Integrating UAS, Computer Vision and AI for Targeted Management of Invasive Insect Pests in Vineyards

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Abstract

The increasing globalisation of trade and climate change are accelerating the spread of invasive pest species, posing significant threats to agriculture. The Japanese beetle (Popillia japonica Newman), first recorded in northern Italy in 2014, is a highly destructive pest with severe economic impacts, particularly in viticulture. Effective monitoring is essential for timely intervention, yet conventional field-based surveys are resource-intensive and limited in spatial coverage.

This study presents a novel UAV-based monitoring framework integrating near-infrared (NIR) imaging and machine learning algorithms to detect Popillia japonica adults in vineyard environments. Field experiments were conducted in two commercial vineyards in northern Italy during the beetle's summer flight season. A standardised and replicable aerial data acquisition protocol was developed using lightweight multispectral sensors mounted on rotary-wing UAV platforms. Detected insect signatures were processed through a custom CV pipeline and validated through entomological ground truthing via manual counts.

Results show a strong correlation between CV-derived detections and manual observations, with Pearson correlation coefficients ranging from 0.89 to 0.96. Although the system tends to overestimate insect counts under certain canopy conditions slightly, its integration into a GIS environment enabled the near real-time generation of prescription maps. These maps were used to guide site-specific drone spraying treatments, applying insecticides only in hotspot areas where infestation thresholds were exceeded.

This UAV-enabled, semi-automated monitoring approach significantly reduces survey time and human exposure to agrochemicals, while supporting precision pest management at scale. The methodology offers a promising framework for integrating remote sensing, AI, and entomological validation, with broader applications for managing invasive species in precision agriculture contexts.

1. Introduction

Globalisation has significantly accelerated the movement of goods, services, and people, contributing to rapid economic growth in recent decades. However, it has also facilitated the transboundary spread of invasive species, particularly agricultural pests, which now threaten global food security and local economies. Climate change further exacerbates this issue, which expands the suitable habitat range for many invasive organisms (Early et al., 2016). A striking example is the Japanese beetle (Popillia japonica Newman, PJ), a coleopteran species native to Japan and accidentally introduced to North America and, more recently, Europe.

PJ is a highly destructive pest, exhibiting a holometabolous life cycle. Larvae feed on the roots of grasses and crops belowground, while adults are highly polyphagous, attacking over 300 plant species, including grapevine, maize, apple, rose, and soybean (EPPO, 2018; Ebbenga et al., 2022). The adult beetles typically consume leaf tissue between the veins, a process known as skeletonization (figure 2), and may also feed on flowers and fruits. Aggregation behaviour frequently leads to the complete defoliation of individual plants, causing a significant reduction in photosynthetic capacity, yield losses, and in severe cases, plant death (Ebbenga et al., 2022).

Since its first detection in northern Italy in 2014, P. japonica has rapidly spread throughout the Ticino Valley, affecting economically important crops, particularly grapevines. Viticultural systems are especially vulnerable due to the long lifecycle of vines and the delayed return on investment from newly planted vineyards. In response, the Italian government has enacted emergency containment measures and provided financial support to affected farmers (figure 4).

In this critical context, improving pest monitoring strategies is a key priority to enable early detection and timely intervention. Based on manual visual inspections and trapping, conventional monitoring methods are labour-intensive, time-consuming, and spatially constrained. As a result, there is growing interest in developing automated solutions leveraging recent advances in computer vision (CV) and sensor technologies.

Among the various automated approaches explored in recent literature, image-based systems have shown particular promise for insect identification (Martineau et al., 2017; Ahmad et al., 2022; Júnior & Rieder, 2020). Unlike acoustic or olfactory techniques, which are often limited to specific taxa (Cui et al., 2018), image-based systems can be applied broadly due to the visual morphological traits that distinguish insect species. Furthermore, digital imagery can be archived, enabling reproducibility and longitudinal analyses.

Recent applications of CV in entomology include pest classification in agricultural and forestry systems (Domingues et al., 2022; Duarte et al., 2022), detection of fruit fly parasitisation (Marinho et al., 2023), pine pest identification (Ye et al., 2022), and automated counting of mosquito eggs (Javed et al., 2023). CV enables the automated extraction of ecologically relevant features—such as presence, abundance, morphology, and behaviour—without direct human observation (Bjerge et al., 2022).

Image acquisition strategies range from handheld cameras to fixed smart traps and curated datasets (Gao et al., 2024; Nawoya et al., 2024). However, Uncrewed Aerial Systems (UAS) offer several advantages for practical, large-scale field monitoring. These include flexible navigation, the ability to cover extensive areas, integration of diverse sensors, and reduced human exposure to field hazards. Yet, field-acquired images present new challenges, such as complex backgrounds and object occlusion due to vegetation. In particular, PJ exhibits a reflective green dorsal surface, rendering it challenging to distinguish from foliage in RGB images.

To address this, near-infrared (NIR) imaging has emerged as a valuable technique for enhancing contrast between insects and host plants. Vegetation strongly reflects in the NIR band, while the beetle's exoskeleton has low NIR reflectance, enabling easier discrimination (Brusco et al., 2023, Matrone et al., 2022). This spectral separation supports more accurate segmentation and classification, even in cluttered outdoor environments (Figure 3). Building on this foundation, the present study explores a CV-based methodology for the detection of PJ using NIR sensors mounted on UAS platforms. The objective is to assess the feasibility of this approach in operational field conditions and to develop a replicable monitoring protocol that integrates automated detection with geospatial analysis for precision pest management.

Figure 1. An adult insect of Popillia Japonica on a vine plant.

Figure 2. The effects of PJ on a vineyard

2. The case study

This contribution is grounded in the complex and urgent context of managing the invasive species PJ. It presents the results of a multitemporal field trial aimed at monitoring adult beetles using a machine learning algorithm applied to two commercial vineyards in Ghemme and Briona (Province of Novara, northern Italy). The study is part of the DANTE project (Longhi, 2024) (Drone-based Experimental Survey for the Monitoring and Protection of Vineyards against the Quarantine Pest Popillia japonica Newman), which aims to optimise the timing and spatial targeting of UAS-based treatments. The overarching objective is to minimise pesticide use by confining applications to infested areas, thereby reducing environmental impact and improving treatment efficiency.

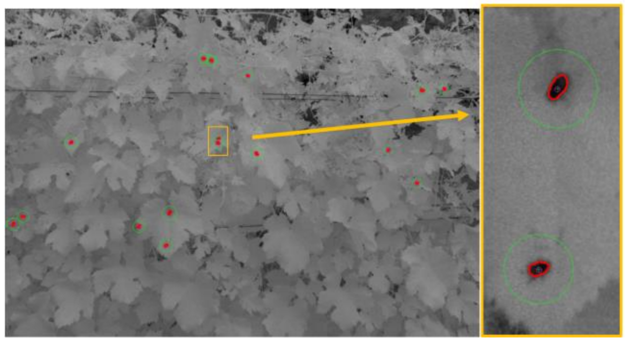

Figure 3. An example of an NIR image of Popillia insects in the studied vineyards was recognised with the algorithm described below.

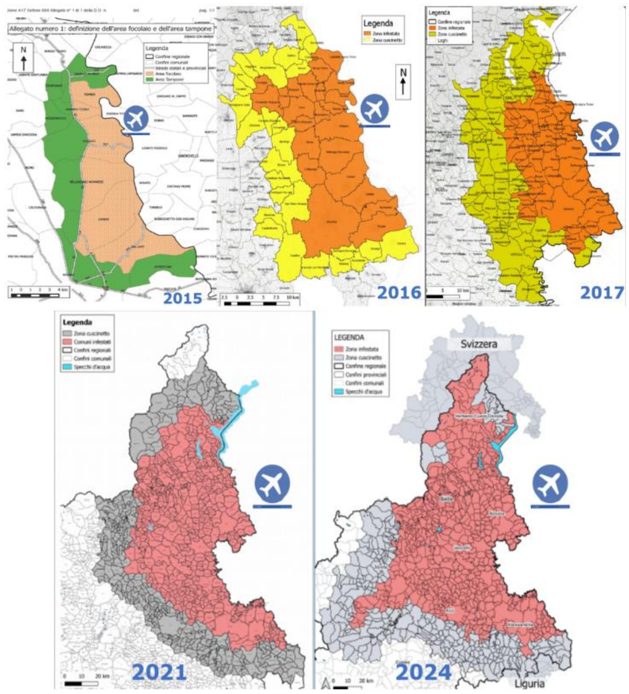

Figure 4. The spread dynamics of Popillia japonica in the Upper Piedmont region (from a presentation by Dr. Michele Colombo at the workshop "DANTE2 Project: the use of drones to counter Popillia japonica in vineyards", April 17, 2025).

Regione Piemonte funds the project and involves a multidisciplinary partnership including: the Department of Environmental and Land Engineering (DIATI) of Politecnico di Torino, the Department of Agricultural, Forestry and Food Sciences (DiSAFA) of the University of Turin, ARPA Piemonte (Regional Agency for Environmental Protection), Regione Piemonte, and the Consorzio di Tutela Nebbioli dell'Alto Piemonte.

The activities undertaken within the DANTE project include developing and validating a ML (Machine Learing) based detection method, UAV-assisted and manual monitoring of

Popillia populations, targeted treatments, damage assessment, and evaluating environmental impacts resulting from pesticide applications.
This paper focuses specifically on the project's insect detection and monitoring components. The goal is to assess the effectiveness of a ML algorithm for identifying adult P. japonica using near-infrared (NIR) optical sensors mounted on UAS platforms. The broader aim is to define a replicable and standardised data acquisition protocol suitable for operational pest monitoring. The analysis presented here addresses three main aspects:

- the implementation of the machine learning algorithm for beetle detection from NIR imagery,
- the spatial mapping of detected insects onto a georeferenced 3D model of the vineyards, and
- the overall accuracy and reliability of the detection method in a real-world monitoring scenario.

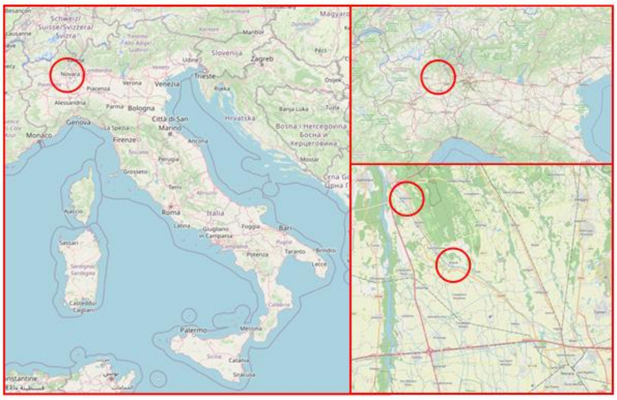

Figure 4. The study area: in the bottom right picture, Ghemme and Briona towns are highlighted by red circles. (Images acquired from OpenStreetMap)

Two vineyard plots were selected as study sites in the municipalities of Ghemme and Briona, located in the Province of Novara within the Piedmont region of northern Italy (Figure 4). This area is renowned for its high-quality wine production and has been affected by infestations of Popillia japonica since its initial detection in the summer of 2014. The selection of this region was based on three main criteria: the urgency of addressing the pest outbreak, logistical accessibility for field operations, and the economic relevance of viticulture in the area.
At the outset of the study, two subplots of comparable size were delineated within each vineyard and assigned to different treatment protocols. The first subplot, designated as "Conventional" (C), was managed through manual pesticide application conducted by trained field operators. The second subplot, referred to as "Drones" (D), was treated using a DJI Agras MG-1P RTK Uncrewed Aerial vehicle (UAV) equipped for precision spraying.
The treatment areas were defined based on a digital surface model (DSM) generated through aerial photogrammetry at the beginning of the study (baseline timepoint T0). The two experimental plots had similar surface areas—approximately 2,000 m² in Briona and 3,000 m² in Ghemme. Notably, the Briona vineyard is situated on flat terrain. In contrast, the Ghemme vineyard lies on sloped ground, a factor considered during UAV flight planning and mission design.

3. The methodology

The adopted methodology is presented in Figure 5 and will be discussed in detail in the following sections.

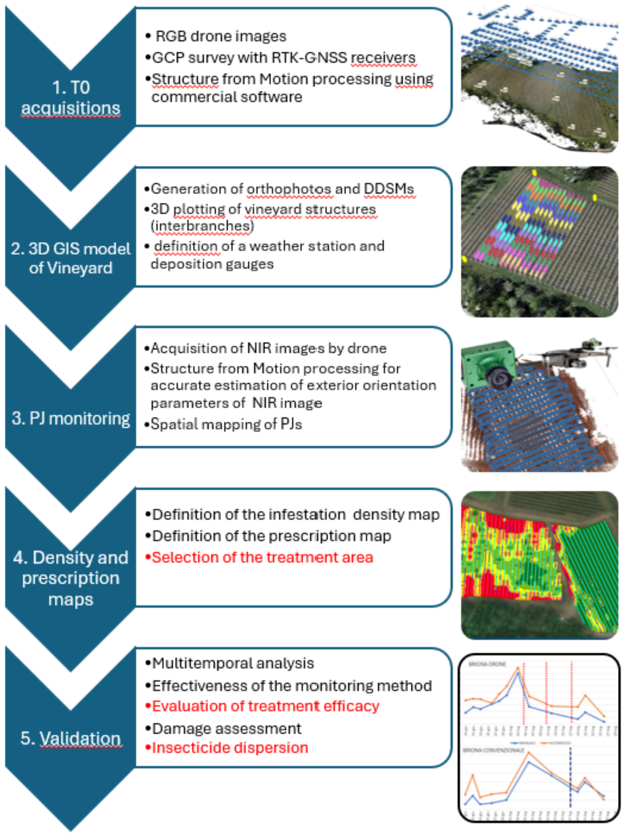

Figure 5. The T0 orthomosaic of Briona displayed in GIS and representation of the interbranches.

3.1 Initial Data Acquisition

At the onset of the project, a high-resolution 3D model of the two study areas was generated as part of the T0 acquisition to improve understanding of vineyard geometry. Aerial photogrammetry was conducted using a DJI Matrice 300 UAV equipped with a Zenmuse P1 RGB sensor. Ground control points (GCPs) were established through markers either anchored to the soil or affixed to the heads of vine rows. Their coordinates were acquired using high-precision GNSS receivers (Stonex S990A and Leica GS18 in Real Time Kinematic solution using the regional SPIN service).
A Structure from Motion (SfM) technique (Teppati Losè et al., 2020), implemented in Agisoft Metashape, produced the following geospatial outputs:

- An orthophoto with 1 cm resolution,
- A Digital Surface Model (DSM, 5 cm GSD), and
- A Digital Terrain Model (DTM, 20 cm GSD).

3.2 3D Vineyard Modeling in GIS environment

These geospatial products supported the structural definition of the vineyard using ArcGIS 3D, resulting in a simplified 3D model encompassing:

- The geometry of vine rows and their vertical partitions (inter-pole segments or "interbranches"), used as census units;

- The spatial location of weather stations for environmental parameter monitoring;
- The placement of deposition collectors to assess insecticide distribution.

Figure 6 shows the 3D GIS view of Briona vineyard.

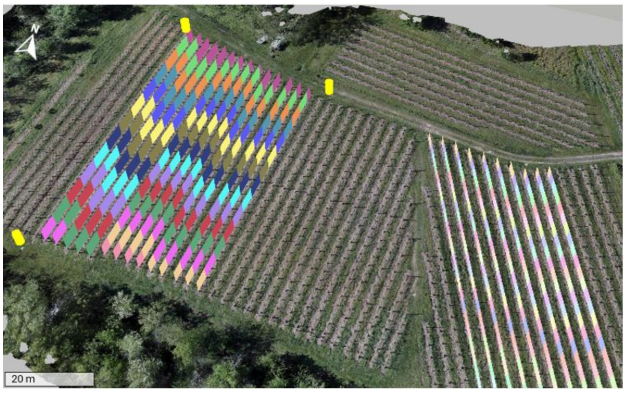

Figure 6. The T0 orthomosaic of Briona displayed in GIS and representation of the interbranches.

3.3 NIR-Based Monitoring Flights

Monitoring data were acquired through low-altitude UAV surveys using a DJI Mavic 2 Pro equipped with a Sentera Single NIR sensor. The flight protocol included:

- A camera tilt of about 45° (oblique images),
- Flight paths orthogonal to vine rows,
- Altitude of 2–3 meters above the canopy, and
- Flight speed of about 2 m/s.

Considering the behavior of Popillia japonica, which remains stationary during early morning and begins flying as solar radiation increases, all flights were conducted between 6:00 and 9:00 a.m. These operational conditions enabled the acquisition of high-resolution, close-range imagery of the pest (Brusco et al., 2023). The used drone and sensor are showed in figure 7 (a) and (b)

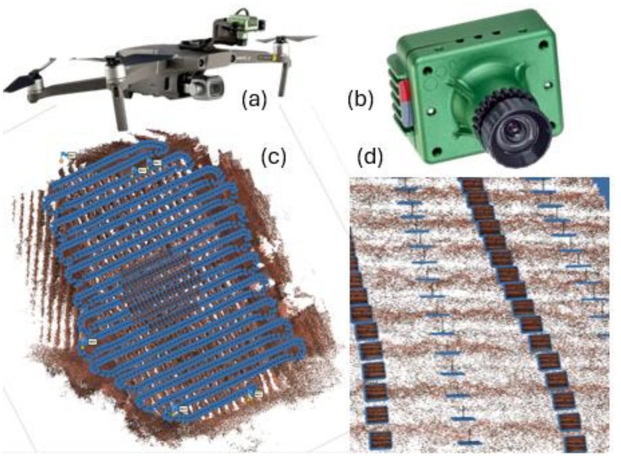

Figure 7. (a) the used drone, (b) the NIR sensor for monitoring, (c) and (d) an example of Agisoft Metashape processing result of Ghemme vineyard, using 1711 NIR images, 15 markers, and 1.78 million tie points.

3.4 Machine Learning Workflow for Insect Detection

Each monitoring session involved the processing of NIR imagery to detect and count insects on vine foliage using artificial intelligence and computer vision techniques. The method comprised three main phases:

- reconstruction and orientation refinement: due to the UAV's lack of high-precision onboard navigation, camera exterior orientation was recalculated in Agisoft Metashape. By generating a sparse point cloud and referencing a minimum of three GCPs from T0, more accurate georeferencing was achieved (Figure 7c,d);
- detection: a custom algorithm, developed in MATLAB, was applied to the NIR images to identify potential insect targets. For each detected blob, a set of 13 descriptive features is calculated, encompassing both morphological (geometric) and radiometric properties (- Geometric Descriptors: Area, MajorAxisLength, MinorAxisLength, Eccentricity, Circularity, EulerNumber, EquivalentDiameter, Solidity, Extent, Perimeter - radiometric Descriptors: MeanIntensity, MinIntensity, MaxIntensity).
- extraction: using MATLAB environment, a Feedforward Neural Network (FFN) was trained using manual annotations to distinguish insects from other dark blobs detected in the images in previous step. The procedure used is described in detail in Section 3.5;
- Spatial projection and de-duplication: Detected insect coordinates were reprojected onto the vineyard's 3D volume using MATLAB. The algorithm utilized the T0 DTM, camera poses, and image geometry to spatially assign insects to interbranches (Figure 9). A 5 cm spherical proximity threshold was applied to merge duplicate detections across overlapping images.

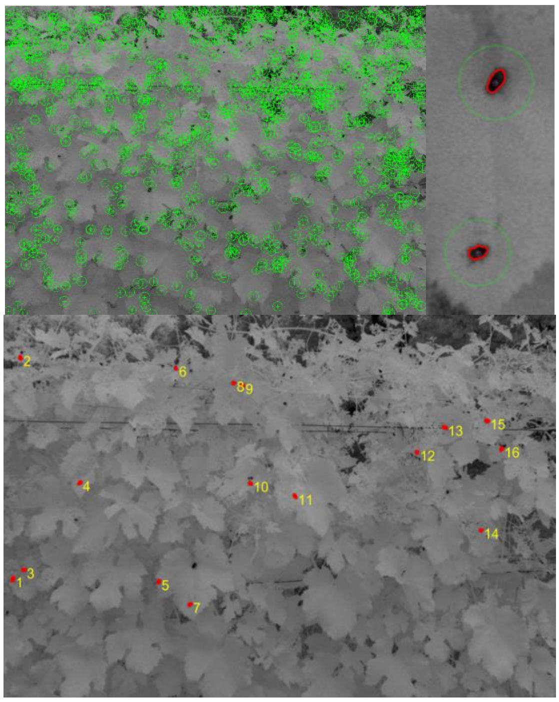

Figure 8. Example of NIR image processed by the machine learning algorithm: the green circles in the top left image are all the possible targets detected by the method; in the top right image, two Popillia are detected, and the bottom photo shows the final counting of the estimated insects on the image.

3.5 FNN network architecture

To discriminate in the recognized blobs the insects from the foliage holes, we decided to use a Feedforward Neural Network (FNN) for the purposes of our study because it is a suitable choice for simple data due to several reasons. Firstly, FNNs are straightforward and easy to implement, making them accessible for simple tasks where complex architectures might be unnecessary (Aggarwal, C.C., 2018). Their simplicity facilitates rapid prototyping and experimentation with different network architectures and hyperparameters (Müller, A.C. and Guido, S., 2016). Secondly, FNNs excel at learning linear and non-linear relationships between input features and target variables (Goodfellow I. et al, 2016).

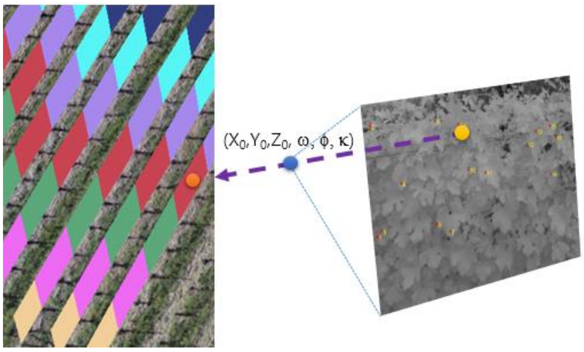

Figure 9. Representation of the reprojection of the detected insects on an image on the interbranch.

For datasets with simple structure, clearly defined patterns, or linearly/separably distributed classes, feedforward neural networks (FNNs) can effectively capture and model underlying relationships without the need for more sophisticated architectures. FNNs are also computationally efficient, making them well suited for processing small- to medium-sized datasets commonly encountered in low-complexity classification scenarios (Géron, 2019). Their efficiency leads to faster training and inference times, which is particularly advantageous when computational resources are limited or rapid prototyping is required. Overall, FNNs offer a balanced solution by combining performance, simplicity, and computational economy in the context of straightforward data analysis tasks.
The first stage of the methodology consisted of data annotation to establish a ground truth dataset. This was carried out through manual labeling of NIR images acquired from two vineyard plots under varying conditions, including differences in acquisition angle, distance, illumination, and plant health status. Annotation was performed using the open-source tool labelImg (Tzutalin, 2015), which enables object labeling in a simple, text-based format. The final dataset consists of approximately 300 annotated images and 15,000 labeled blobs, categorized based on visual cues suggestive of insect presence.
The next step involved the definition and configuration of the FNN architecture. The implementation was carried out in MATLAB, where a specific pipeline was executed for training and validation. The ground truth dataset was split into three subsets: 70% for training, 15% for validation, and 15% for testing. The training set consisted of input vectors (X_train) representing the 13 descriptors and corresponding categorical labels (Y_train). The validation (X_val, Y_val) and test (X_test, Y_test) sets were used to monitor performance and evaluate generalization.
The network architecture was designed based on several key considerations. The input layer contains 13 neurons, corresponding to the number of input descriptors. Two hidden layers were included to balance model expressiveness and complexity. First hidden layer consists of 64 neurons and employs ReLU (Rectified Linear Unit) activation functions to introduce non-linearity. Dropout layers with a rate of 0.2 were added after each hidden layer to reduce overfitting. The second layer consist in a 32 neurons and a similar dropout layer. The output layer comprises 3 neurons activated by a Softmax function, suitable for multiclass classification into the categories: insect, non-insect, and possible insect. The architecture is illustrated in Figure 10.

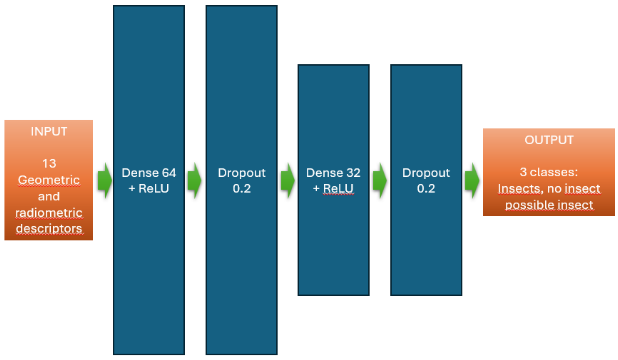

Figure 10. Block diagram of the FNN architecture used for insect classification.

The Adam optimizers were selected for their ability to perform adaptive learning rate adjustments, improving convergence in high-dimensional feature spaces. The number of training epochs was set to 100, balancing learning depth with the risk of overfitting. During training, the data were shuffled at each epoch to ensure robust learning and to minimize order-induced biases. The validation set was used for interim evaluation every 10 epochs, allowing early detection of overfitting and guiding the tuning of training strategies.
Once training was complete, the trained network was evaluated on the validation and test sets. Predictions were generated using the trained model, and outputs (Y_pred) were compared to ground truth labels. Correlation coefficients between predicted and actual labels (Y_val and Y_test) were calculated to assess the linear relationship between predictions and true outcomes. These coefficients range from -1 to +1, where values close to +1 indicate strong predictive alignment.
Under evaluation conditions, the model achieved the following classification metrics: Accuracy: 0.857, precision: 0.9236, Recall: 0.91683, F1-score: 0.8760.

3.6 Data Integration, Visualization, and Validation

The final insect counts were attributed to individual interbranch segments and subsequently integrated into ArcGIS Pro through a custom workflow developed using ModelBuilder. The count data were joined to the corresponding interbranch shapefile, enabling spatial association between insect occurrences and their respective vine segments.
To generate a continuous spatial representation, Inverse Distance Weighting (IDW) interpolation was applied, with predicted values projected at the centroid of each interbranch segment.
The resulting maps were visualized using a traffic-light color scheme, facilitating intuitive interpretation of insect density levels: Green: <10 insects, Yellow: 10–50 insects, Red: >50 insects. These classifications were validated against ground-truth data collected manually by entomologists, shown on the same map using a blue–purple color scale for comparative purposes (Figure 11). This dual representation facilitated a rapid assessment of infestation levels and algorithm performance.
All spatial data were dynamically managed in a multi-temporal geodatabase within ArcGIS Pro (Figure 11), coordinated by the Geomatic Laboratory of Politecnico di Torino. For stakeholder access and operational planning, a Web App (Web AppBuilder for ArcGIS) was developed, enabling temporal navigation of

infestation maps via a dedicated time slider (Figure 12). This allowed experts from DISAFA–University of Turin, Regione Piemonte, and the Consorzio Tutela Nebbioli Alto Piemonte to identify critical treatment zones and plan drone-based pesticide applications accordingly (figure 13a)
The effectiveness of treatments, carried out only during the 2023 DANTE project (authorized by the Italian Ministry of Health), was assessed through follow-up monitoring (Figure 13b). In 2024 (DANTE2), no treatments were applied due to delays in navigating updated and more complex authorization procedures required by the Ministry. Thus, activities in 2024 were limited to parcel-scale monitoring.

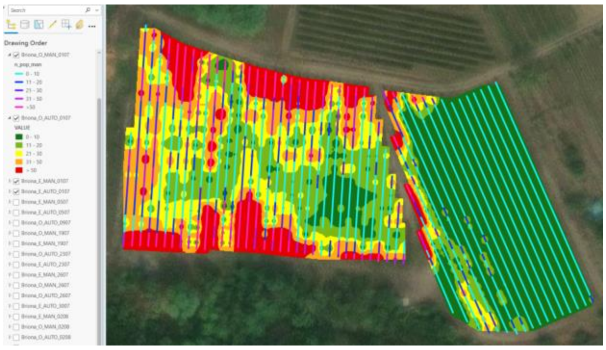

Figure 11. An example of result representation

Figure 12. The webGIS developed with ESRI tools

4. Results and validation

The monitoring activity was conducted in accordance with the methodology described above, with surveys initiated in mid-June and completed by the end of July in the 2023 and 2024, coinciding with the peak period of adult Popillia japonica activity. Monitoring operations were performed at approximately three-day intervals, in order to evaluate the potential need for insecticide treatment. In total, 13 surveys were carried out in the Briona vineyard and 14 in the Ghemme vineyard.
During each survey, NIR images were acquired and processed, enabling near real-time estimation of both the number and spatial distribution of Popillia individuals. The results were visualized within a Geographic Information System (GIS) environment and compared against ground truth data obtained through manual counting.
Figure 11 presents a sample thematic map generated in ArcGIS Pro for one of the surveys conducted in the Ghemme vineyard. The two areas of interest, delineated by orange and blue polygons, correspond to study zones C and D, respectively. The number of insects detected via computer vision (CV) is displayed using a traffic-light color scheme. For Area C, the CV-based count indicates fewer than 10 insects per interbranch across most of the region, a finding corroborated by the ground truth data, represented by a light blue to purple gradient on the row segments. Conversely, Area D exhibits several locations where the infestation exceeds 30 insects per interbranch, as detected by both the CV algorithm and manual annotations. These results demonstrate a strong correspondence between automated and manual insect counting.

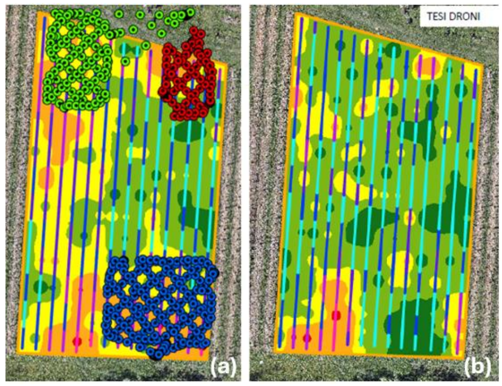

Figure 13. (a) Selection of the treatment areas with corresponding UAV flight paths displayed in green, red, and blue (points and lines); (b) the outcome observed after treatment.

Figure 13 illustrates the number of Popillia specimens detected in each survey across the study areas, comparing the two counting methods: manual (blue) and CV-based (orange). The temporal trends of the two approaches are highly consistent, as confirmed by the Pearson correlation coefficient, which ranges between 0.89 and 0.96—values indicative of a strong positive correlation (with 1.0 representing perfect agreement).

Table 1 provides the basic statistics of the difference between CV-based and manual counting, computed per interbranch unit:

- Averages are always positive: this means that the machine learning method is affected by a mean systematic error, which makes the algorithm overestimate the number of insects. The error, computed on the number of insects detected over the entire study area at each survey, is about 40% (with a minimum of about 10%, and maximum of about 80%).
- The maxima may be due to limitations in the quality of acquired images (low resolution) and navigation sensors (poor quality). Further experimentation and testing of new sensors could help improve this issue.

Statistics	Briona Area C	Briona Area D	Ghemme Area C	Ghemme Area D
Average	3.5	2.9	5.2	4.2
Max	33	23	40	35
Min	-25	-10	-35	-45
Std	8.5	5.7	12.7	15.7

Table 1. Statistics of the difference between CV-based and manual counting.

- The minima could be caused by acquisition holes. Specifically, in some cases, the SfM approach applied to NIR images encountered problems resulting in insufficient

information or incorrect external orientation parameters that affected the final results of insect recognition.
- The standard deviation indicates the precision of the method and ranges from 5.7 to 15.7 insects per interbranch, with an average of 3-5 insects. This enables accurate spatialisation of insects detected in vineyards, laying the foundation for phytosanitary intervention maps.

Overall, the CV-based monitoring method is effective, with an overestimation that provides a safety measure. However, the overestimation may be reduced by fine-tuning the detection algorithm, for example, using adaptive cut-off scores instead of fixed ones over the extraction features. Finally, it has sufficient precision to discriminate areas that do not require treatment from those that need it.

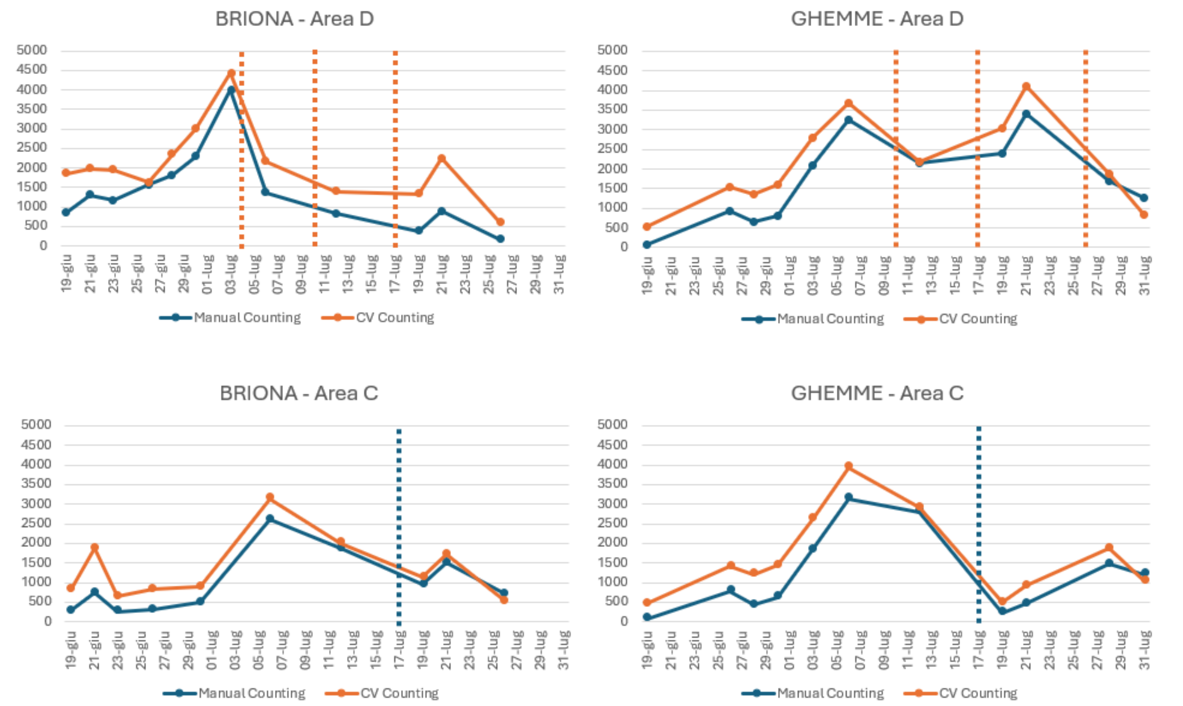

Figure 13. The number of Popillia detected by the two methods, manual and CV counting, during each survey. The vertical dotted lines indicate when pesticides were spread over the vineyards, which justifies the following decrease in the number of insects.

5. Conclusions

In conclusion, the integration of uncrewed aerial systems (UAS) equipped with suitable sensors and tailored acquisition protocols provides a fast and reliable approach for the temporal monitoring of Popillia japonica infestations in vineyards. The application of machine learning algorithms, combined with near-infrared (NIR) imagery, has demonstrated considerable potential in the detection and quantification of insect populations, as supported by prior research.
Building upon this foundation, the proposed monitoring method employs NIR sensors mounted on UAV platforms for data collection and comprises three principal components:

(1) insect detection and counting using a custom machine learning algorithm,
(2) recalibration of exterior camera orientation, and
(3) spatial mapping of detected insects on georeferenced 3D vineyard models.

The results reveal a strong correspondence between UAV-based and manual insect counts, with Pearson correlation coefficients ranging from 0.89 to 0.96, confirming the robustness and reliability of the automated method. While the proposed approach may slightly overestimate insect abundance, it nonetheless provides valuable decision-support information for targeted pest control interventions and damage risk assessment.
Future improvements—such as the use of high resolution sensors as for esample DJI MAVI 3 M—may further enhance detection accuracy and reduce false positives. Overall, this work establishes the basis for a standardized, replicable protocol for monitoring Popillia japonica in viticultural systems, offering a promising tool to support precision agriculture practices and mitigate both economic losses and environmental impacts associated with this invasive pest.

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This manuscript reflects only the authors' views and opinions, neither the European Union nor the European Commission can be considered responsible for them.

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