Autonomous Robotic Spraying System for Weed Management in Woody Perennial Crops

M. Pérez-Ruiz[1], L. Sánchez-Fernández[1], O. E. Apolo-Apolo[2], A. Nizzoli[1]

[1]Department of Aerospace Engineering and Fluid Mechanics, University of Seville, 41004 Sevilla, Spain

[2]Postharvest Programme, Institute of Agrifood Research and Technology (IRTA), Edifici Fruitcentre, Parc Agrobiotech Lleida, Parc de Gardeny, 25003 Lleida, Spain

A paper from the Proceedings of the

17th International Conference on Precision Agriculture and 11th Brazilian Congress on Precision and Digital Agriculture

13-15 July 2026

Porto Alegre, Brazil

Abstract.

Weed management in woody crops remains a major agronomic, economic, and environmental challenge. In orchard environments, tree trunks, low canopies, and narrow intra-row spacing severely restrict conventional machinery access to the under-canopy zone. As a result, weed control near tree trunks remains predominantly manual. In addition, conventional total herbicide applications in orchards often result in spray reaching the trunk, increasing the risk of phytotoxic damage. These current limitations motivate the development of autonomous systems capable of operating in complex orchard geometries. This work presents the development and field validation of a modular autonomous robotic platform designed for selective weed detection and targeted herbicide application in woody crops. The system integrates three subsystems: (i) a perception unit for real-time weed detection based on deep learning, (ii) an autonomous navigation, and (iii) a precision actuation system enabling localized spraying near tree trunks. Weed perception relies on a YOLOv8 convolutional neural network and stereo vision. Navigation was based on GNSS-RTK combined with LiDAR-based trunk detection for obstacle avoidance. A six-degree-of-freedom robotic arm enabled precise positioning of spray nozzles at detected weed locations and provided trunk avoidance capabilities. Field trials were conducted in a commercial almond orchard in south Spain. Results highlight the difficulty of deploying computer vision-based systems in an environment where the heterogeneous canopy shadows pose one of the most challenging scenarios for agricultural field perception. Spray coverage results show the robotic platform gradually reduced coverage to negligible levels closer to the trunk. This study demonstrates the capabilities of autonomous robotic platforms to operate under conditions currently inaccessible to conventional machinery. By simultaneously reducing labor requirements and preventing herbicide contact with the trunk, the proposed system offers a promising pathway towards safer and more sustainable weed management in woody cropping systems.

Keywords.

Autonomous Robotics, Precision Agriculture, Precision Spraying, Orchard Robotics

1. Introduction

Sustainable weed management remains a key challenge in woody perennial cropping systems such as almond (Prunus dulcis). Weeds compete with crops for essential resources like water, light, and nutrients, reducing yields and potentially hosting pests and diseases. Unlike annual row crops, orchard systems are characterized by permanent plant structures, heterogeneous canopies, and spatially constrained under-canopy zones that limit the applicability of conventional mechanical weed control. As a result, broadcast application of non-selective herbicides continues to be the dominant weed management strategy used in orchard systems, entailing considerable environmental and economic costs. In European orchards, herbicide treatments may represent up to 30% of plant protection expenditures, while contributing to soil and water contamination, biodiversity loss, and the emergence of herbicide-resistant weed populations (Osipitan et al., 2020; Strandberg et al., 2021; Vázquez-García et al., 2021). These concerns directly conflict with regulatory frameworks such as the EU's Green Deal "Farm to Fork" strategy, which calls for a 50% reduction in pesticide use and associated risks by 2030 (Calatrava et al., 2021) and align with the shift toward precision and site-specific management approaches (Cabot et al., 2022).

Apart from the environmental concerns associated with herbicide use in orchards, herbicide-based weed control in woody crops can also generate direct phytotoxic effects on the crop itself. Off-target herbicide deposition through spray drift, runoff, or root uptake may expose non-target plant tissues, producing physiological stress or growth alterations even when applications are intended only for weeds (Kanissery et al., 2019). Repeated or chronic exposure to herbicides has been linked to the development of basal trunk cankers, increased susceptibility to environmental stress, and internal fruit disorders, indicating that herbicide contact near trunks can compromise long-term crop health and productivity (Martinelli et al., 2022; Rosenberger et al., 2013). Knowing these risks, farmers frequently avoid spraying in the immediate vicinity of tree trunks, leaving narrow unmanaged weed zones that must be controlled manually or mechanically—an approach that is labor-intensive, costly, and operationally inefficient.

Robotic and autonomous systems have emerged as promising solutions to reduce herbicide inputs through selective, site-specific weed control. Advances in agricultural automation, particularly in multi-sensor perception and artificial intelligence (AI), have enabled the development of field robots capable of weed detection and site-specific herbicide application (Slaughter et al., 2008). Bechar and Vigneault (2016) further emphasized the importance of robotics in automating complex farming operations. These platforms typically integrate computer vision, GNSS-based navigation, and spectral imaging to discriminate between crops and weeds with high spatial precision (Wu et al., 2020). Coupled with intelligent actuation systems, such robots allow herbicide application to be confined strictly to the locations of detected weeds, reducing input use and minimizing environmental impact (Zhang et al., 2022).

Early work in robotic weed control focused primarily on row crops and horticultural systems with relatively simple geometries (Åstrand and Baerveldt, 2002; Gerhards et al., 2024). In contrast, woody perennial crops present a markedly different operational context. Tree trunks act as frequent obstacles, inter-row and intra-row spacing may vary between orchards, and canopy development throughout the crop cycle introduces strong spatial and temporal heterogeneity in lighting (Li et al., 2009; Sun et al., 2010). Under-canopy areas often present deep shadows, partial occlusions, and high background texture from fallen leaves, branches, or irrigation elements (Fang et al., 2025; Huang et al., 2025). Additionally, real-time kinematic (RTK) GNSS positioning faces significant limitations in woody crop environments due to the structural complexity of tree canopies (Navone et al., 2025; Osman et al., 2026; Usu et al., 2025).

More recently, researchers have been working on the development of weeding robots integrating AI. Jin et al. (2023) developed a smart sprayer for weed control in bermudagrass turf using convolutional neural networks to detect three weed types. Similarly, Upadhyay et al. (2024) developed a machine vision-based sprayer robot integrating an AI weed detection algorithm and tested it in a soybean field. Despite significant progress, there is a lack of fully integrated robotic platforms capable of performing selective weed control under woody crop canopies.

This study addresses this gap by presenting the development and field validation of a modular autonomous platform designed for selective weed control under the canopy of woody perennial crops. The system integrates multi-sensor perception, a trunk detection pipeline, a 6-DOF spraying arm, and cloud-based mission control to enable precise, under-canopy herbicide application. Field trials in commercial almond orchards assessed navigation accuracy, weed discrimination, and operational performance.

The main contributions of this study are:

1. The design and integration of a modular autonomous robotic platform combining multi-sensor perception, RTK-GNSS navigation, trunk avoidance, and precision spraying for orchard environments.

2. The construction of a weed image dataset tailored to Mediterranean orchard conditions.

3. A field-based evaluation revealing both the capabilities and current limitations of perception-driven selective weed control under real orchard conditions.

2. Materials and Methods

The modular robotic platform consists of three main functional modules:

- Perception unit based on YOLOv8-L, trained to detect three common weed species (*Cynodon dactylon*, *Lolium rigidum*, and *Malva sylvestris*).
- Navigation system built on a commercial steered platform.
- Spraying module comprising a 6-DOF robotic arm, a trunk avoidance mechanism, a 20 L tank, and nozzles controlled by solenoid valves.

2.1. Unmanned Ground Vehicle

The modular robotic platform testbed was built on an Ackermann-steered, battery-electric robotic platform capable of achieving speeds up to 0.8 $m \cdot s^{-1}$. For spraying tasks, its nominal operating range was limited to 0.4–0.5 $m \cdot s^{-1}$, and the speed was set to 0.5 $m \cdot s^{-1}$ during trials. Reverse motion was mechanically restricted by the design of the robotic arm trunk avoidance mechanism.

The control and navigation stack was hosted on a ruggedized NVIDIA Jetson Orin NX (NVIDIA Corporation, Santa Clara, CA, USA), which managed sensor fusion, motion control, and communication with all peripheral devices. Localization relied on a dual-antenna GNSS-RTK receiver (ZED-F9P, u-blox AG, Thalwil, CH) integrated with a 9-DoF IMU (MTi-680 IMU, Xsens Technologies B.V., Enschede, NL), providing centimeter-level accuracy and stable heading estimation. A 32-beam mechanical LiDAR (LSLiDAR, Leishen Intelligent System Co., Ltd., Shenzhen, CN) and encoder feedback were used to monitor local drift and obstacle proximity.

Mission routes were defined and uploaded through the uPathWay mission management system (GMV, Tres Cantos, ES), which transmitted navigation commands to the vehicle controller. The control loop operated at 20 Hz. To support safe operation, a trunk-avoidance mechanism combined LiDAR-based detection with mechanical redundancy from the rear-mounted robotic arm. All sensor coordinate frames were registered to the robot's base link via extrinsic calibration. Communication and supervision were supported by a 5G router (RUTX50, Teltonika, Kaunas, LT). The integration of all platform elements was performed with ROS2 Humble Hawksbill middleware (Quigley, 2009).

Fig. 1. Integrated robotic platform composed of: a) commercial Ackermann-steered robotic platform with IMU, RTK-GNSS and LiDAR for navigation; b) a 6-DOF robotic arm and a trunk avoidance mechanical device for reaching the intra-row space; and c) a precision spraying subsystem composed of a 20 L tank, spray nozzles, and an RGB-D camera for weed detection.

2.2. Perception Unit

The perception module was designed to deliver real-time weed detection by combining high-resolution visual sensing with embedded deep learning inference. A ZED 2i stereoscopic RGB camera (Stereolabs, San Francisco, CA, USA) was mounted at 50 cm above ground with a downward tilt of 20°, providing full coverage of the 1.4 m intra-row area in a single pass. The perception system was based on a NVIDIA Jetson AGX Orin 64 GB (NVIDIA Corporation, Santa Clara, CA, USA). The detection framework used YOLOv8-L (Ultralytics LLC, USA), trained following a two-phase strategy. The perception stack was implemented in PyTorch (Paszke et al., 2019) with CUDA acceleration. Inference results were transmitted in real time to the spraying controller via the robotic arm (XB7L, ROKAE Robotics Co., Ltd., Beijing, CN).

To train and evaluate the weed detection system, a dedicated image dataset was constructed focused on three representative species commonly occurring in Mediterranean almond orchards: *Cynodon dactylon*, *Lolium rigidum*, and *Malva sylvestris*. A total of 500 plants of each species were cultivated and transplanted to controlled plots at the University of Seville (37° 21.07′ N, 5° 56.33′ W). A second dataset (714 images) was collected in a commercial almond orchard (37° 29.32′ N, 5° 59.79′ W). After annotation, a total of 3,021 images from both sites were merged into a single dataset. A stratified sampling strategy was applied to generate training (70%), validation (15%), and test (15%) subsets.

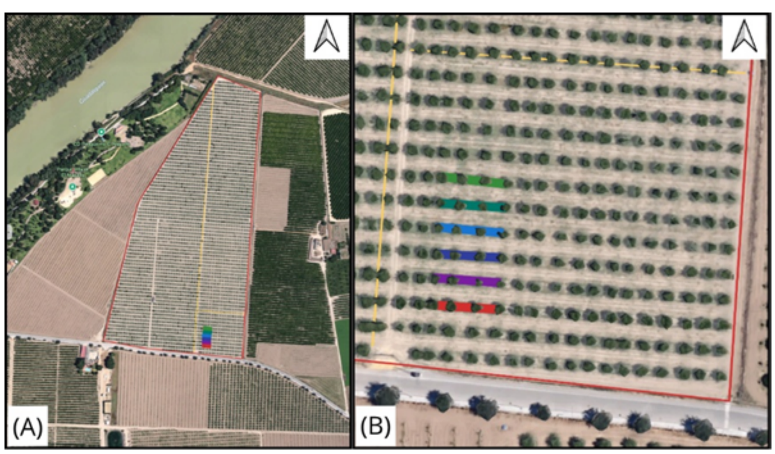

Fig. 2. Commercial almond orchard in which validation of the modular system was carried out (A), and detail of the position and distribution of the target area (B).

The YOLOv8-L model was trained in two phases. In Phase 1, the model was trained from 2,307 images acquired under uniform early-season lighting for 100 epochs at 1280 px input resolution. Phase 2 fine-tuned the best Phase 1 weights on 714 images collected under dense canopy cover during late spring, where deep shadows, high contrast, and partial occlusions were the norm. For every detection, the bounding-box center point was projected into robot-centered 3D coordinates using ZED 2i depth information, and these coordinates were sent to the robot controller to position the robotic arm.

2.3. Actuation System

The actuation system was designed to perform two critical functions: (i) avoiding tree trunks during navigation, and (ii) delivering spray with precision at detected weed locations. The system combined a six-degree-of-freedom (6-DOF) robotic manipulator with a mechanical trunk avoidance system and a selective spraying module. The robotic arm provides a maximum reach of 707 mm, a payload capacity of 7 kg, and a total weight of approximately 52 kg.

2.3.1. Trunk Avoidance System

To enable navigation near the orchard's crop rows and spraying in the intra-row area, a trunk-avoidance system was developed. The system reacted to the pressure exerted by the tree trunk and retracted, allowing the platform to avoid collision and enabling spraying of the area at the opposite side of the tree while preventing the spraying of the tree trunk. Nozzles were integrated in both arms of the trunk-avoidance device structure, enabling spraying even in the area behind the tree trunks.

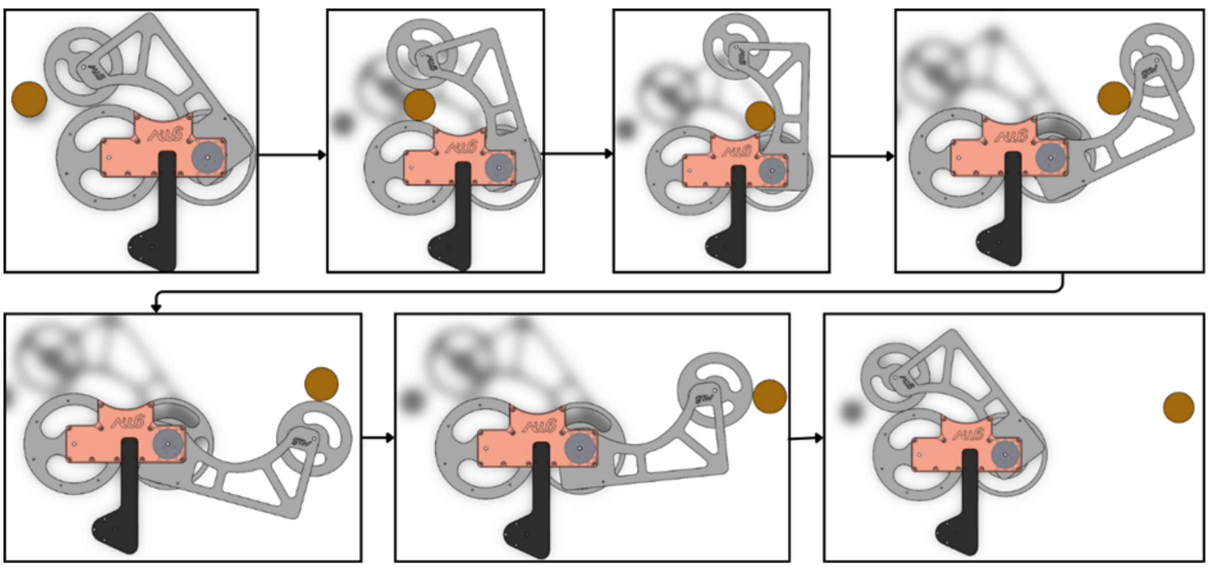

Fig. 3. Visual progression of the operation of the trunk avoidance system prototype. When contact with the tree trunk occurs, the trunk avoidance system retracts to create clearance, enabling the platform to follow its path.

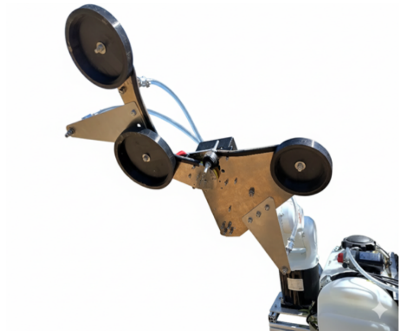

Fig. 4. Detailed views of the trunk avoidance device prototype mounted at the tip of the robotic arm. Nozzles were integrated into the trunk-avoidance system structure to enable spraying behind the tree trunks.

2.3.2. Precision Spraying Module

The precision spraying module consisted of four 60° flat-fan nozzles (Model 610.514, Lechler GmbH, Metzingen, GE) operating at 5 bar, providing a flow of 2.9 $L \cdot min^{-1}$ at working pressure (verified following ISO 16122, 2015). The configuration was designed to spray at 0.3 m above the target area. The module has two operation modes: selective spraying (each nozzle independently operated via solenoid valves) and band spraying (all four valves activated simultaneously upon a detection event, providing a 1.5 m swath width).

Spray coverage around the tree trunk was evaluated using 26 × 76 mm water-sensitive papers (Syngenta, Basel, CH). Arrays were placed in four directions (N, E, S, W) around three randomly chosen trunks, with five dosimeters per direction spaced every 0.1 m (first at 5 cm from the trunk). The analysis was carried out using ImageJ (v1.52p, NIH, USA).

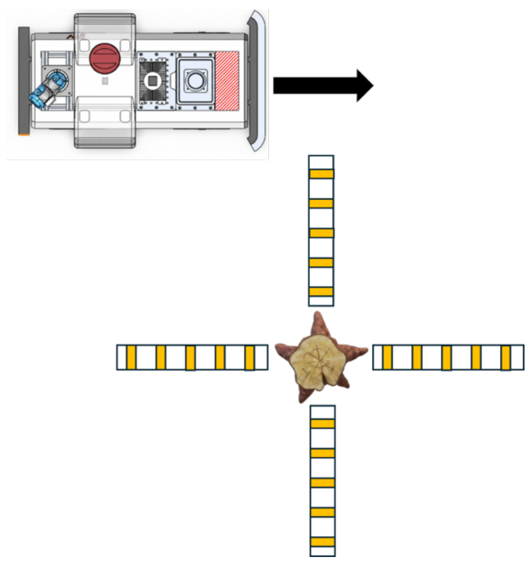

Fig. 5. Diagram of the water-sensitive paper arrays placed around each sampled tree. Papers were placed every 0.1 m, the first at 5 cm from the trunk surface. The spraying robot advanced in the arrow direction at 0.5 $m \cdot s^{-1}$.

3. Results

3.1. Perception System

As shown in Table 1, the YOLOv8-L model achieved excellent performance under controlled illumination conditions, with a mAP@0.5 of 93.5% and mAP@0.5-0.95 of 65.7%. In the commercial orchard, performance declined substantially: mAP@0.5 reached 39.5% and mAP@0.5-0.95 of 19.5% under winter/no-leaf conditions, and mAP@0.5 of 44.3% and mAP@0.5-0.95 of 20.2% during spring/summer with fully developed canopy.

Table 1. Performance of the weed identification model under different scenarios.

Dataset	mAP@0.5	mAP@0.5-0.95
Controlled Conditions	93.5%	65.7%
Winter (no-leaf)	39.5%	19.5%
Summer (full canopy)	44.3%	20.2%

Cynodon dactylon and *Malva sylvestris* achieved the highest average precision values (AP@0.5 of 0.634 and 0.582, respectively), demonstrating relatively strong detection capabilities. In contrast, *Lolium rigidum* obtained a markedly lower score (0.112), indicating significant challenges in distinguishing this species from the background. The mean average precision across all classes (mAP@0.5) reached 0.443 under orchard conditions. The final model required 165 Giga Floating Point Operations (GFLOPs) per inference, yielding a device inference time of 22–180 ms per image on the Jetson AGX Orin.

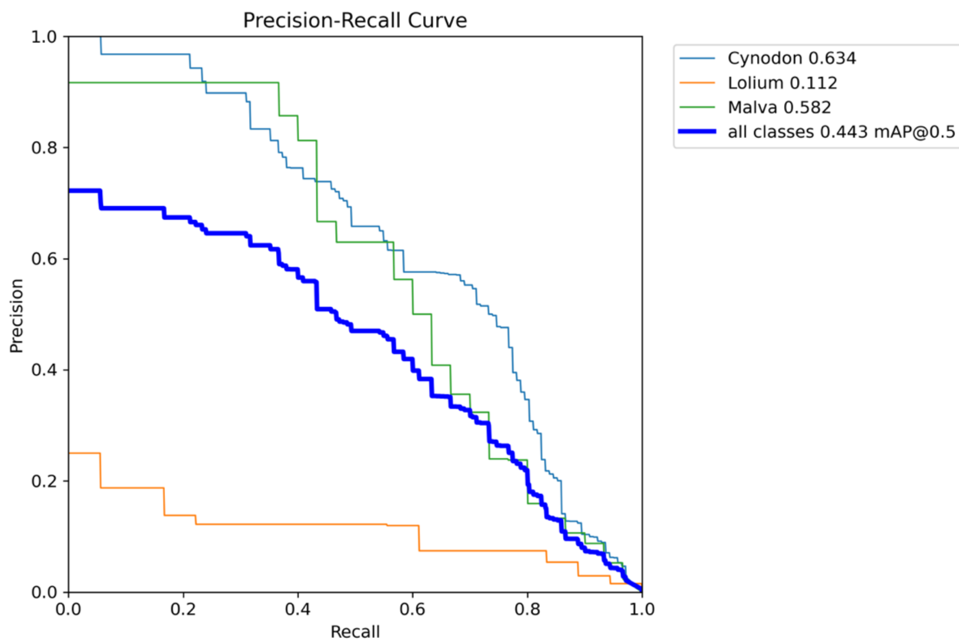

Fig. 6. Precision–Recall (PR) curves for each class and overall model performance. Cynodon dactylon (AP@0.5 = 0.634), Malva sylvestris (AP@0.5 = 0.582), Lolium rigidum (AP@0.5 = 0.112). Overall mAP@0.5 = 0.443.

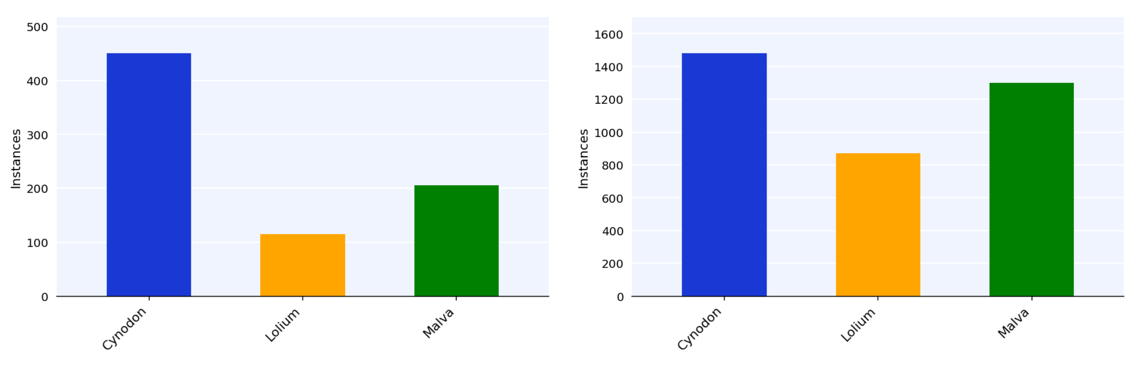

Fig. 7. Number of instances under winter conditions (A) and summer conditions (B). The number of instances during summer is substantially larger than during winter.

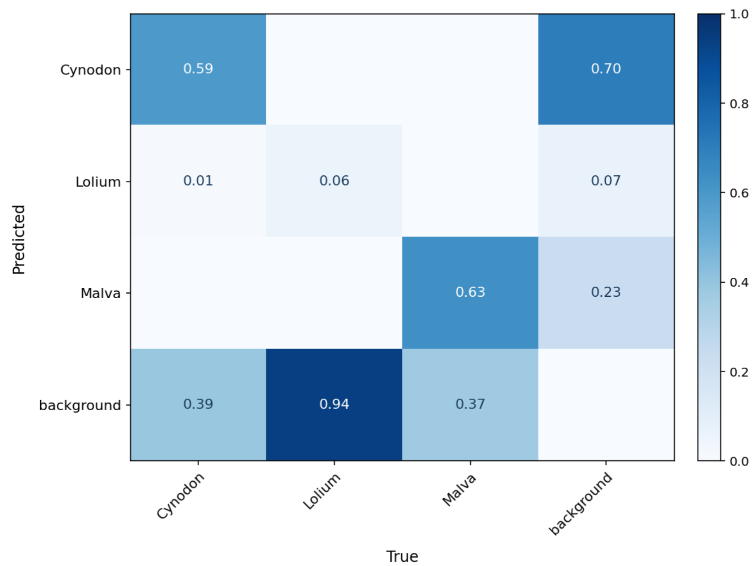

Fig. 8. Normalized confusion matrix of the model under summer orchard conditions. Malva presents the highest classification accuracy (0.63). Cynodon and Lolium exhibit substantial confusion with the background class (0.39 and 0.94, respectively).

3.2. Precision Spraying System

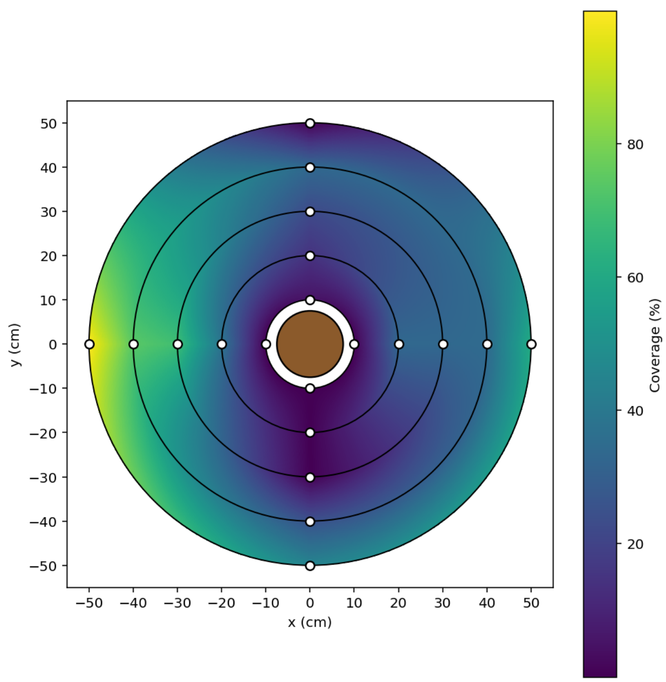

Fig. 9. Average spray coverage achieved during spraying trials in a commercial almond orchard. Four sampling arrays of water-sensitive paper were placed around tree trunks, sampling a total distance of 50 cm from the trunk (5 dosimeters spaced 10 cm apart). Trunk diameter was 15 cm.

Results of the precision spraying system trials show that water-sensitive papers located immediately adjacent to the tree trunk received reduced spray, with an average coverage of 1.28%. Coverage increased progressively with distance from the trunk, forming a clear radial gradient. Additionally, deposition was not spatially uniform around the trunk: higher coverage values were observed on the side facing the advancing direction of the platform, indicating a directional bias in spray distribution.

4. Discussion

4.1. Perception System

Differences in precision obtained between datasets collected under controlled lighting conditions, winter conditions, and summer conditions suggest considerable variability that limits transferability to orchard field conditions with under-canopy shadows. This problem is present in most agricultural applications of AI models given the intrinsic variability of agricultural systems and environmental conditions (Shafay et al., 2025; Zhao and Wang, 2026). The higher precision observed during summer trials suggests the model is more suitable in summer than in winter, likely related to the relatively homogeneous lighting conditions a fully developed canopy shade offers compared to the heterogeneous lighting of an underdeveloped canopy shade, a behavior previously observed by Lu et al. (2022).

Species-level detection performance was influenced by a combination of leaf morphology and class representation. The relatively strong performance of *Cynodon dactylon* despite its narrow-leaf morphology is likely attributable to its dominant representation in the training dataset (Dyrmann et al., 2016). The relatively high AP@0.5 of *Malva sylvestris* is attributable to its distinctive broad-leaf architecture, which provides a large target with clear boundaries (Garibaldi-Márquez et al., 2022). In contrast, *Lolium rigidum* showed substantially lower detection performance and high rates of misclassification as background, consistent with the known difficulty of detecting narrow-leaved species (Wang et al., 2019, 2022).

The YOLOv8-L model required 165 GFLOPs per inference, with an observed inference time of 180 ms on the NVIDIA Jetson AGX Orin. These results highlight a key limitation of the current perception system: its dependence on GPU-capable hardware constrains deployment to platforms equipped with dedicated AI accelerators (Hussain, 2024).

4.2. Precision Spraying System

The spray coverage results confirm that the trunk-avoidance system successfully prevented herbicide deposition near tree trunks, with average coverage of just 1.28% at the closest sampling position (5 cm from the trunk surface). This result is of particular relevance given that herbicide contact near trunks has been associated with basal trunk cankers, increased susceptibility to environmental stress, and internal fruit disorders (Martinelli et al., 2022; Rosenberger et al., 2013). The near-zero deposition levels demonstrate that the mechanical trunk-avoidance system functions as an effective spray barrier.

The directional asymmetry in coverage, showing higher deposition on the side facing the advancing direction of the platform, is consistent with spray dynamics reported for moving spraying systems (Butts et al., 2024). This effect should be accounted for in future calibration of the spraying system, particularly for band-spraying applications where uniform coverage is desirable.

4.3. System Integration

The results demonstrate that each individual subsystem achieved functional performance under field conditions. However, translating subsystem-level performance into fully autonomous selective weed control requires tight coupling between these components, and several findings are best understood as integration constraints rather than failures of individual modules.

In the developed platform, information flows sequentially from perception to actuation, with navigation operating in parallel on a separate control loop. The perception unit generates weed detections at approximately 5 Hz (governed by YOLOv8-L inference time of 180–220 ms per frame), while the navigation stack operates at 20 Hz and the LiDAR-based trunk detection pipeline provides point clouds at 5 Hz. This asynchronous structure is consistent with distributed robotic systems reported in precision agriculture (Shamshiri et al., 2024; Emmi et al., 2014).

The 180 ms latency was compatible with the platform's 0.5 m·s^{-1} operating speed—the robot travels approximately 9 cm between consecutive detection frames, well within the nozzle swath (Sunil et al., 2024). The most significant integration limitation was the absence of bidirectional communication between the perception unit and navigation module, which constrains the platform to a fixed-path spraying mode. Future iterations could implement stop-and-spray approaches (Visentin et al., 2023; Balasingham et al., 2024), which reduce operational complexity while enabling more direct perception–navigation coupling.

5. Conclusions

This paper described the development and field testing of a modular robotic platform for selective weed control in woody perennial crops, integrating RTK-GNSS/IMU navigation, LiDAR-based trunk detection, a six-degree-of-freedom robotic arm, and a real-time deep learning perception unit. The results show that these components can be integrated into a functional, field-operable system.

Field trials in a commercial almond orchard confirmed reliable trunk avoidance without collisions or spray deposition near the trunk, and successful real-time synchronization between weed detections and nozzle activation. On the perception side, the developed model showed mAP@0.5 values of 39.5% in winter and 44.3% in summer, making clear that the detection system is not yet ready for unsupervised deployment.

Several priorities stand out for future development. Perception is the most pressing: closing the gap between controlled and field performance will require considerably more training data collected across seasons, canopy stages, and orchard types, with particular attention to narrow-leaved species like *Lolium rigidum*. Tighter integration between perception and navigation is equally important: in its current form the platform follows fixed waypoints and cannot redirect based on detection outputs. Complementary sensing modalities such as multi-camera, multispectral imaging, or depth-based segmentation may also help with plant–soil separation under variable canopy light.

References

Åstrand, B., Baerveldt, A.J. (2002). An agricultural mobile robot with vision-based perception for mechanical weed control. Autonomous Robots, 13, 21–35.

Balasingham, D., Samarathunga, S., Arachchige, G.G., Bandara, A., Wellalage, S., Pandithage, D., Hansika, M.M.D.J.T., de Silva, R. (2024). SPARROW: Smart Precision Agriculture Robot for Ridding of Weeds. 2024 5th International Conference for Emerging Technology, INCET 2024.

Bawden, O., Kulk, J., Russell, R., McCool, C., English, A., Dayoub, F., Lehnert, C., Perez, T. (2017). Robot for weed species plant-specific management. Journal of Field Robotics, 34, 1179–1199.

Bechar, A., Vigneault, C. (2016). Agricultural robots for field operations: Concepts and components. Biosystems Engineering, 149, 94–111.

Butts, T.R., Fritz, B.K., Davis, J.A., Spurlock, T.N. (2024). Spray coverage and deposits from a remotely piloted aerial application system using various nozzle types. Frontiers in Agronomy, 6, 1493799.

Cabot, M.I., Lado, J., Clemente, G., Sanjuán, N. (2022). Towards harmonised and regionalised life cycle assessment of fruits: A review on citrus fruit. Sustainable Production and Consumption, 33, 567–585.

Calatrava, J., Martínez-Granados, D., Zornoza, R., González-Rosado, M., Lozano-García, B., Vega-Zamora, M., Gómez-López, M.D. (2021). Barriers and Opportunities for the Implementation of Sustainable Farming Practices in Mediterranean Tree Orchards. Agronomy, 11.

Dyrmann, M., Karstoft, H., Midtiby, H.S. (2016). Plant species classification using deep convolutional neural network. Biosystems Engineering, 151, 72–80.

Emmi, L., Gonzalez-De-Soto, M., Pajares, G., Gonzalez-De-Santos, P. (2014). New Trends in Robotics for Agriculture: Integration and Assessment of a Real Fleet of Robots. The Scientific World Journal, 2014, 404059.

Fang, T., Chen, W., Han, L. (2025). Location Research and Picking Experiment of an Apple-Picking Robot Based on Improved Mask R-CNN and Binocular Vision. Horticulturae, 11, 801.

Garibaldi-Márquez, F., Flores, G., Mercado-Ravell, D.A., Ramírez-Pedraza, A., Valentín-Coronado, L.M. (2022). Weed Classification from Natural Corn Field-Multi-Plant Images Based on Shallow and Deep Learning. Sensors, 22, 3021.

Gerhards, R., Risser, P., Spaeth, M., Saile, M., Peteinatos, G. (2024). A comparison of seven innovative robotic weeding systems in sugar beet and rapeseed. Weed Research, 64, 42–53.

Huang, Y., Xu, S., Chen, H., Li, G., Dong, H., Yu, J., Zhang, X., Chen, R. (2025). A review of visual perception technology for intelligent fruit harvesting robots. Frontiers in Plant Science, 16, 1646871.

Hussain, M. (2024). YOLOv5, YOLOv8 and YOLOv10: The Go-To Detectors for Real-time Vision.

ISO International Organization for Standardization (2015). ISO 16122:2015 - Agricultural and forestry machines - Inspection of sprayers in use.

Jin, X., McCullough, P.E., Liu, T., Yang, D., Zhu, W., Chen, Y., Yu, J. (2023). A smart sprayer for weed control in bermudagrass turf based on the herbicide weed control spectrum. Crop Protection, 170, 106270.

Kanissery, R., Gairhe, B., Kadyampakeni, D., Batuman, O., Alferez, F. (2019). Glyphosate: Its Environmental Persistence and Impact on Crop Health and Nutrition. Plants, 8, 499.

Li, M., Imou, K., Wakabayashi, K., Yokoyama, S. (2009). Review of research on agricultural vehicle autonomous guidance. International Journal of Agricultural and Biological Engineering, 2, 1–16.

Lu, Z., Qi, L., Zhang, H., Wan, J., Zhou, J. (2022). Image Segmentation of UAV Fruit Tree Canopy in a Natural Illumination Environment. Agriculture, 12, 1039.

Martinelli, R., Rufino, L.R., Alcántara-De la Cruz, R., Conceição, P.M., Monquero, P.A., de Azevedo, F.A. (2022). Glyphosate Excessive Use Affects Citrus Growth and Yield. Agronomy, 12.

Navone, A., Martini, M., Ambrosio, M., Ostuni, A., Angarano, S., Chiaberge, M. (2025). GPS-free autonomous navigation in cluttered tree rows with deep semantic segmentation. Robotics and Autonomous Systems, 183, 104854.

Osipitan, O.A., Yildiz-Kutman, B., Watkins, S., Brown, P.H., Hanson, B.D. (2020). Impacts of repeated glyphosate use on growth of orchard crops. Weed Technology, 34, 888–896.

Osman, A., Shamsfakhr, F., Vecchio, M., Antonelli, F. (2026). Adaptive GNSS–UWB Sensor Fusion for Reliable Localization in Precision Agriculture. Smart Agricultural Technology, 13, 101846.

Paszke, A., Gross, S., Massa, F., Lerer, A., et al. (2019). PyTorch: An Imperative Style, High-Performance Deep Learning Library. Advances in Neural Information Processing Systems, 32.

Quigley, M. (2009). ROS: an open-source Robot Operating System. IEEE International Conference on Robotics and Automation.

Rosenberger, D., Watkins, C., Miranda-Sazo, M., Kahlke, C., Fargione, M., Nock, J., Rugh, A. (2013). Effects of Glyphosate on Apple Tree Health. Cornell Cooperative Extension, Lake Ontario Fruit Program.

Shafay, M., Hassan, T., Owais, M., Hussain, I., Khawaja, S.G., Seneviratne, L. (2025). Recent advances in plant disease detection: challenges and opportunities. Plant Methods, 21, 140.

Shamshiri, R.R., Navas, E., Dworak, V., Auat Cheein, F.A., Weltzien, C. (2024). A modular sensing system with CANBUS communication for assisted navigation of an agricultural mobile robot. Computers and Electronics in Agriculture, 223, 109112.

Slaughter, D.C., Giles, D.K., Downey, D. (2008). Autonomous robotic weed control systems: A review. Computers and Electronics in Agriculture, 61, 63–78.

Strandberg, B., Sørensen, P.B., Bruus, M., Bossi, R., Dupont, Y.L., Link, M., Damgaard, C.F. (2021). Effects of glyphosate spray-drift on plant flowering. Environmental Pollution, 280, 116953.

Sun, H., Slaughter, D.C., Ruiz, M.P., Gliever, C., Upadhyaya, S.K., Smith, R.F. (2010). RTK GPS mapping of transplanted row crops. Computers and Electronics in Agriculture, 71, 32–37.

Sunil, G.C., Upadhyay, A., Sun, X. (2024). Development of software interface for AI-driven weed control in robotic vehicles. Smart Agricultural Technology, 9, 100678.

Underwood, J.P., Calleija, M., Taylor, Z., Hung, C., Nieto, J., Fitch, R., Sukkarieh, S. (n.d.). Real-time target detection and steerable spray for vegetable crops.

Upadhyay, A., G C, S., Zhang, Y., Koparan, C., Sun, X. (2024). Development and evaluation of a machine vision and deep learning-based smart sprayer system for site-specific weed management in row crops. Journal of Agriculture and Food Research, 18, 101331.

Usu, K., Yamasaki, Y., Ishii, K., Noguchi, N. (2025). Global self-localization and navigation using 3D-LiDAR for headland turning in vineyards. Smart Agricultural Technology, 12, 101296.

Vázquez-García, J.G., Rojano-Delgado, A.M., Alcántara-de la Cruz, R., Torra, J., Dellaferrera, I., Portugal, J., De Prado, R. (2021). Distribution of Glyphosate-Resistance in Echinochloa crus-galli Across Agriculture Areas in the Iberian Peninsula. Frontiers in Plant Science, 12, 617040.

Visentin, F., Cremasco, S., Sozzi, M., Signorini, L., Signorini, M., Marinello, F., Muradore, R. (2023). A mixed-autonomous robotic platform for intra-row and inter-row weed removal for precision agriculture. Computers and Electronics in Agriculture, 214, 108270.

Wang, A., Zhang, W., Wei, X. (2019). A review on weed detection using ground-based machine vision and image processing techniques. Computers and Electronics in Agriculture, 158, 226–240.

Wang, P., Tang, Y., Luo, F., Wang, L., Li, C., Niu, Q., Li, H. (2022). Weed25: A deep learning dataset for weed identification. Frontiers in Plant Science, 13, 1053329.

Wu, X., Aravecchia, S., Lottes, P., Stachniss, C., Pradalier, C. (2020). Robotic weed control using automated weed and crop classification. Journal of Field Robotics, 37, 322–340.

Zhang, W., Miao, Z., Li, N., He, C., Sun, T. (2022). Review of Current Robotic Approaches for Precision Weed Management. Current Robotics Reports, 3, 139–151.

Zhao, H., Wang, Y. (2026). Deep learning–based approaches for weed detection in crops. Frontiers in Plant Science, 16, 1746406.