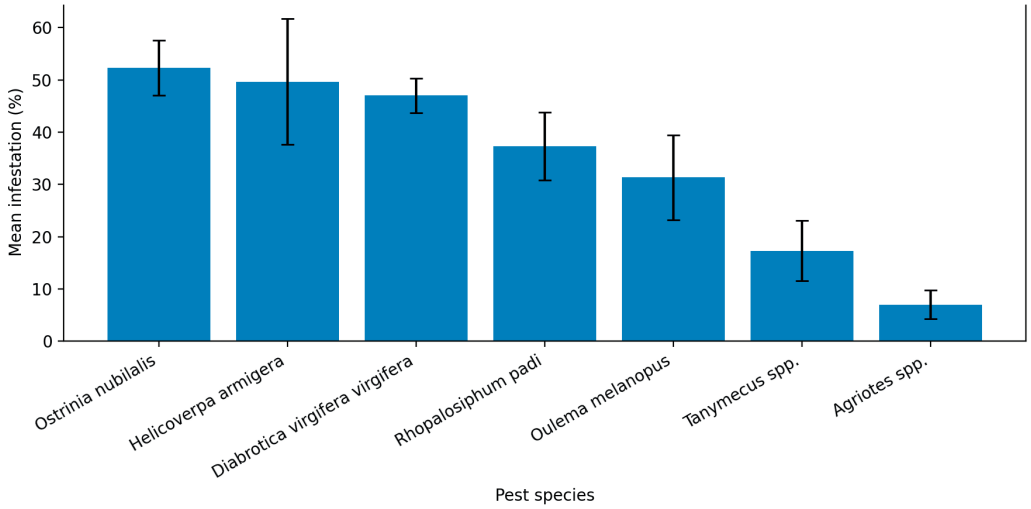

Figure 2. Mean infestation rate (%) recorded for the monitored maize pest

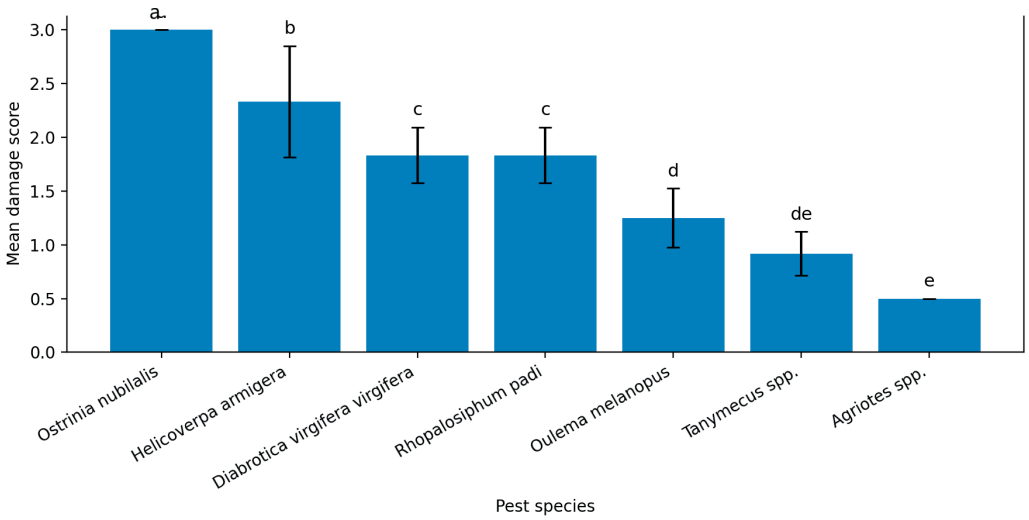

Figure 3. Mean damage severity score for maize pests with Tukey HSD grouping letter

Pest occurrence in relation to maize phenology

The relationship between pest occurrence and crop development stage is summarized in Table 4, while its graphical distribution along BBCH stages is illustrated in Figure 4. Pest detection clearly varied with maize phenology, and the statistical analysis confirmed a highly significant effect of crop developmental phase on both damage score and infestation level. ANOVA showed significant differences among phenological phases for damage, $F(2.39) = 40.45$, $p<0.001$, and infestation, $F(2.39) = 28.31$, $p<0.001$ (Table 5).

During early vegetative stages, the most relevant pests were those associated with seedling and early foliar damage, such as *Tanymecus* spp., *Agriotes* spp., and partly *O. melanopus.* At these stages, detection was frequently based on indirect evidence, including irregular plant stand, leaf notching, or reduced plant vigor. In contrast, during later vegetative and reproductive stages, the pest complex shifted toward species such as *O. nubilalis, H. armigera*, and adult *D. virgifera virgifera*, which were associated with more specific and visually recognizable symptoms, including stem perforation, frass deposits, silk damage, and ear injury (Table 4, Figure 5).

This phenology-dependent pattern is highly relevant for smart pest management because it shows that detection efficiency changes with crop stage. Therefore, a single scouting approach is insufficient; instead, field inspection should be adapted to the expected pest spectrum and symptom expression at each BBCH phase.

Detection of developmental stages and diagnostic complexity

A central objective of the study was to demonstrate that smart pest detection should not rely exclusively on adults or other easily visible stages. The pest detectability matrix, presented in Table 6, shows that the monitored pests differed not only by species but also by developmental stage and diagnostic complexity. Easy-detection cases were mainly represented by visible adult stages, such as *Diabrotica virgifera virgifera* and *Oulema melanopus*, whereas eggs, pupae, and concealed larvae were more frequently assigned to moderate or difficult detection categories.

Table 3. Analysis of variance (ANOVA) results for infestation rate and damage severity among maize pest species

Response	Model	Statistic	p-value	Effect size (η^2)
Damage score	One-way ANOVA (Pest)	F (6.35) = 59.27	<0.001	0.91
Infestation %	One-way ANOVA (Pest)	F (6.35) = 37.42	<0.001	0.865
Damage score	Two-way ANOVA (Pest + Field + Interaction)	Pest: F (6.28) = 52.50; Field: F (1.28) = 0.29; Pest×Field: F(6.28) = 0.45	Pest <0.001; Field = 0.597; Interaction = 0.837	-
Infestation %	Two-way ANOVA (Pest + Field + Interaction)	Pest: F (6.28) = 31.08; Field: F (1.28) = 0.54; Pest×Field: F (6.28) = 0.09	Pest <0.001; Field = 0.468; Interaction = 0.997	-

Table 4. Occurrence of maize pest species across crop phenological stages (BBCH scale)

Phenology phase	n	Mean infestation ± SD (%)	Mean damage ± SD
Early vegetative (BBCH 13–34)	20	20.8 ± 13.1	0.97 ± 0.44
Mid season (BBCH 35–66)	10	45.6 ± 10.2	2.55 ± 0.60
Late season (BBCH 67–78)	12	48.3 ± 8.5	2.08 ± 0.47

The representative developmental stages documented during the study are illustrated in Figure 1, which includes original photographic documentation of adult, egg, larval, and pupal stages. These images provide direct support for the diagnostic framework by showing that the study incorporated not only field-visible insects but also less accessible stages confirmed through targeted observation and laboratory examination.

The statistical relationship between biological status and diagnostic detectability is summarized in Table 7 and graphically represented in Figure 5. The Chi-square test showed a significant association between stage status (active vs. inactive) and detection difficulty, $\chi^2(2) = 7.22$, $p = 0.027$ (Table 7). Inactive stages were significantly more represented in the difficult-detection category, while active stages were more frequently associated with easy or moderate detection. This finding strongly supports the main premise of the study: pest diagnosis in maize is stage-dependent, and different biological stages require different detection tools.

Role of macro imaging and digital microscopy in smart detection

The methodological workflow used in this study is summarized in Figure 1, which outlines the sequence from field scouting and preliminary recognition to developmental stage detection, high-resolution imaging, and laboratory confirmation. This framework illustrates how symptom recognition, stage detection, and imaging-based verification were combined into a structured decision-support system.

The inclusion of high-resolution macro photography and portable digital microscopy considerably improved the diagnostic value of the observations.

Table 5. Effect of maize phenological stage on pest infestation and damage severity (ANOVA results)

Response	ANOVA	p-value	Effect size (η^2)
Damage score	F (2.39) = 40.45	<0.001	0.675
Infestation %	F (2.39) = 28.31	<0.001	0.592

While adults of *D. virgifera virgifera* and *O. melanopus* could be recognized directly in the field, stages such as Oulema eggs or pupae of *O. nubilalis* and *H. armigera* required closer examination and confirmatory documentation (like in previous Figure 1). In this respect, the use of imaging did not merely serve an illustrative purpose, but functioned as a diagnostic tool within the monitoring framework.

This aspect is particularly important for smart pest management, because it demonstrates that accurate pest recognition depends not only on pest abundance, but also on the observer's ability to detect the biologically relevant stage. In practical terms, the results support a multi-level diagnostic system based on: field symptom recognition, targeted suspicion, selective specimen collection, and image-assisted confirmation.

Symptom-based detection as a decision trigger

The results indicate that symptomatology was an essential component of the diagnostic process, especially for pests with concealed feeding behavior or cryptic developmental stages. Stem galleries, frass deposits, ear injury, silk damage, and irregular crop establishment acted as practical indicators guiding targeted sampling and confirmation. Thus, the first diagnostic signal was often not the pest itself, but the pattern of plant damage.

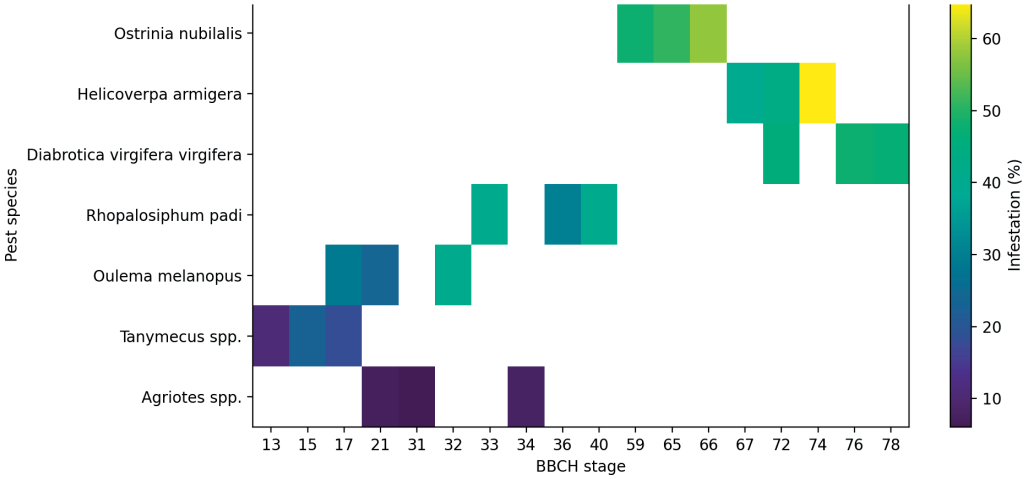

Figure 4. Distribution of pest infestation across maize phenological stages (BBCH scale)

Table 6. Diagnostic detectability of maize pest species based on developmental stages and observation method)

Species	Stage	Status	BBCH	Diagnostic/ symptom location	Detection method
Ostrinia nubilalis	larva	active	66	Panicle / ear zone	Portable digital microscope (Forte)
Ostrinia nubilalis	pupa	inactive	66	Panicle / ear zone	Portable digital microscope (Forte)
Tanymecus spp.	adult	active	17	Aerial plant parts; searched under soil clods near seedlings	Plant inspection and soil surface search within a 0.25 m radius around the plant
Diabrotica virgifera virgifera	adult	active	76	Collected from maize silk	Portable digital microscope (Forte)
Helicoverpa armigera	pupa	inactive	72	Collected from ear zone	Portable digital microscope (Forte)
Helicoverpa armigera	larva	active	72	Identification assisted by portable digital microscope to avoid misidentification	Surface soil inspection around the plant
Oulema melanopus	egg	inactive	21	Eggs located on the upper side of the leaf	Portable digital microscope (Forte) + digital binocular microscope with HD touchscreen
Rhopalosiphum padi	larva	active	40	Colonies on leaves	Inspection of colonies on the underside of leaves
Rhopalosiphum padi	adult	active	40	Colonies on leaves	Inspection of colonies on the underside of leaves
Agriotes spp.	adult	active	34	Direct field observation	Leaf inspection
Agriotes spp.	larva	active	34	Root zone + soil	Inspection of roots and soil within a 0.10 m radius around the root system

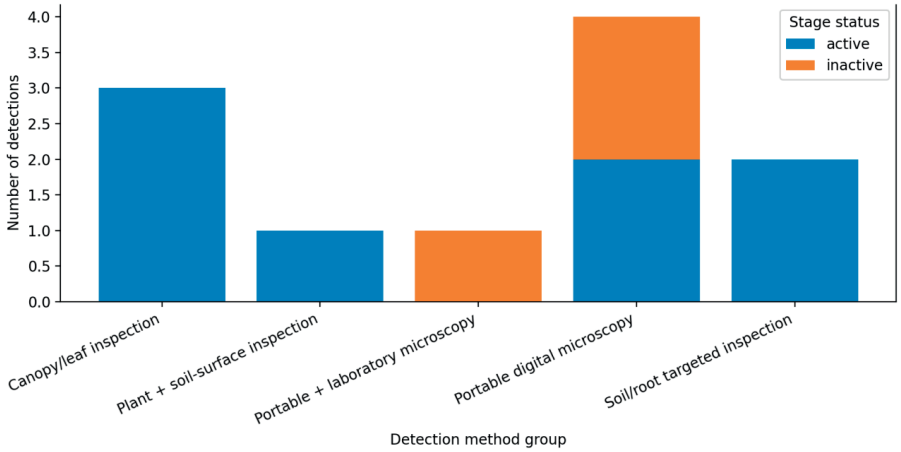

Figure 5. Detection method groups associated with active and inactive pest developmental stages

Table 7. Association between pest developmental stage status (active vs. inactive) and detection method groups.

Test	Statistic	p-value	Interpretation
Status × detectability (chi-square)	$\chi^2(2)=7.22$	0,027	Inactive stages were concentrated in the difficult-detection category.
Status × microscopy-assisted method (Fisher exact)	Odds ratio=∞	0,061	Microscopy-assisted detection was used more often for inactive stages; trend limited by small n.

This observation has direct management relevance. In field practice, decisions are often made before all developmental stages are directly observed. Therefore, a smart detection system must begin with symptom interpretation and then proceed to species- and stage-specific verification. The present study shows that combining symptom recognition with stage-based diagnostics improves both the speed and accuracy of pest identification, while reducing the risk of misclassification. Taken together, the results presented in Tables 1-7 and Figures 1-5 show that maize pests differ significantly in abundance, damage potential, phenological timing, and detectability. Species such as *O. nubilalis* and *H. armigera* produced the highest damage scores and infestation rates, while *Agriotes spp*. and *Tanymecus spp*. showed lower visible damage but remained agronomically relevant in early stages. More importantly, the significant association between developmental status and detectability demonstrates that the recognition of eggs, pupae, and concealed larvae is essential for a truly smart pest detection system. Overall, the study supports a decision-oriented framework in which pest diagnosis is based on the integration of crop phenology, symptomatology, developmental stage, and imaging-assisted verification. This approach offers a realistic basis for more precise and resilient pest management in maize.

CONCLUSIONS

The study highlighted significant differences in infestation levels and damage severity among the monitored maize pest species, confirming the major impact of *Ostrinia nubilalis*, *Helicoverpa armigera* and *Diabrotica virgifera virgifera* under the studied conditions. Pest occurrence was closely associated with maize phenological stages, with early-season pests dominating vegetative phases and Lepidopteran and coleopteran pests becoming more prevalent during reproductive stages. The results also demonstrated that pest detectability varies according to developmental stage. Active stages such as adults and exposed larvae were more easily identified in field conditions, while inactive or concealed stages required targeted inspection and microscopic confirmation. The integration of field scouting, symptom recognition and digital imaging proved to be an effective approach for improving pest diagnostics. This smart detection framework can support more accurate monitoring and contribute to better decision-making within

integrated pest management programs for maize.

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