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Development of an optoelectronic tool for the detection of Cotonet de les Valls in citrus crops

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ABSTRACT

Delottococcus aberiae, or "Cotonet de les Valls," is an invasive pest responsible for substantial yield losses in citrus crops across the Mediterranean region of Spain. This study reports developing and validating a novel portable optoelectronic nose that integrates optical and electrochemical sensors for early pest detection in the field. The system demonstrated selectivity towards *D. aberiae* under both controlled and field conditions. Principal Component Analysis (PCA) revealed clear separation between infested and pest-free samples, and the ability to distinguish *D. aberiae* from other pests such as *Bemisia tabaci*. Partial Least Squares Discriminant Analysis (PLS-DA) models achieved perfect classification metrics (accuracy, precision, recall = 1.000) under in vitro conditions and high accuracy in field trials, even at early infestation levels. Partial Least Squares (PLS) regression models yielded R^2 values above 0.95 for predicting incidence and over 0.91 for severity when using a reduced 8-sensor array, significantly simplifying the system without compromising performance. These results highlight the robustness, accuracy, and field applicability of the optoelectronic system as an effective decision-support tool in integrated pest management programs.

1. Introduction

In recent decades, agriculture has undergone a profound transformation driven by the expansion of cultivated areas, mechanization, and the development of new agronomic techniques. The use of pesticides has been a key element, enabling pest and disease control, improving both crop yields and food quality [1]. However, this model has also generated negative impacts, such as groundwater contamination, toxic residues in food, harm to local fauna, and the development of pesticide resistance. These resistances have reduced the effectiveness of conventional treatments, making pest management increasingly difficult, particularly in crops such as citrus, where the incidence of new pests has risen considerably in recent decades [2].

As a response to these challenges, there has been a shift towards more sustainable agriculture. Within this framework, Integrated Pest Management includes pest sampling and quantification, data-driven decision-making, and the implementation of biological and biotechnological controls, along with the rational use of pesticides [3]; European regulations such as Directive 2009/128/EC encourages the adoption of technologies for pest monitoring as a tool to apply less and more specific phytosanitary treatments [4]; and precision agriculture relies on the collection and analysis of spatial and temporal data on crops, soils, and environmental conditions, enabling more efficient decision-making [5]. These strategies can greatly benefit from using monitoring tools; however, despite the interest in the topic, the presence of in-field sensors for the detection of pests is not widely extended. Thus, the development of novel sensing systems for this purpose is of interest.

Technologies such as drones and satellites, through multispectral imaging, allow for the early detection of diseases and pests by identifying changes in the spectral signatures of affected plants [6,7]. Simultaneously, image and sound sensors on autonomous vehicles enable continuous real-time monitoring [8], while electronic traps provide ongoing surveillance of pest insects [9]. However, most of them are based on variations in the spectra of the plant surface of image recognition; none of them explore the use of the volatile fingerprint.

Internet of Things (IoT), a set of sensors to be placed in orchards working autonomously, can be a good opportunity for large-scale crop monitoring and improved control strategies [10]. However, its

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application in real field conditions still presents considerable limitations, mainly due to factors such as environmental variability, terrain heterogeneity, and the need for a robust and reliable communication infrastructure [11–14]. Recently, innovative approaches based on biomimetic technologies, AI, and miniaturised devices have been developed that could overcome these limitations. Manduca et al. [15] have demonstrated the use of lab-on-a-chip microfluidic systems to study insect behaviour with high resolution and efficiency in the laboratory, while other studies have explored the application of AI and computer vision to solve key challenges in the production and management of insects of agro-industrial interest. For example, the black soldier fly (Hermetia illucens), a key species for nutrient recycling and the sustainable production of proteins and biofuels, has been the subject of advanced developments that combine deep learning and optical flow analysis to accurately identify its different stages of development, achieving accuracy values of over 96 % in real scenarios [15]. In addition, IoT-based solutions have also been proposed to optimise environmental parameters in the breeding of insect to valorise organic wastes, achieving significant increases in egg production [16]. Romano [17] reviews advance in automation, artificial intelligence and bio-inspired sensors applied to the study and management of insect pests. In the field of early pest detection, Mohamed et al. [18] proposed an acoustic system based on neural networks which, using spectrograms and acoustic characteristics extracted by MFCC, can detect the presence of Rhynchophorus ferrugineus larvae with 99.2 % accuracy. Also, there are tools such as monitoring stations equipped with image sensors that allow remote transmission of traps, which have demonstrated efficiencies of over 80 % in the control of pests such as fruit flies [19–21], with access to data via mobile applications [22,23]. The development of feasible devices to the used in field require a full set of innovations that go from the device to attract/capture the insects, to the collection of the images and their processing. Recent innovation on the combination of AI Convolutional Neural Networks (CNN) and microcontroller based field devices has allowed the identification and monitoring of insects Tabanidae, Hippoboscidae, Muscidae, Tephritidae, or Grapholita [24,25]. Also, the integration of the devices with cloud external platforms can be an interesting approach [26]. The implementation of these technologies in specific crops such as citrus remains insufficiently characterised and validated. These advances show a growing trend towards the integration of AI, signal analysis, computer vision and IoT to improve the efficiency of insect monitoring and management, although their application to citrus fruits and their validation in the field for specific pests such as *D. aberiae* is still non-existent. Furthermore, in general, these systems are not based on the detection of volatile compounds, which restricts their usefulness for early identification of infestations, before the manifestation of visible symptoms or economic damage. Also, their application in citrus and their integration into field-validated portable tools for specific species, such as *Delottococcus aberiae,* is still lacking.

Among recent innovations, electronic noses stand out. These devices are designed to mimic the human sense of smell using sensors and pattern recognition algorithms capable of detecting volatile organic compounds (VOCs) emitted by pest-affected crops. Although these technologies have shown high effectiveness in the food industry for detecting contaminants and assessing product freshness [27–29], their application in agriculture is still incipient, though promising. They have been successfully used to detect microbial pests in plants [30–32] and to monitor soil conditions in precision agriculture [33]. These tools enable the rapid identification of VOCs released by plants in response to invasive species attacks [34,35], facilitating early detection of infestations. They have been evaluated for detecting a range of pests, from caterpillars and red palm weevils [36] to pests in fruit crops [37], positioning themselves as an innovative option for early pest diagnosis. Moreover, in crops such as wheat, electronic noses equipped with gas sensors and near-infrared spectroscopy (NIR) have been developed to detect aphid infestations before irreversible damage occurs [38]. In rice, they have been used to identify volatiles emitted by insects during activity, enabling constant monitoring without manual intervention [39], and to detect *Nilaparvata lugens* infestations using systems combined with gas chromatography-mass spectrometry (GC-MS) [40]. However, many of these solutions present limitations such as high cost, instrumental complexity, lack of validation under real field conditions, or the absence of correlation with agronomic parameters such as infestation incidence and severity, which hinders their effective integration into large-scale agricultural management programs.

Considering the relevance of *D. aberiae*, commonly known as 'Cotonet de les Valls', in the Valencia region, with yield reductions of up to 80 % in affected citrus fields [41], it was selected as an initial application for the proof of concept of a novel type of optoelectronic nose. We hypothesize that the combination of unspecific optical and electrochemical gas sensors in an array can be a competitive approach for the detection and quantification of pests in citrus. To our knowledge, this is the first portable hybrid optical-electrochemical sensor validated in the field for *D. aberiae*.

2. Materials and methods

2.1. Sensing technology

In order to detect the presence of *Delottococcus aberiae* in citrus crops, a portable optoelectronic nose prototype was developed that integrates optical sensors and MQ-type metal oxide electrochemical sensors. Table 1 lists the 14 sensor systems used. A detailed summary of the components and their configuration is presented in Table 2. The system combines visual detection based on colour changes with real-time gas analysis. The optical sensors were synthesised by impregnating three inorganic materials -UVM-7, silica, and alumina- with several dyes (see Table 2). The preparation of the sensing elements consisted of stirring the inorganic support in an ethanolic dye solution for 10 min, followed by a 24-hour rest at room temperature to promote adsorption. Subsequently, the solvent was removed by rotary evaporation under reduced pressure, yielding ready-to-use sensor materials. Infrared spectra of the sensing materials can be found in Figure S1 (supplementary material). They were arranged on ELISA plates with three replicates per sensor to ensure homogeneity and reproducibility of the system. For the definition of the electronic nose, in a first step, a library of combinations of dyes and support as sensor units were prepared and exposed to the in vitro environment containing *D. aberiae*, selecting the 10 optical sensors that showed the most appropriate colour changes for the in-vitro and in-vivo studies.

For the electrochemical sensors, commercial sensing units MQ-3, MQ-4, MQ-8, and MQ-137 were used. They typically show a response to diverse gases such as alcohol, LPG, CO, CH_4, hexane, H_2, or NH_3. These sensors operate by measuring variations in the electrical resistance of the active material when exposed to VOCs. Each sensor was connected to an ESP8266 microcontroller board with Wi-Fi connectivity, responsible

Table 1
Sensors selected to form part of the optoelectronic nose.

Sensing material	Dye/Support or electrochemical sensor
S1	Methylene blue / Alumina
S2	Victoria blue B / Silica
S3	Fluorescein / UVM−7
S4	Chromocyanin / Silica
S5	Malachite Green / Silica
S6	Dichlorofluorescein / Silica
S7	Thionine acetate / Silica
S8	0-Dianisidine / UVM−7
S9	Potassium indigotrisulfonate / Silica
S10	Rhodamine 6 G / Silica
S11	MQ−3
S12	MQ−8
S13	MQ−4
S14	MQ−137

Table 2
Complete technical specifications of the optoelectronic nose.

Component	Technical specification		
Optical sensors	Dye	Support	mg dye/g support
	Methylene blue	Alumina	2.12
	Victoria blue B	Silica	0.28
	Fluorescein	UVM-7	0.50
	Chromocianin	Silica	5.56
	Malachite green	Silica	1.13
	Dichlorofluorescein	Silica	0.46
	Thionine acetate	Silica	1.00
	o-Dianisidine	UVM-7	1.67
	Potassium indigotrisulfonate	Silica	0.32
	Rhodamine 6 G	Silica	0.23
Electrochemical sensors	MQ−3 MQ−4 MQ−8 MQ−137		
Microcontroller	ESP8266 (80 MHz CPU, 10-bit ADC, integrated WiFi, low power consumption)		
Auxiliary processing unit	Raspberry Pi 3 (1.2 GHz quad-core CPU, 1 GB RAM, integrated WiFi/Bluetooth)		
Data acquisition	Real-time readings every minute, storage on microSD card, serial communication via WiFi		
Optoelectronic nose housing	Thermoplastic box with side air inlet hole		
Power supply	Portable battery (26800 mAh)		
Software	ESP8266 firmware and Raspberry Pi script for reading, transmitting, timestamping and storing data in MongoDB and.txt files.		
Optical interfaz	ELISA plates with fixed optical sensors (3 replicates per type), standardized photographs taken with a Samsung Galaxy A71 mobile phone		
Optical processing	Calculation of RGB and ΔE values from ImageJ software images		

for acquiring, preprocessing, and sending data to a central processing unit based on a Raspberry Pi 3, where they were stored for further analysis. Since MQ sensors require an operating voltage of 5 V, the device was powered by a 26800 mAh portable battery, which provided an operating autonomy of approximately 9 h under continuous use.

The complete system was integrated into a 3D printed housing made of commonly used thermoplastic material, designed to house and protect all electronic components and sensors (see Fig. 1).

2.2. In-vitro and in-field experiments

The in vitro experiments were carried out in containers containing specimens of *D. aberiae* at different stages of development, kept on pumpkin fruit as a host substrate. A container in the same conditions in the absence of *D. aberiae* was used as a control. A total of eight independent experiments were carried out. The sensors were placed on the perforated lid of each container, allowing direct exposure to the atmosphere, thus ensuring controlled and reproducible conditions for sensory interaction. In the in vitro tests, the temperature and humidity were controlled (21.4 ± 1.1 °C, 63 ± 6 % RH), and sensors ran simultaneously in the presence and absence of pests in two separate rooms.

Twelve field trials were conducted on an orange grove characterized by a documented history of infestation by *D. aberiae*. A preliminary study of the spatial distribution of the pest determined that the optimal location for installing the optoelectronic nose was a representative tree located in the centre of the plot, positioning the sensor system in the tree canopy at eye level, the area where the insect is most frequently found. Measurements were taken during different phases of the pest's biological cycle, from an initial low incidence to the peak of infestation, allowing for detailed monitoring of its evolution. The sensors were installed early in the morning and removed the following day; the

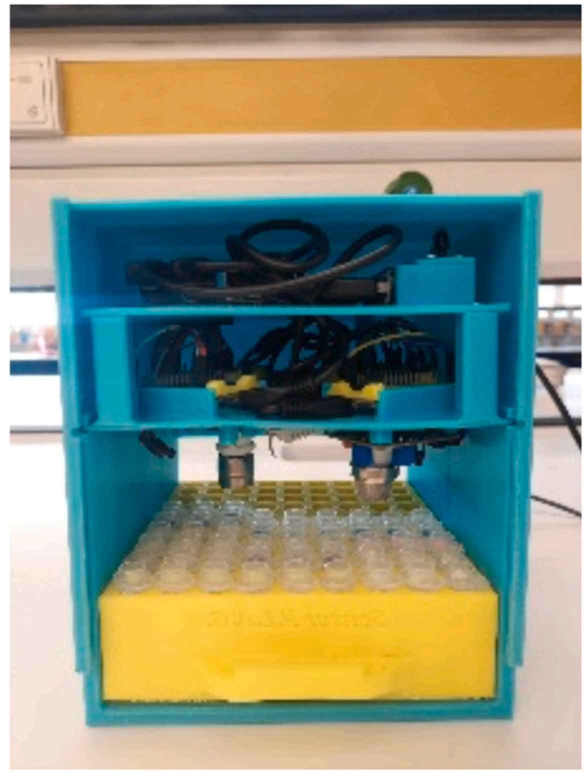

Fig. 1. Optoelectronic nose prototype with integrated arrangement of electrochemical and colorimetric optical sensors for the detection of *Delottococcus aberiae*.

electrochemical sensors operated for approximately 9 h, while the optical sensors remained exposed for 24 h, allowing continuous monitoring of the environment.

The identification and quantification of the presence of *D. aberiae* was carried out by direct visual inspection by specialized agricultural technicians, who identified individuals morphologically through in situ observation with a handheld magnifying glass. These evaluations were carried out simultaneously with the optoelectronic nose tests, allowing for a direct comparison between traditional and technological methods. To this end, a standardized protocol was applied, consisting of random sampling of twenty-five trees per plot, evaluating three fruits per tree in the canopy, at eye level. The presence of visible pseudococcids and associated symptoms such as deformities or honeydew secretions were recorded on each fruit. The incidence of the pest was defined as the percentage of infested trees out of the total number of trees sampled, while the severity was quantified based on the number of individuals observed on the affected fruits.

As part of the experimental design, two additional plots were included for control and validation purposes. One of them, with no significant presence of *D. aberiae*, acted as a negative control. The other plot, infested with *Bemisia tabaci* (whitefly), was used to evaluate the specificity of the optoelectronic nose's response to other pests. In both cases, three independent trials were conducted. In these complementary trials, the same experimental protocol used in the rest of the study was applied: the optoelectronic nose was installed in the central tree of each plot, at eye level in the canopy, to ensure maximum exposure to the volatile compounds emitted by the target insects and to simulate real field sampling conditions. In the field tests, it was not possible to perform a strict control of temperature and humidity. The measurements of incidence and severity were done at the orchard level, and the pest was present for a short period. Thus, it was not possible to locate infested and not-infested areas in the same field. In any case, the temperatures and humidities were relatively homogeneous during the experiments, with average daily temperatures of 24 ± 4 °C, and humidities in the range of 45 ± 5 % RH for field tests with *D. aberiae*, *B. tabaci*, or the absence of pest.

2.3. Data acquisition and processing

Data acquisition from the optical sensors was carried out by image capture of the sensor plates before and after exposure to the ambient air during 24 h. To ensure colour fidelity and minimise light interference, a light box with side LED spotlights was used to provide homogeneous and reproducible illumination. Images were taken with the main camera of a Samsung Galaxy A71 mobile device, equipped with a 64-megapixel sensor (f/1.8, 1/1.72", 0.8 μm) and phase detection autofocus, which provided high-resolution and analytical quality records suitable for spectral analysis. The RGB values of each sensor were extracted from the images using ImageJ image analysis software. The data acquisition system was robust and reliable through the assays, however, the RGB coordination of the white background was measured in each photo. This value was used to correct the rest of data collected form the image. This relative correction approach ensures inter-session consistency and reduces bias, from lighting variations. From these values, the parameter ΔE (Eq. 1) was calculated as a quantitative indicator of the colour difference between unexposed plates (control, R_0) and plates after exposure to the volatile compounds (R_1). This metric, based on the overall difference in colour space, offers high sensitivity and the advantage that the same parameter can be used for all the sensing materials independently of their colour.

$$\Delta E = \sqrt{(R_1 - R_0)^2 + (G_1 - G_0)^2 + (B_1 - B_0)^2} \tag{1}$$

Data acquisition from the MQ-type electrochemical sensors was performed in real time by collecting the voltage value. Before the start of each test, the MQ sensors were stabilised using a warm-up step followed by a 30-minute adaptation to the experimental environment. Readings obtained during this initial interval were discarded to avoid distortions due to signal drift. The response of each sensor was normalised to its resistance in clean air (Ro), measured before the experiment. The resistance in the (Rs) was used to calculate the Rs-Ro parameter, thus facilitating comparison between test days, varying environmental conditions and sensors. This procedure ensured an adequate relative interpretation of the signals, improving the robustness of the developed models. The electrochemical sensors' readout is based on a low-cost ESP8266 microcontroller board, which also provides the power supply for the electrochemical sensor. Each ESP8266 has one analogue input that was used for the readout of the electrochemical sensor at periodic time intervals of 1 min. The WiFi interface of the ESP8266 was used to send the sensor readout to a Raspberry Pi, where the measurements from all electrochemical sensors were gathered and stored in a MongoDB database. The Raspberry Pi wireless interface was configured as a WiFi access point, thus providing wireless connectivity to all ESP8266 boards. Each measurement was timestamped on its reception on the Raspberry Pi; these timestamps were afterwards considered for the fusion of the measurements registered on all the sensors. Both the timestamp and the measurement were stored in a MongoDB database as well as in a text file that was used for the posterior analysis of the measurements from all the electrochemical sensors.

2.4. Data analysis

Data generated by the electrochemical and optical sensors was integrated into a structured database manually. Before applying multivariate statistical models, data preprocessing based on autoscaling was performed in both IBM SPSS Statistics and R. This procedure was essential to ensure the comparability of the variables and prevent those with greater variance from dominating the analysis, thus ensuring an equal contribution of all variables to the models.

Exploratory data analysis was carried out using Principal Component Analysis (PCA) with IBM SPSS Statistics software. To enhance the interpretability of the components, the Varimax rotation method was applied, which maximizes the variance of squared loadings within each component, thereby facilitating the identification of relevant patterns in the data. On the other hand, partial least squares discriminant analysis (PLS-DA) and partial least squares (PLS) regression models were developed using the R programming language, with the mdatools and pls libraries, respectively. Model validation was performed using the Leave-One-Out Cross-Validation (LOOCV) technique, which enabled the assessment of model reliability and generalization capability while efficiently utilizing the available dataset.

3. Results and discussion

3.1. Development of a selective optoelectronic nose for D. aberiae detection

Despite the economic impact of *Delottococcus aberiae*, most studies have focused on its sex pheromones for monitoring and control, leaving the volatile organic compounds (VOCs) emitted throughout its life cycle largely unexplored [42]. While it is known that it produces various volatiles, their study remains limited, whereas other mealybug species, such as *Planococcus citri*, have been more extensively studied in terms of their emissions. This species also belongs to the Pseudococcidae family and, like *D. aberiae*, affects citrus crops. It has been identified to emit compounds such as (S)-lavandulyl isobutyrate [43], terpenes, alcohols, and other compounds that form a unique chemical signature useful for detecting the pest and monitoring its population dynamics, with variations depending on the host plant, the insect's development, and physiological conditions [44].

In this context, the development of an optoelectronic nose is proposed for the early detection of *D. aberiae* in citrus crops, combining electrochemical and colorimetric optical sensors in a portable and cost-effective device. This system, designed for direct field use by technical personnel, aims to overcome the limitations of conventional methods by providing real-time results. Our optoelectronic nose employs a combination of 4 electrochemical sensors, with 10 strategically selected supported dyes for selective analysis of *D. aberiae* in orange groves. Electrochemical ones, despite their preference for the determination of certain gases, are not completely selective and have a certain cross-response to other gases. For the optical units, the use of lab-synthetised selective chromoreagents has been avoided. The dyes used are of commercial origin to reduce the cost and facilitate scale-up of the application. Also, we selected dyes with a high molar extinction coefficient to reduce the amount of dye necessary. A key feature of this proposal is the use of colorimetric sensors, which offer high sensitivity and selectivity for detecting VOCs, enabling visual monitoring through colour changes without the need for complex equipment. To enhance detection efficiency, the optical sensors were deposited on three inorganic supports: mesoporous silica (UVM-7), aluminium oxide, and silica, which provide high stability to the dyes. Furthermore, the substrates, with their differences in surface area, concentration of silanols, and acid-base character, modulate the response of the dyes to the environment. The mesoporous silica UVM-7, with its high specific surface area (~1200 m^2/g) and bimodal structure, facilitates the diffusion of volatile compounds, significantly increasing the sensitivity of the system [45].

3.2. Sensor array response

The performance of the optoelectronic system was evaluated through both in vitro and field tests. Colorimetric and electrochemical optical sensors were exposed to *Delottococcus aberiae* (Cotonet de les Valls) under controlled conditions, followed by trials in a commercial citrus orchard and a plot affected by *Bemisia tabaci* (whitefly), to assess the sensitivity and selectivity of the device against different pest species.

The response profiles of the sensors (Fig. 2) were analyzed in the presence of these pests and in conditions without significant infestation. The sensor data were normalized to facilitate comparison and minimize bias. The resulting chart shows the relative intensity of the sensor's response under the evaluated experimental conditions. The results show variations in the sensor responses depending on the presence or absence of pests. The correlation of this approach with traditional techniques validates the accuracy of the optoelectronic nose for detecting *D. aberiae*. Furthermore, its ability to differentiate between pest species enhances its robustness and selectivity, positioning it as a promising technology for integrated pest management in citrus crops.

Principal Component Analysis (PCA) was used to reduce the complexity of the data obtained from chromogenic and electrochemical sensors. This statistical technique allowed for the projection of sensor responses in a multivariate space defined by the first three principal components (PC1, PC2, and PC3), providing a clearer representation of the relationships among the recorded variables. The in vitro analysis (Fig. 3A) clearly distinguished between samples affected by D. aberiae (group "D") and control samples with no pests (group "C"), highlighting the relevance of the first principal component (PC1) for discriminating the presence of the pest. This pattern was also observed in the field trials (Fig. 3B), where three groups were analyzed: *D. aberiae* (D), whitefly (W), and control (C). The PCA revealed a clear separation between the groups, suggesting that different pest incidences generate chemically distinct patterns, with the "D" group consistently clustering in a specific region of the multivariate space, demonstrating the characteristic impact of this pest on the analyzed variables. The "W" group, though with some overlap, also showed defined clustering, while the "C" group appeared more dispersed, likely due to higher natural variability in pest-free conditions.

The PCA analysis revealed differences in the sensor distribution between in vitro and field trials (Figs. 4a and 4b, respectively). In the in vitro trials, the sensors showed a structured distribution, with S4, S5, and S7 standing out due to their positive contribution to the first principal component (PC1), while S9, S6, S10, and S14 showed a significant negative influence. This separation suggests that these sensors are sensitive to specific volatile compounds, which could be useful for developing more selective detection systems. In contrast, the field trials showed a more scattered and less structured distribution. However, some sensors, such as S1, S5, and S7, continued to show a positive contribution to PC1, while S2, S6, and S13 had a significant negative influence. This indicates that these sensors are important for explaining variability under real conditions. Additionally, the third principal component (PC3) captured more variability in the field environment, suggesting that the complexity and heterogeneity of the open environment affect the sensor responses.

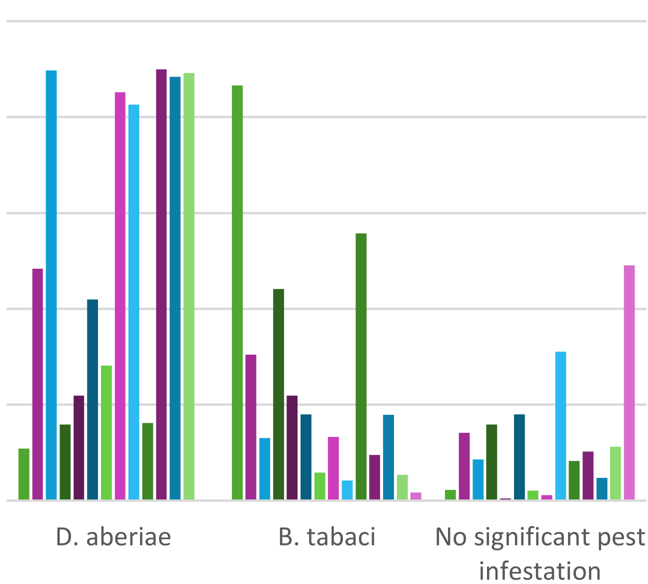

Fig. 2. Response profiles of the sensor array following exposure to volatile organic compounds emitted in the presence of *Delottococcus aberiae*, *Bemisia tabaci*, and under conditions with no significant infestation.

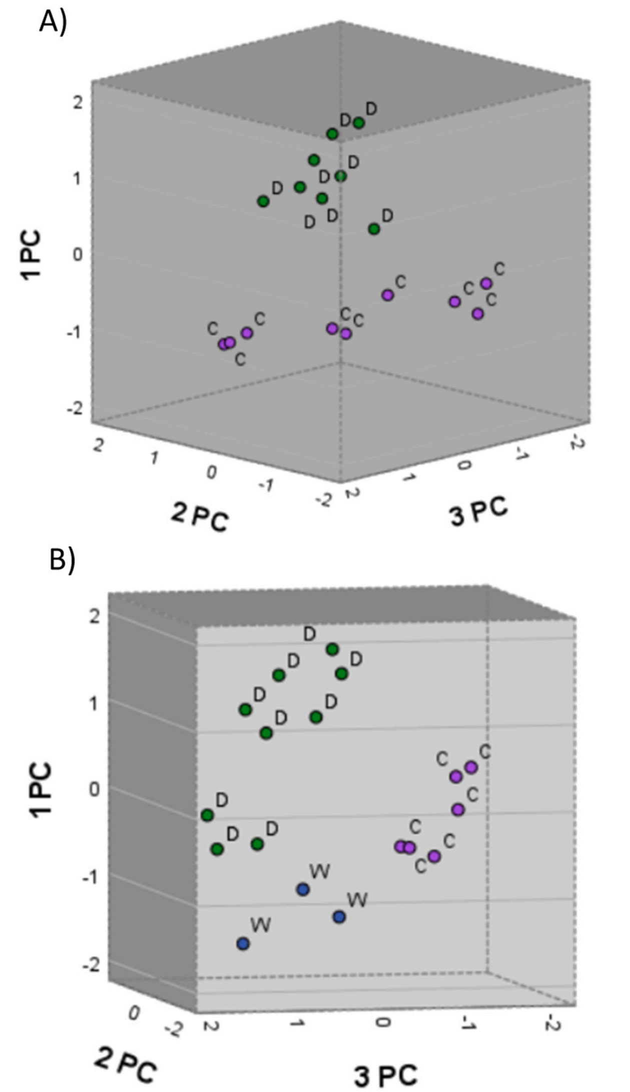

Fig. 3. A) PCA projection of the optoelectronic nose system responses under *in vitro* conditions for samples with (D) and without (C) the presence of *D. aberiae*. B) PCA representation of field measurements for samples with *D. aberiae* (D), whitefly (W), and without pests (C).

This analysis highlights how the environment influences the response of chemical sensors. While some sensors perform well in laboratory conditions, their performance may decrease in the field due to increased environmental variability. Therefore, validating the system under real-world conditions is crucial to identify the most robust and effective sensors, ensuring their usefulness for monitoring in citrus cultivation. The variation in the values of temperature and relative humidity during the experiments in the field is not very large, and probably temperature and humidity have a minor effect (within the conditions of the assay), but with the data available, we cannot discard a significant effect. The clear separation between measurements affected by *D. aberiae* and those from the control, as well as the ability to differentiate this pest from others like whitefly, emphasizes the strong performance of the optoelectronic nose system in detecting and discriminating between different pest incidences in citrus crops. These findings suggest that the system can effectively interpret the complexity

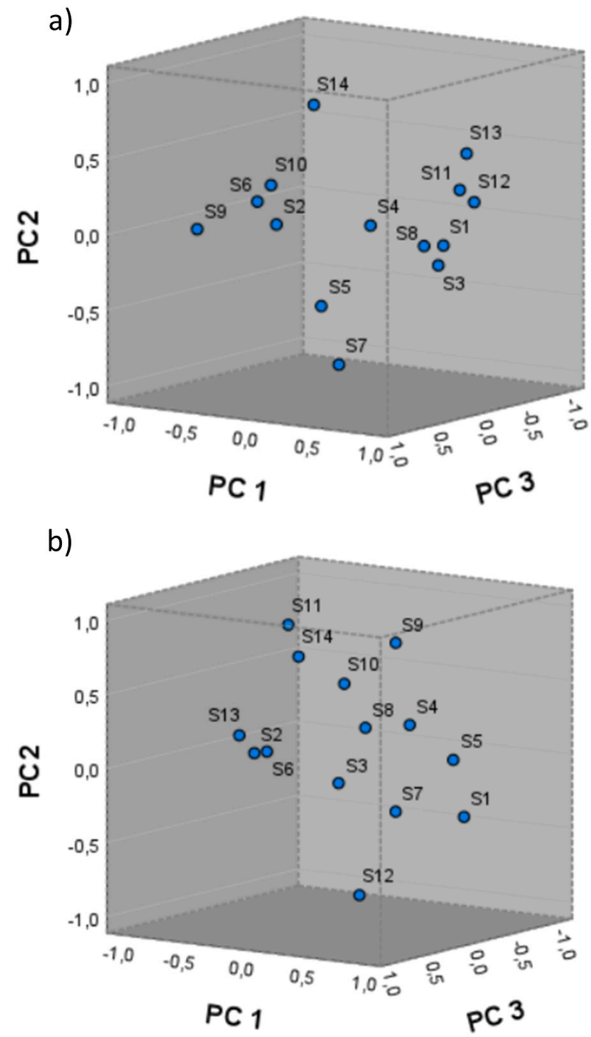

Fig. 4. Distribution of sensors loadings in the PCA space: a) *in vitro* assays and b) field assays.

of the pest-modified atmosphere.

3.3. PLS-DA statistical analysis

To evaluate the classification capability of the detection system under controlled laboratory conditions, partial least squares discriminant analysis (PLS-DA) models were developed using the full array of 14 sensors. PLS-DA is particularly suitable for categorical outcomes, as it enables binary or multiclass classification. This methodological distinction justified the use of PLS-DA for the analysis of *in vitro* measurements, where the objective was to discriminate between samples with (Yes) and without (No) the presence of *Delottococcus aberiae*.

The PLS-DA models demonstrated excellent classification performance. During both the calibration and cross-validation phases, the models achieved perfect discrimination between the two classes, with all performance metrics—accuracy, recall, precision, F-score, and true negative rate (TNR)—equal to 1.000 (Table 3). This perfect separation highlights the high sensitivity and specificity of the detection platform under controlled conditions and underscores its potential as a robust diagnostic tool for early pest detection.

Additionally, the PLS-DA model was applied to data collected under real field conditions, using both the full array of 14 sensors and the optimized configuration of 8 sensors. Remarkably, perfect classification performance was maintained in both cases, with values for precision, sensitivity, specificity, and accuracy consistently equal to 1.000 across

Table 3
Summary of PLS-DA (cross-validation (CV) and calibration (Cal)) under in vitro and field conditions with arrays of 14 and 8 sensors.

Conditions	D. *aberiae*	TPR (Recall)	TNR	Precisión	F-score	Accuracy
In Vitro (Cal) 14-sensors	No	1.000	1.000	1.000	1.000	1.000
	Yes	1.000	1.000	1.000	1.000	1.000
In Vitro (CV) 14-sensors	No	1.000	1.000	1.000	1.000	1.000
	Yes	1.000	1.000	1.000	1.000	1.000
Field (Cal) 14-sensors	No	1.000	1.000	1.000	1.000	1.000
	Yes	1.000	1.000	1.000	1.000	1.000
Field (CV) 14-sensors	No	1.000	1.000	1.000	1.000	1.000
	Yes	1.000	1.000	1.000	1.000	1.000
Field (Cal) 8-sensors	No	1.000	1.000	1.000	1.000	1.000
	Yes	1.000	1.000	1.000	1.000	1.000
Field (CV) 8-sensors	No	1.000	1.000	1.000	1.000	1.000
	Yes	1.000	1.000	1.000	1.000	1.000

all scenarios (calibration and cross-validation). These results further reinforce the system's reliability even in complex and variable field environments, confirming its practical applicability in real-world agricultural settings.

3.4. PLS statistical analysis

In this study, partial least squares (PLS) regression was applied to correlate data from optoelectronic sensors with the incidence and severity of *D. aberiae* infestations in citrus crops. To this end, the incidence and severity values obtained through traditional visual counting were used as response variables. The incidence presented values between 0 % and 16 % at different times. Severity recorded values of 0–0.3. These data served as a reference for evaluating the sensory system's ability to discriminate between levels of infestation and for validating the usefulness of PLS models in quantitatively predicting the presence of the pest.

The model using the full array of 14 sensors demonstrated good performance for predicting incidence ($R^2 = 0.921$; RMSEP = 1.37; relative error = 28.2 %), whereas the prediction of severity was more limited ($R^2 = 0.835$; RMSEP = 0.0434; error = 52.1 %), reflecting its greater complexity and dependence on environmental variables (Table 5).

To enhance the system's efficiency and practical feasibility, the sensor array was optimized by reducing it to 8 sensors with the highest discriminative power (Table 4). With this optimized configuration, predictive accuracy under field conditions improved: the incidence model achieved an R^2 of 0.952 and a relative error of 22.1 %, while the severity model reached an R^2 of 0.913 and a relative error of 37.8 %. Therefore, the optimized version not only maintained high predictive performance but also reduced the complexity of the model, as shown in Table 5.

Fig. 5 supports these findings through validation plots of the PLS models, where predicted values are compared with corresponding measured values. In general, the data points align closely with the diagonal, indicating a good model fit. Plots A and C (field incidence using 14 and 8 sensors, respectively) show strong agreement, confirming the reliability of the models under real-world conditions. In contrast, plots B and D (field severity) display greater dispersion, especially at lower severity levels, suggesting reduced predictive precision in that range, likely due to the complexity of chemical signals or limited statistical representativeness. The system's ability to differentiate between similar pests, such as *D. aberiae* and whitefly, represents a significant result. This discriminative capacity improves field reliability and enables the

Table 4
A) Selected array for predicting incidence. B) Selected array for predicting severity.

Sensing material	Dye/Support or electrochemical sensor
(A)	
S2	Victoria blue B / Silica
S4	Chromocyanin / Silica
S6	Dichlorofluorescein / Silica
S7	Thionine acetate / Silica
S9	Potassium indigotrisulfonate / Silica
S12	MQ−8
S13	MQ−4
S14	MQ−137
(B)	
Sensing material	Dye/Support or electrochemical sensor
S2	Victoria blue B / Silica
S4	Chromocyanin / Silica
S7	Thionine acetate / Silica
S8	0-Dianisidine / UVM−7
S10	Rhodamine 6 G / Silica
S12	MQ−8
S13	MQ−4
S14	MQ−137

Table 5
Parameter fitting and LOOCV results for PLS prediction models of field incidence and severity assays using 14-sensor and 8-sensor arrays.

Conditions	R^2	RMSEP	Error (%)	PC
Incidence 14-sensors	0.9211	1.3780	28.2	4
Severity 14-sensors	0.8346	0.0434	52.1	3
Incidence 8-sensors	0.9517	1.0780	22.1	3
Severity 8-sensors	0.9127	0.0315	37.8	2

implementation of more precise pest control strategies, thereby reducing unnecessary treatments and supporting a more sustainable agricultural approach.

The analysis of the loading coefficients obtained from the PLS model (Table 6) allowed for assessing the individual relevance of each sensor in predicting the incidence and severity of *D. aberiae*, revealing distinct patterns depending on the sensor configuration used. Overall, sensor S4 (Chromocyanine/Silica) emerged as the most significant, showing high loading values under all evaluated conditions. Its prominent contribution—particularly in the incidence model with 14 sensors (0.336) and the severity model with 8 sensors (0.390)—suggests high sensitivity to volatile compounds associated with both pest presence and damage severity under both controlled and field conditions. Sensor S10 (Rhodamine 6 G/Silica) also exhibited a strong contribution to the prediction of severity using the 14-sensor configuration (0.650), indicating high sensitivity to compounds released as infestation progresses. This highlights its potential role as a chemical marker for damage quantification. Sensor S7 (Thionine Acetate/Silica) was especially relevant in the incidence model using the reduced 8-sensor array (0.699), suggesting a key role in early detection of *D. aberiae* presence under real cultivation conditions. Likewise, sensor S2 (Victoria Blue B/Silica), although with minor influence in other scenarios, was significant in predicting severity with the optimized array (0.168), pointing to its complementary role in compact sensor configurations. MQ-based sensors (S11–S14) showed more dispersed and generally lower contributions, though not negligible. Notably, sensor S12 (MQ-8) showed some relevance in predicting both incidence and severity with the 14-sensor setup (0.110 and 0.146, respectively), confirming its responsiveness under field conditions. Finally, sensors S5 (Malachite Green/Silica) and S6 (Dichlorofluorescein/Silica) exhibited more specific contribution patterns. S6 showed a notable response in the incidence models for both configurations (14 and 8 sensors), with loading coefficients of 0.164 and 0.180, respectively. This behavior may be related to its sensitivity to volatiles released during intermediate stages of infestation, potentially adding value to the dynamic characterization of damage progression.

Compared to previously developed detection systems for insect pests, the optoelectronic nose proposed in this study offers key differential advantages. Most approaches described in the literature, such as those based on computer vision or remote sensing, focus on pests that cause visible damage to the foliage or aerial parts of the plant, thus facilitating their visual or spectral identification. However, *Delottococcus aberiae* is a sub-cryptic pest that primarily affects the fruit and does not produce noticeable morphological alterations in the tree canopy during the early stages of infestation, which complicates its detection by conventional means. In this context, the use of a chemical sensor system such as the optoelectronic nose enables the capture of specific volatile signals associated with either the insect's presence or the plant's metabolic response, without requiring visible manifestations of damage. This capability for early and non-invasive detection of pests that are difficult to identify visually positions this technology as an innovative and complementary tool to traditional methods, expanding the scope of action in integrated pest management programs.

3.5. Comparison with conventional and emerging technologies

Early monitoring and diagnosis of pests in agriculture continues to be a key challenge, especially in crops such as citrus fruits, where emerging pests such as *Delottococcus aberiae* have shown rapid expansion and high damage potential. Traditional methods, such as visual inspections and pheromone traps [46,47], although low-cost and easy to implement, have notable limitations: they require specialized personnel, do not allow for early detection, and provide mostly qualitative information. In contrast to these limitations, the optoelectronic nose developed in this work offers a more efficient approach, allowing the identification of the pest in its early stages through the volatile fingerprint and generating quantitative data on the incidence and severity of the infestation.

Among the most widely used technological tools in precision agriculture are remote sensing systems using satellites and drones equipped with spectral sensors [6,7,48]. These technologies have proven useful in monitoring large crop areas, but their effectiveness is conditioned by several factors: the high cost of the equipment, the complexity of data processing, and the inability to detect infestations in asymptomatic stages. Studies such as those by García-Ruiz et al. [49] and Abdulridha et al. [50] have reported applications in citrus fruits for diseases such as huanglongbing or citrus canker. Analysis of satellite images allows the analysis of the temporal evolution of the Delottococcus aberiae pest in citrus orchards, demonstrating that it is possible to detect spectral differences associated with the presence of this scale insect. However, these approaches still require validation and improvement for routine use in early diagnosis [51]. Furthermore, these systems detect changes in plant physiology once the damage is already visible, reducing their capacity as early diagnostic tools.

Intermediate technologies, such as the Unmaned Aerial Vehicles (UAV) with RGB or multispectral cameras, have been applied in diverse agricultural applications. crops such as tomatoes [52]. Although they allow for continuous monitoring, their implementation in citrus fruits has not been sufficiently validated, and their effectiveness is subject to factors such as lighting, foliage position, or weather conditions, which negatively affect the accuracy of the system.

Image recognition has appeared as an efficient approach for the detection and quantification of pests. It follows the usual practices of the technicians based on in person evaluation of the traps and visual counting and identification. The implementation of image collection and transmission systems to be used in field has certain complexity and require the incorporation of attracting systems in systems designed to protect electronics and save energy without disturbing the behaviour of the insects [24–26]. Also, the inclusion of complementary sensors (i.e. T,

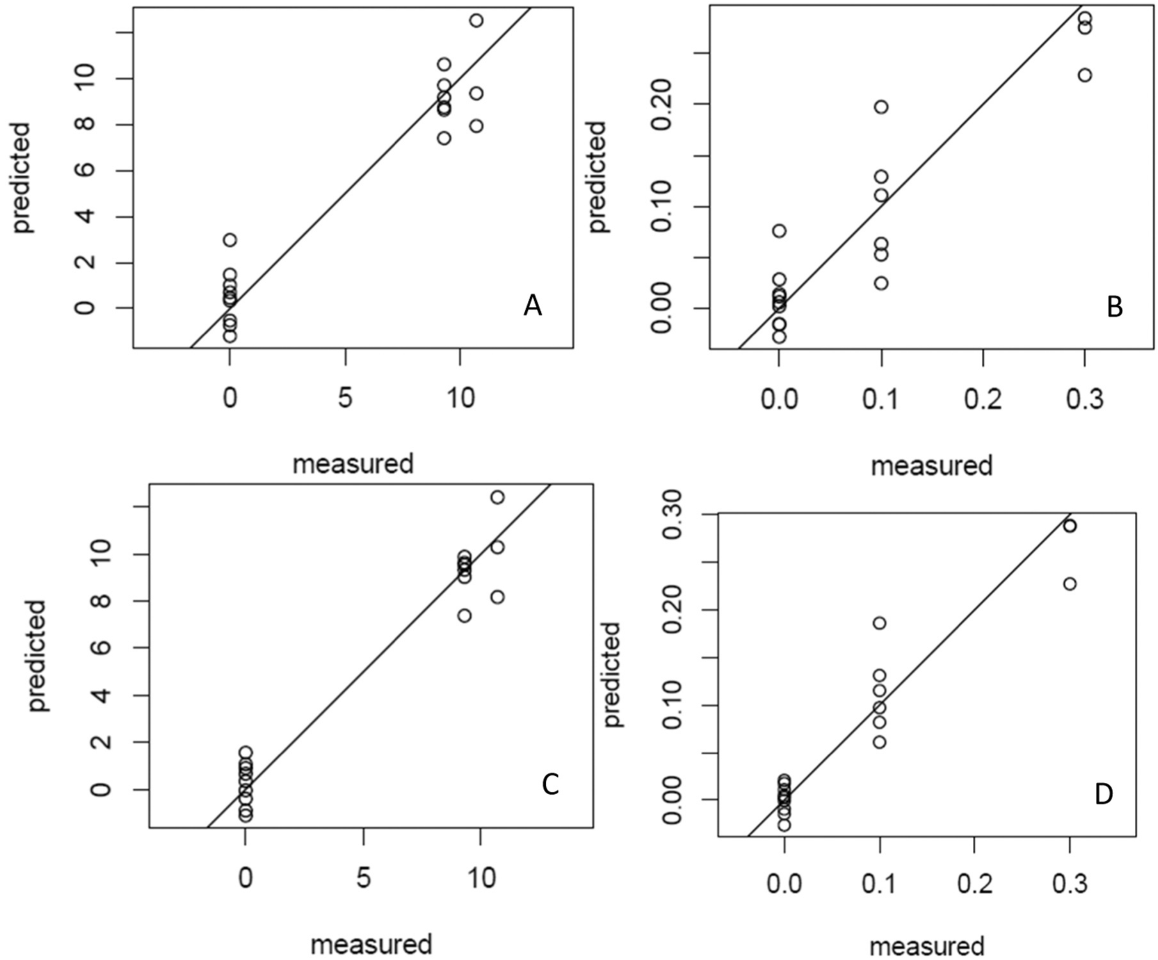

Fig. 5. Validation plot of the PLS prediction model results (predicted vs. actual values) for A) Field assay for incidence with the 14-sensor array, B) Field assay for severity with the 14-sensor array, C) Field assay for incidence with the 8-sensor array, and D) Field assay for severity with the 8-sensor array.

Table 6
Sensor loading coefficients as a function of each tested condition, obtained through the partial least squares (PLS) regression model.

Sensor	Incidence 14-sensors	Severity 14-sensors	Incidence 8-sensors	Severity 8-sensors
S1	0.0757	0.0104		
S2	0.0128	0.0048	0.0074	0.1678
S3	0.0512	0.0110		
S4	0.3358	0.1337	0.0119	0.3903
S5	0.2244	0.0076		
S6	0.1637	0.0628	0.1799	
S7	0.0084	0.0001	0.6988	0.0759
S8	0.0111	0.0209		0.2081
S9	0.2806	0.0188	0.0627	
S10	0.0216	0.6498		0.1619
S11	0.0080	0.0718		
S12	0.1097	0.1461	0.0131	0.0176
S13	0.0004	0.0186	0.0000	0.0251
S14	0.0001	0.0351	0.1810	0.0150

humidity, or gases) can reinforce the operation of the device. In a promising approach to simplify the devices, the image analysis usually is performed in external devices after the transmission of the images. This analysis can be performed in an external standardized cloud platform such as iNaturalist [26]. However, most of the systems develop their own CNN models calibrated with the images taken form their devices. Image recognition must deal with the presence of other insects, and of leaves that complicate the process. Despite these difficulties, optimizing data acquisition and the parameters of CNN accuracies close to 90 % can be achieved [24,25].

In the field of emerging technologies, electronic noses have gained prominence in recent years as tools for detecting VOCs associated with diseases or pests [30–32]. These are mainly based on metal oxide sensors (MOS), which, although sensitive, have problems with selectivity and stability in the face of environmental interference. Furthermore, most of these devices have been evaluated under controlled laboratory conditions and lack field validation. Our optoelectronic system, which incorporates optical and electrochemical sensors, improves the specificity of the analytical signal and offers greater operational robustness under real agricultural conditions.

Other advanced techniques, such as gas chromatography coupled with mass spectrometry (GC-MS) or FTIR spectroscopy, provide high analytical resolution for the detection of VOCs [38–40], but require a target molecule, sample preparation, laboratory infrastructure, and qualified technical personnel, making them unsuitable for direct field monitoring.

In terms of technologies still in the development phase, NIRS spectroscopy, bio-inspired sensors, and AI-based biomimetic systems stand out [15–18]. Although these approaches promise more adaptive and sensitive solutions, their technical complexity, high cost, and limited validation in specific crops limit their applicability in the short term. Bio-inspired sensors have shown potential in detecting VOCs emitted by insects, but they remain prototypes that have not been applied in real agricultural management situations.

In this context, the optoelectronic nose described in this paper represents a significant advance for several reasons: it has been specifically designed for use in citrus fruits; it allows early detection of *D. aberiae* before visible symptoms appear; and it has been validated under real field conditions. Its compact and low-cost architecture, based on microcontrollers and commercial sensors, facilitates its integration into conventional farms without requiring technical personnel. Furthermore, unlike other similar devices, our system provides not only a presence/absence signal but also a quantitative estimate of the incidence and severity of the infestation, which is essential for planning actions within integrated pest management (IPM) programs.

According to the review, this would be the first optoelectronic system specifically designed, calibrated, and validated for the early detection of *Delottococcus aberiae* in citrus fruits under real conditions, reinforcing its innovative nature and high potential for commercial transfer.

4. Conclusions

The development and evaluation of an optoelectronic nose system for the detection of the *Cotonet de les Valls* (*Delottococcus aberiae*) in citrus crops has proven to be an innovative, effective, and promising tool for the early monitoring of this invasive pest. Through the combined use of colorimetric optical sensors and electrochemical sensors, the device has demonstrated high sensitivity and selectivity in detecting the presence of the insect, both under controlled conditions and in the field. The results obtained show the system's ability to differentiate not only between the presence and absence of the *D. aberiae*, but also from other pests such as the whitefly (*Bemisia tabaci*), reinforcing its value as a discriminative tool in integrated pest management programs. Statistical analysis using PLS showed high levels of accuracy, especially with optimized sensor configurations. The application of PLS-DA models enhanced the classification ability of the system, achieving perfect metrics under several experimental conditions. This approach proved particularly effective for detecting different levels of incidence and severity of *Delottococcus aberiae*, demonstrating its usefulness in real field scenarios. The complementarity between PLS and PLS-DA provides a more robust characterization of the sensing system, covering both continuous prediction and categorical classification.

Reducing the sensor array to eight elements allowed the system to maintain—and even improve—its predictive performance, enhancing its practical applicability by simplifying the design without compromising accuracy. In addition, key sensors such as S4, S7, and S10 were identified as highly relevant across different detection scenarios, which will enable the design of even more specific and efficient devices in the future.

Overall, these findings confirm that the developed optoelectronic nose represents a significant advancement in the early detection of *Delottococcus aberiae*, offering a portable, accessible, and effective alternative to more complex and costly traditional methods. Although advances in hardware and software, a better understanding of the effect of temperature and humidity, and a large-scale field evaluation are needed before its implementation, this result represents a proof of concept towards a precise and sustainable management of citrus crops, reducing economic losses and the unnecessary use of phytosanitary treatments.

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CRediT authorship contribution statement

Carlos Montesinos: Methodology, Investigation, Conceptualization. **Sheila Sánchez-Artero:** Writing – original draft, Methodology, Investigation, Data curation, Conceptualization. **Jose Vicente Ros-Lis:** Writing – original draft, Supervision, Methodology, Investigation, Conceptualization. **Pedro Amorós:** Writing – original draft, Supervision, Methodology, Investigation, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.snb.2025.139021.

Data Availability

Data will be made available on request.

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