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Abstract

Globalisation has contributed to rapid economic growth but has also exposed vulnerabilities such as the spread of pests in agriculture. An example is the *Popillia Japonica Newman* beetle, introduced to Italy in 2014, which has caused significant economic losses, mainly affecting vine cultures. Reliable identification of pests is essential for its management, but it is time-consuming and laborious. This has prompted growing interest in image-based methods, supported by computer vision (CV), which can significantly improve efficiency in insect detection. This study aims to evaluate a CV algorithm's effectiveness in identifying adult specimens of Popillia using Near-Infrared sensors on Uncrewed Aerial Systems (UAS). The project, conducted in two vineyards in northern Italy, intends to establish a replicable and standardised data acquisition protocol for future monitoring activities. Insects detected by the CV-based method are validated by manual counting performed by entomologists. In a GIS environment, prescription maps are generated in near real-time to identify where the vineyard is most affected and to guide the drone spraying treatment only on the areas in which the threshold is exceeded. The study demonstrates effective semi-automated monitoring, with a clear correlation between CV-based and manual insect measurements, as indicated by the Pearson correlation coefficients ranging from 0.89 to 0.96. Although the CV-based method may overestimate insect numbers, it provides valuable insights for targeted pest management interventions and damage assessment. The project outcomes offer a promising approach to safeguarding agriculture against invasive species, enhancing regional economic resilience while minimising the spread of insecticide, the required time, and human interaction with harmful substances.

1. Introduction

Globalisation supports and speeds up the exchange of goods, services and the movement of people, factors that have allowed rapid economic growth in the last century, but it has also exposed new risks. The spread of pests and parasites is one of them: facilitated by climate change, it poses a significant challenge to global food security and a threat to the economic system, especially for small-scale farmers. This is mostly evident in the case of *Popillia Japonica Newman*, a beetle native to Japan, accidentally introduced to Europe, the USA and Canada. This insect of the Coleoptera order causes substantial economic losses and requires high containment costs, representing a serious threat to the local agricultural system, which is not able to fight and eliminate this exotic pest.

Popillia Japonica has a holometabolous life cycle. As larvae, they damage the roots of several grasses, living beneath the soil. As adults, these beetles are extremely polyphagous and can attack a wide range of plant species, estimated at around 300 wild and cultivated varieties. Among the most susceptible plants are apple, bramble, elm, grapevine, linden, maise, maple, rose, peach, and soybean. These insects start feeding on the aerial part of the plant, where they consume leaves by skeletonising them, chewing away the tissue between the veins. They may also feed on flowers and fruit. Additionally, adult beetles tend to gather in groups on a single plant, often leading to complete defoliation of individual plants or trees. Consequently, the plant's photosynthetic capacity decreases, leading to reduced production or even death (Ebbenga et al., 2022; EPPO, 2018).

Popillia was first found in the north of Italy in the summer of 2014, spreading in a large area of the Ticino Park between the Piedmont and Lombardy regions. Grapevines are the primary cultivations affected so far. Of particular relevance is the impact that the insect has on plants such as the vine, which requires several years from planting before the production of fruits and significant revenues. The situation has become severe enough that the Italian government has provided financial aid to affected farmers.

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

In this urgent scenario, improving monitoring is needed for early pest identification and effective pesticide intervention. There is growing interest in developing automated systems for rapid and reliable insect identification to replace much of the human labour traditionally required. Image-based systems (Martineau et al., 2017), audio sensor-based systems (Chen et al., 2014; Noda et al., 2019; Phung et al., 2017), and E-noses/olfactory devices (Cui et al., 2018) are some of the successful techniques used to identify insects. Among these methods, image-based systems are extensively used by entomologists to distinguish insect species, as visual evidence is the primary means of identifying insect species. Moreover, visual morphological differences can be captured using image sensors. Therefore, images can be used to

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classify a wide range of insect species, while acoustic and olfactory devices are limited to only a set of species. Additionally, compared to other techniques, images can be easily processed and stored for future reference. Automatic image identification technologies based on computer vision are promising in insect detection, as documented in the literature (Ahmad et al., 2022; Júnior and Rieder, 2020; Zacarés et al., 2018). They have been implemented in numerous applications in managing insect disease vectors and controlling pests, such as agricultural and forest pests (Domingues et al., 2022; Duarte et al., 2022; Mendoza et al., 2023), in the classification of parasitised fruit fly pupae (Marinho et al., 2023), the detection of pine pests (Ye et al., 2022), the segmentation of ecological images featuring (Filali et al., 2022), the identification of whitefly (Kamei, 2023), and the automated counting of mosquito eggs (Javed et al., 2023).

CV allows machines to extract significant information from digital images, enabling detection, identification, and automation by integrating inputs from the physical world (Wiley and Lucas, 2018). It involves different concepts including digital image processing, machine learning and pattern recognition. CV technologies are non-invasive, non-destructive, can be completely automated, and can provide data on species' occurrences, abundances, morphology, biomass, and movement (Bruijning et al., 2018; Schneider et al., 2022), along with insights into behaviour and interactions (Bjerge et al., 2022). Object detection and segmentation are important tasks of CV (Matrone et al., 2022) to perform automated extraction and counting of insects from pre-processed image data.

Image acquisition methods for insect detection can be several, and from the review of the research published in the last decade (Gao et al., 2024; Nawoya et al., 2024), they include various devices like handheld cameras (digital cameras, smartphones), and mobile or fixed smart trap systems, but also datasets such as IP102, as well as photographs downloaded from search engines like Bing and Google. Uncrewed Aerial Systems (UAS) can play an important role in getting on-site images, since they can move and navigate automatically, support various sensors, and provide safe access to difficult locations. On-site images are more useful for practical applications than laboratory images. However, locating insects within the frame can be challenging due to the cluttered backgrounds caused by leaves and other objects. This makes it more difficult compared to lab-based images, which have a blank background. Moreover, these beetles have a highly reflective green dorsal plate with a spectral signature similar to the surrounding vegetation. In response to this challenge, using a Near-Infrared (NIR) camera can help amplify the contrast between the Popillia and the vine plants. In fact, in an RGB image, the insect results green as the leaves, while in the NIR band, the vegetation exhibits a peak in reflectivity and the insect appears dark (low reflectivity) (Brusco et al., 2023).

This contribution lays its foundation in this complex scenario, exposing a field trial for multitemporal monitoring of Popillia through a computer vision algorithm on two vineyards in the towns of Ghemme and Briona (in the province of Novara, in the north of Italy). It is framed in the DANTE project (experimental investigative survey to evaluate the effectiveness of drones for monitoring and defence of vineyards from the priority quarantine insect Popillia Japonica Newman), which has the objective of identifying areas and timings for precise treatment by UAS, minimising the use of pesticides to the specific locations where it is actually needed within the vineyard.

Figure 2. An example of an NIR image of Popillia insects in the studied vineyards.

The project is funded by Regione Piemonte and involves the following partners: the Department of Environmental and Land Engineering (DIATI) of Polytechnic of Turin, the Department of Agricultural, Forestry and Food Sciences (DiSAFA) of the University of Turin, ARPA Piemonte (Regional Agency for the Protection of the Environment), Regione Piemonte and Consorzio di Tutela Nebbioli dell'Alto Piemonte. The project involved the development of a CV-based method for insect detection, the monitoring and the treatment of Popillia both by drone and manually, the estimation of insect-driven damages and, finally, the assessment of environmental impacts of the treatments.

In this work only the methodology of insect detection and the monitoring phase are exposed: the aim is to evaluate the effectiveness of the computer vision algorithm to identify adult specimens of Popillia using NIR optical sensors mounted on UAS, intending to establish a replicable and standardised data acquisition protocol for future monitoring activities. Specifically, this paper will analyse: i) the CV-based detection algorithm from NIR image data, ii) the spatialisation of the detected insects on a georeferenced 3D model of the vineyards, and iii) the effectiveness of the detection method for monitoring.

2. The Study Area

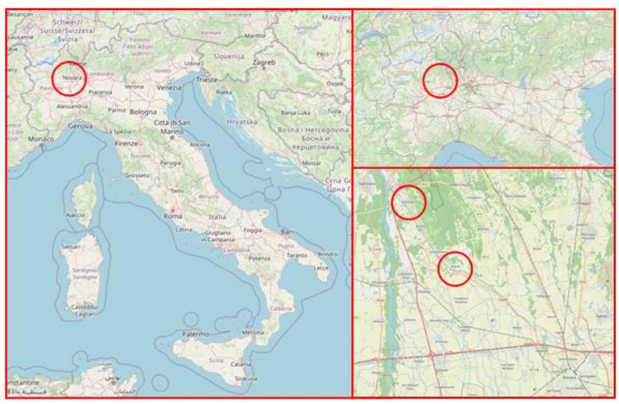

Figure 3. The study area: in the bottom right picture, Ghemme and Briona towns are highlighted by red circles. (Images acquired from OpenStreetMap)

Two vineyards were selected as study areas in two towns in the north of Italy, Ghemme and Briona, in the province of Novara in the Piedmont region (Figure 3). This area is acknowledged for the quality of its wines, and its vineyards have been affected by Popillia since the summer of 2014. Hence, this work selected this area for its urgency in fighting the pest, its easy accessibility for field surveys and its importance in local wine production. At the beginning of the project, two areas of comparable sizes for each vineyard were chosen and classified based on the type of treatment they would receive. The first one, called "Conventional" (C), involves manual treatment by specialised operators, while the second, called "Drones" (D), involves insecticide being spread by a DJI Agras MG-1P RTK drone. The two areas have similar surfaces (about 2000 m^2 in Briona and about 3000 m^2 in Ghemme) and were defined based on a 3D model generated by aerial photogrammetry at the beginning of the project (time 0 [T0] acquisition). The vineyard in Briona is located on flat ground, while the one in Ghemme is on a slope, a feature to consider when planning a UAV survey.

3. The methodology

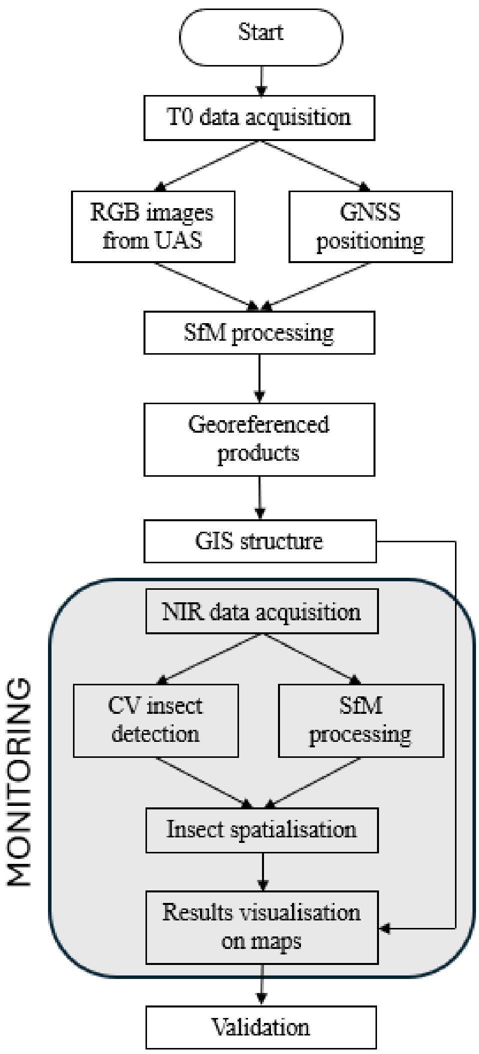

Figure 4. Methodological workflow.

3.1 Time zero acquisition

At the beginning of the project, a high-resolution 3D model of the two areas was generated as a result of the T0 acquisition for a better comprehension of the vineyards geometry. Hence, aerial photogrammetry technique was applied using the drone DJI Matrice 300 with the Zenmuse P1 sensor (Table 1). Reference stable points were established by positioning markers firmly on the ground, or materialised on the heads of the rows delimiting the areas. Their coordinates were measured using the Stonex S990A and Leica GS18 GNSS receivers (Table 2).
By a Structure from Motion (SfM) approach performed in the commercial software Agisoft Metashape, and by collimating the stable points with known coordinates, the following products are obtained: an orthomosaic with a resolution of 1 cm, and elevation models, specifically a Digital Surface Model (DSM) and a Digital Terrain Model (DTM), with a resolution of 20 cm. These products were used for the preliminary analysis of the structure of the vineyards, performed in a GIS environment. The aim was to understand the geometry of the vineyards, select the two areas of study, C and D, count their number of rows, and define the sampling unit for the insect counting: the interbranch, which can be defined as the row section delimited by two poles (Figure 5). The DTM was also used as input in the CV algorithm, as detailed in the following paragraphs.

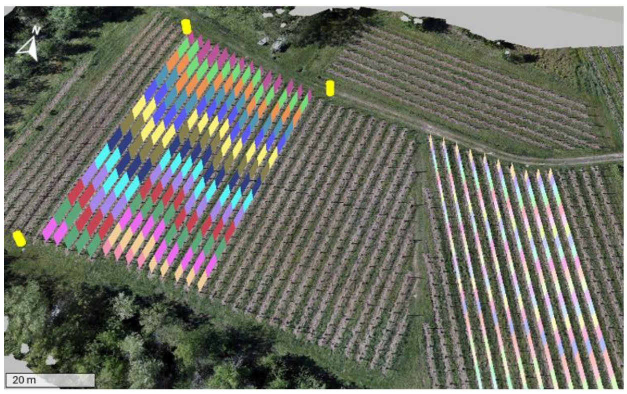

Figure 5. The T0 orthomosaic of Briona displayed in GIS and representation of the interbranches.

3.2 NIR data acquisition

The data acquisition step is done through aerial surveys using the DJI Mavic 2 Pro, with a Sentera NIR (Near-Infrared) single sensor (Table 1). The designed survey protocol involves flying with an oblique inclination of the camera (approximately 45°), with a direction orthogonal to the rows, a flight height ranging between 2-3 m above the head of the rows and a flight speed of about 2 m/s. As the Popillia remains steady in the early morning and typically starts flying when the sun is higher, all the flights were performed between 6 and 8 a.m. With these flight characteristics, having high-resolution and close-range pest images was possible (Brusco et al., 2023).

UAS	DJI Matrice 300	DJI Mavic 2 Pro
Sensor	Zenmuse P1 - RGB	Sentera Single - NIR
Resolution	8192 × 5460	1248 × 950
Focal Length	35 mm	4.14 mm
Pixel Size	4.39 × 4.39 µm	3.75 × 3.75 µm
Flying altitude	26.7 m	7.3 m
GSD	4.06 mm/pix	6.49 mm/pix

Table 1. Main specifications of sensors and UAS.

Receiver	Stonex S990a	Leica GS18
Dimensions and Weight	151 x 151 x 95.4 mm; 1.4 kg	173 x 173 x 109 mm 1,23 kg/3,53 kg
Sensors	E-Bubble, IMU	Tilt sensor, IMU
RTK Accuracy	5 mm ± 0.5 ppm RMS (Horizontal) 10 mm ± 0.5 ppm RMS (Vertical)	8 mm + 0,5 ppm (Horizontal) 15 mm + 0,5 ppm (Vertical)
Satellite Signals	GPS: L1 C/A, L1C, L1P, L2C, L2P, L5 GLONASS: L1 C/A, L1P, L2 C/A, L2P, L3 BEIDOU: B1, B2, B3, ACEBOC GALILEO: E1, E5a, E5b, ALTBOC, E6 QZSS: L1 C/A, L1C, L2C, L5, L6 IRNSS: L5 SBAS: L1, L5	GPS: L1, L2, L2C, L5 GLONASS: L1, L2, L2C, L3 Galileo: E1, E5a, E5b, AltBOC, E6 BeiDou: B1I, B1C, B2I, B2a, B3I QZSS: L1, L2C, L5, L62; NavIC: L53 SBAS: WAAS, EGNOS, MSAS, GAGAN TerraStar: L-Band, IP

Table 2. Main specifications of Stonex S990A and Leica GS18 GNSS receivers.

3.3 The CV algorithm

The NIR imagery collected during the field surveys is processed to detect and count the insects on the leaves of the vines. The detection method has three main steps: i) the application of the detection and counting algorithm, ii) the recalculation of the camera exterior orientation, and iii) the spatialisation of the detected insects on the vineyards, removing possible double counting.

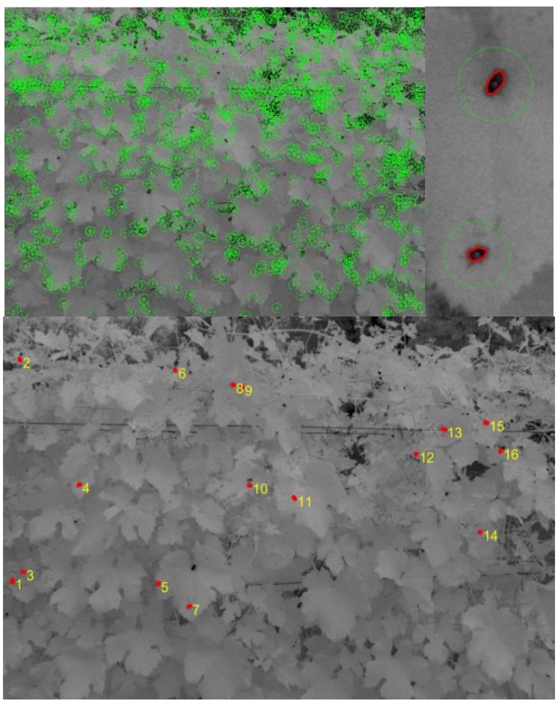

Figure 6. Example of NIR image processed by the CV algorithm: the green circles in the top left image are all the possible targets detected by the method; in the top right image, two Popillia are detected, and the bottom photo shows the final counting of the estimated insects on the image.

The first step is implemented in Matlab software using a computer vision algorithm developed by the authors, which exploits an object extraction approach over the collected NIR images (Figure 6). It performs recognition and localisation tasks to detect the insects based on a fixed cutoff score on extraction parameters previously calibrated and weighted using many training images. The extraction parameters include geometric and radiometric features such as area, eccentricity, circularity, mean, maximum, minimum and standard deviation of intensity.

The second step is calculating the camera exterior orientation using Agisoft Metashape. Starting from the NIR images collected, a sparse point cloud is generated, and through the collimation of at least three of the stable points defined in T0, it is possible to obtain more accurately the NIR camera exterior orientation parameters, since the drone mounting the Sentera sensor was not equipped with accurate navigation sensors (GNSS receiver with Real Time Kinematic corrections and accurate Inertial measurement Unit) (Cortesi et al., 2023, Teppati Losè et al., 2023).

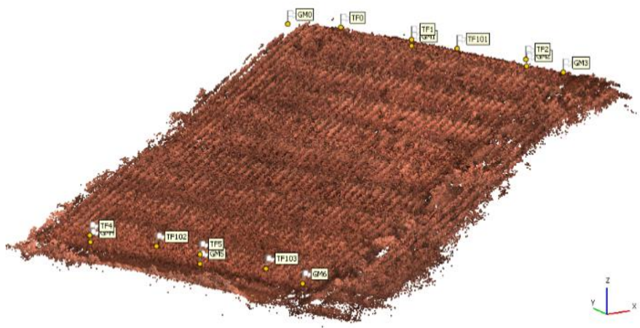

Figure 7. Example of Agisoft Metashape processing result of Ghemme vineyard, using 1711 NIR images, 15 markers, and 1.78 million tie points.

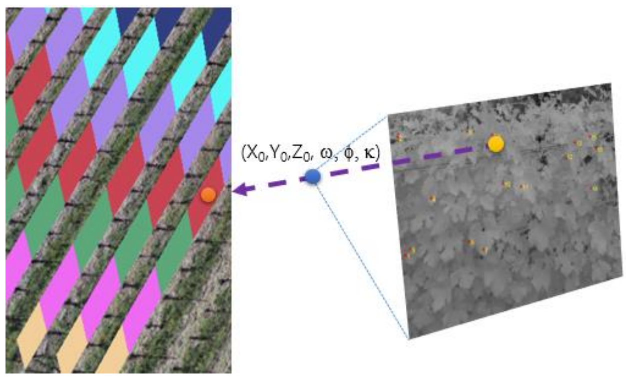

Figure 8. Representation of the reprojection of the detected insects on an image on the interbranch.

The third and last step of the CV-based method is the spatialisation of the detected insects based on the reprojection of their estimated locations in the vineyards. This step is implemented in Matlab and exploits the T0 DTM of the vineyards, the locations of insects, estimated in the first step, and the exterior orientation of the NIR poses, estimated in the second step. The algorithm performs a projection of the images and of

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the detected and labelled insects on the volume of the vineyard for each interbranch (Figure 8). Afterwards, the algorithm performs a coincidence check with a sphere of 5 cm radius: insects extracted from different images but located within a sphere of 5 cm radius are merged and considered the same insect.

3.4 Results visualization on maps and validation

Finally, the estimated measurements of Popillia onto the vineyards are represented in a GIS project, as shown in Figure 9, using a traffic light symbology from green to red applied to the interbranches vector file, where green indicates the presence of less than 10 insects on the interbranch, and red indicates when the number overcomes 50. The estimated number and position of the insects are compared and validated by a manual count made simultaneously by agrarian entomologists (ground truth), represented in a light blue-purple colour scale on the rows with the same counting ranges. This representation provides an easy way to understand the level of infestation in the vineyards and allows to compare the counting estimated by the algorithm to the ground truth.

4. Results and validation

The monitoring activity was performed according to the Methodology detailed above, with surveys starting in mid-June 2023 and concluding at the end of July 2023, the peak activity period for adult Popillia specimens. The monitoring was carried out about every three days, to assess the possible need for treatment. At the end of the monitoring activities, 13 surveys were collected for the vineyard in Briona and 14 for Ghemme.
For each survey, NIR images were collected and processed, and the estimation of the number and position of Popillia was obtained in near real-time. These data were represented in a GIS environment and compared to the ground truth of the manual counting. Figure 9 shows an example of a thematic map developed in ArcGIS Pro for one of the surveys performed in the Ghemme vineyard. The two surfaces delimited by orange and blue polygons are the study areas C and D, respectively. The CV-based counting is represented by the traffic light symbology and shows that most of the C area has less than 10 insects per interbranch. This is also confirmed by the ground truth data, represented by the light blue-purple colour scale on the rows. Instead, area D shows several spots where the infestation overcomes the threshold of 30 insects per interbranch, both in the CV-based and the manual counting. Therefore, Figure 9 shows a clear correspondence between the CV-based and the manual measurements of insects.

Figure 10 shows the number of Popillia detected in each survey for each study area, comparing the two types of counting methods in different colours: manual (blue) and CV-based (orange). The trends of the two methods are similar, as can be confirmed by the Pearson correlation coefficient computed between them, which ranges between 0.89 and 0.96, with 1 being the value for perfect correlation.

Table 3 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 CV 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.
- 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 1.89 to 6.29 insects per interbranch, with an average of 4-5 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.

Statistics	Briona Area C	Briona Area D	Ghemme Area C	Ghemme Area D
Average	2.25	2.16	4.68	1.73
Max	40	33	21	34
Min	-16	-30	-43	-29
Std	6.29	3.86	1.89	5.18

Table 3. Statistics of the difference between CV-based and manual counting.

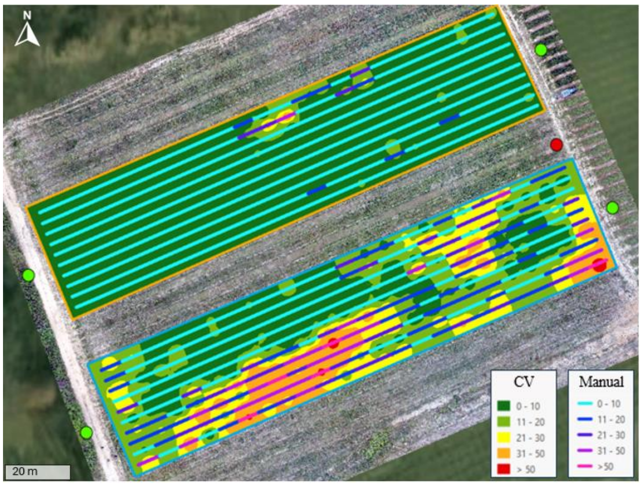

Figure 9. An example of a representation of CV-based and manual insect counting is in ArcGIS Pro for monitoring in Ghemme. CV-based counting is represented by the green-red traffic light symbology over the areas of interest, while manual counting (ground truth) is represented by a blue-purple colour scale over the row lines. The values in the legend refer to the number of insects per interbranch. Each interbranch measures 3-5 m.

Figure 10. 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, drones with appropriate sensors and specific acquisition procedures offer a rapid and reliable solution for temporal monitoring of Popillia Japonica invasion in vineyards. Computer vision algorithms, together with near-infrared imagery, have shown great potential in insect detection and counting, as evidenced by previous studies. The proposed CV-based method for monitoring Popillia in vineyards, employing NIR sensors mounted on UAS for data acquisition, builds upon this foundation. The methodology involved three main steps: insect detection and counting using a CV algorithm, recalibration of exterior camera orientation, and spatialisation of detected insects on georeferenced 3D models of vineyards. The results demonstrate a clear correspondence between CV-based and manual insect measurements, with Pearson correlation coefficients indicating strong agreement between the two methods, ranging from 0.89 to 0.96. Although the proposed CV-based method may overestimate insect numbers, it still provides valuable insights for targeted pest management interventions and damage assessment. Future refinements to the detection algorithm, such as adaptive cut-off scores, could further improve accuracy and reduce overestimation. Overall, the study lays the foundations for a standardised and replicable protocol for monitoring Popillia infestations in vineyards, offering a promising approach to mitigate the economic and environmental impacts of this invasive pest.

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

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