AI-Driven Laser Weeding Robots for Precision Agriculture

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Abstract.

Weeds have long constrained high-quality crop production, whilst prolonged reliance on chemical weed control has raised concerns over pesticide residues, environmental pollution, enhanced herbicide resistance in weeds, and declining agricultural sustainability. Laser weed control, characterised by non-contact operation, residue-free treatment, and strong targeting capability, is emerging as an important physical weed control approach in precision and green agriculture. This review emphasises that the practical value of laser weeding robots cannot be determined by weed recognition accuracy alone. Systems capable of field operation must complete a closed-loop process of movement–perception–positioning–decision–targeting–feedback under mobile platform vibration, varying illumination, crop occlusion, changes in travel speed, and laser safety constraints. The key bottleneck in existing research has gradually shifted from single image recognition algorithms towards whole-machine closed-loop control. An effective laser weeding robot should comprise four coordinated subsystems—a mobile platform, visual perception, control and decision-making, and laser execution—and achieve stable operation through multimodal perception, high-precision positioning, weed meristem identification, visual servoing, motion compensation, and hardware-level safety protection. Therefore, the performance of laser weeding robots should not be assessed solely by mAP, recognition rate, or segmentation accuracy; it should also account for weed control efficacy, crop damage rate, target positioning error, operating speed, energy consumption per unit operation, and long-term field stability.

Keywords.

laser weed control; agricultural robots; precision agriculture; weed meristem localisation; closed-loop control; visual servoing

Introduction

Weeds are an important biological stressor in agricultural production. During the seedling stage in particular, weeds compete with crops for light, water, nutrients, and growing space, directly affecting crop stand establishment and subsequent yield formation. Traditional chemical and mechanical weed control have played an important role in supporting agricultural production, but they also face challenges including pesticide residues, ecological pollution, soil disturbance, rising labour costs, and enhanced herbicide resistance in weeds. Within the Agriculture 5.0 context, which emphasises artificial intelligence, autonomous equipment, and green production, laser weed control has emerged as a precise, non-contact, residue-free physical weed control technology with considerable research value and engineering application potential (Wang et al., 2019; Garibaldi-Márquez et al., 2025).

The mechanism of laser weed control primarily arises from the photothermal interaction between laser radiation and plant tissue. When a high-energy laser beam is focused on weed tissue, especially the growing point or meristematic tissue, light energy is absorbed and rapidly converted into thermal energy. This disrupts cellular structure, protein activity, and water transport, thereby suppressing weed regrowth (Mathiassen et al., 2006; Andreasen et al., 2024). Unlike large-area herbicide application, laser weed control emphasises precise energy delivery to specific target locations. It is therefore better suited to early-stage weeds from the cotyledon stage to approximately the two-leaf and four-leaf stages. At these stages, weeds are relatively small, growing points are easier to identify and target, lower energy inputs are required, and the risk of crop damage is more readily reduced.

The core argument of this review is that laser weed control cannot be reduced to a weed recognition problem alone. Although substantial research has improved crop–weed recognition, weed segmentation, and object detection accuracy (Picon et al., 2022; Garibaldi-Márquez et al., 2025), high recognition rates in laboratory images do not necessarily translate into high targeting accuracy on mobile platforms in the field. Camera calibration error, platform vibration, tyre slip, varying illumination, visual inference latency, coordinate transformation error, galvanometer response speed, and laser safety control all influence final targeting performance. Consequently, the central research question has shifted from whether weeds can be detected to whether a robot can stably, safely, and precisely complete movement, recognition, localisation, targeting, and feedback in dynamic field environments.

Consolidation of core technologies

From a systems perspective, autonomous laser weeding robots mainly comprise a mobile platform, a visual perception unit, a control and decision-making unit, and a laser execution unit. The mobile platform determines whether the robot can travel stably along crop rows and provides a stable operating window for the camera and laser. The visual perception unit is responsible for recognising crops, weeds, and, more critically, weed meristems. The control and decision-making unit converts image coordinates into physical space coordinates and determines the sequence of target engagement. The laser execution unit delivers energy through a laser, galvanometer scanner, or other beam-steering mechanism. Whole-machine performance depends on coordination among these modules rather than on the performance of any single module alone.

At the perception level, deep learning has advanced weed detection, semantic segmentation, instance segmentation, and keypoint localization (Wang et al., 2019; Picon et al., 2022). YOLO-series detection models, segmentation networks, Transformer architectures, and multimodal perception methods are shifting laser weed control from recognising whole weed plants towards localising weed meristems. This shift is critical because the aim of laser weed control is not simply to determine whether a weed is present, but to identify the most suitable biological target for energy delivery. However, fluctuating illumination, leaf overlap, similar soil backgrounds, motion blur, and differences in weed growth stage in field environments all reduce the stability of perception systems. Models best suited to laser weed control are therefore not necessarily those with the largest parameter counts, but those capable of low-latency operation on edge computing devices whilst maintaining localisation robustness in complex environments.

At the navigation and path-planning level, the robot must address both accurate and stable locomotion. Laser weed control is not static image-based recognition, but target acquisition and energy delivery whilst the platform is in motion. GNSS, IMU, visual odometry, LiDAR, and crop-row structure perception can be fused to improve localisation capability in unstructured field environments. Navigation accuracy directly determines whether the camera field of view remains stable, whether targets remain continuously visible, and whether the laser targeting window is sufficient. If travel speed fluctuates substantially or path-tracking error is excessive, even an accurate visual model may fail because the target displaces before laser triggering, resulting in missed strikes or crop damage.

At the closed-loop targeting and servo control level, the final precision of laser weed control arises from the combined effect of multiple error sources, including perception error, depth estimation error, camera–laser calibration error, platform motion error, communication latency, galvanometer dynamic response error, and laser spot offset error. The system cannot therefore adopt a simple one-way recognise-then-strike logic, but should establish real-time feedback and dynamic compensation mechanisms (Han, 2009; Lin et al., 2022). Feasible technical approaches include visual servoing, platform motion estimation, target queue scheduling, galvanometer response modelling, latency compensation, and hardware-level emergency stop protection. Large models or high-level intelligent decision-making can support task planning, anomaly interpretation, and human–machine interaction only; actual laser triggering must remain constrained by low-level deterministic control, safety interlocks, and real-time feedback.

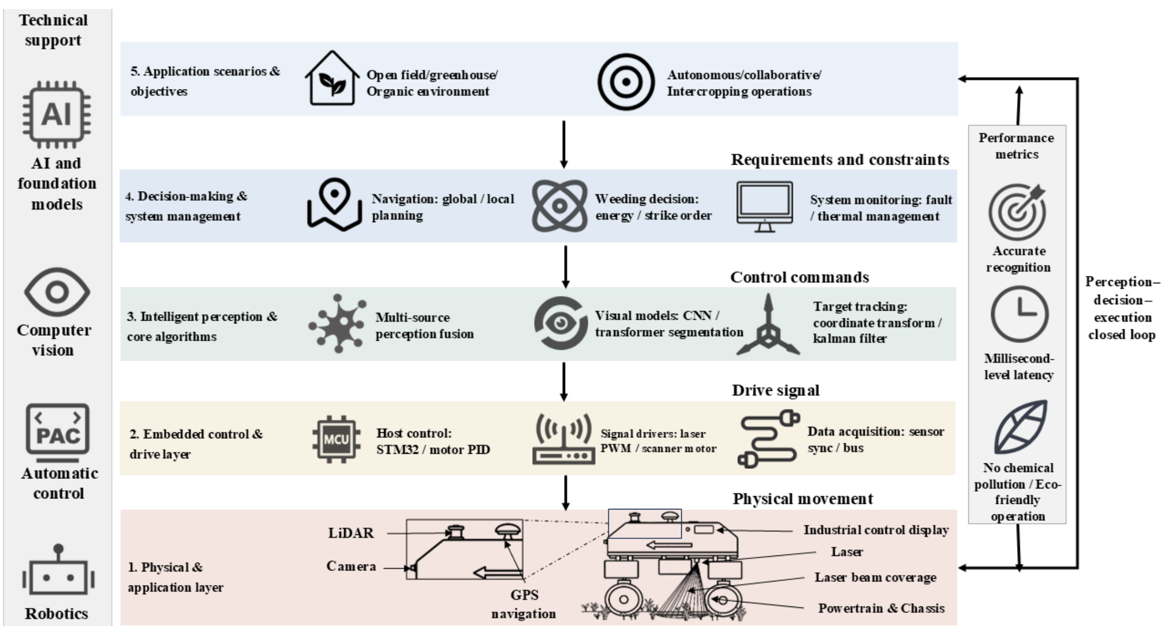

Fig.1 A comprehensive perception–decision–execution framework for laser-based weeding robots.

Engineering evaluation

First, recognition accuracy is a necessary but not sufficient condition. Existing studies often use mAP, precision, recall, and F1-score to evaluate algorithm performance (Garibaldi-Márquez et al., 2025; Picon et al., 2022). These metrics are meaningful for model comparison, but they cannot fully represent the field operational capability of laser weeding robots. Even with high recognition rates, effective targeting may still fail if the target has moved before the laser arrives, if camera–laser coordinate transformation is unstable, or if galvanometer response is delayed. The evaluation framework for laser weed control must therefore extend from image-level metrics to task-level metrics.

Second, subsequent engineering validation should place greater emphasis on weed control efficacy, crop damage rate, laser spot positioning error, single-target processing time, field travel speed, energy consumption per unit area, and stability under varying environmental conditions. These metrics correspond more directly to practical agricultural value. In high-value vegetable production, medicinal crop cultivation, organic farming, and low-residue production systems, crop damage rate is as important as weed control efficacy. A model with high recognition accuracy but slow operation, high power consumption, and difficult deployment may offer less engineering value than a slightly less accurate model that runs stably in real time.

Third, laser weeding robots require co-design of hardware and software. Visual algorithms, edge computing platforms, communication protocols, galvanometer control, laser power modulation, mechanical vibration damping, and safety protection cannot be designed in isolation. A major reason why many laboratory prototypes fail to reach the field is the separation of perception research from mechanical and control research. A more appropriate design approach should start from the complete operational workflow: image acquisition, target recognition, three-dimensional localisation, coordinate mapping, target prioritisation, beam steering, energy delivery, strike verification, and safety shutdown.

Fourth, engineering deployment is better served by modular and scalable design. For large-scale field operations, tractor-mounted or array-based laser weed control systems can improve working width and efficiency. For high-value vegetables, medicinal crops, organic farms, and protected cultivation, lightweight autonomous mobile platforms offer greater flexibility and lower soil disturbance. Regardless of platform type, the core challenge remains the same: the robot must establish a closed loop between perception and execution under real field disturbances.

Engineering significance

From an agricultural application perspective, the value of laser weeding robots is reflected mainly in three aspects. First, targeted weed control can be achieved without introducing chemical residues, making the approach suitable for organic farming, protected cultivation, high-value vegetable production, and medicinal crop cultivation, where quality and safety requirements are stringent. Second, laser weed control can be integrated with intelligent agricultural machinery platforms to reduce manual weeding intensity and alleviate agricultural labour shortages. Third, laser weed control is inherently digital: operational data—including target location, crop status, strike count, energy consumption, and weed control outcomes—can be recorded during field operation, providing a data foundation for subsequent field management decisions.

From an equipment development perspective, laser weed control system design should not be organised solely around algorithm metrics, but around the whole-machine operational chain. In other words, visual models, mobile chassis, actuators, controllers, and safety protection must be designed against a common set of operational metrics. Only when recognition accuracy, positioning accuracy, control latency, laser power, operating speed, and crop safety are balanced can laser weeding robots move from laboratory prototypes to continuous field operation.

Conclusion

Overall, AI-driven autonomous laser weeding robots represent an important pathway towards precise, green, and intelligent weed management under Agriculture 5.0. This review argues that the field usability of laser weeding robots does not depend on whether a single deep learning model can recognise weeds, but on the system-level integration of perception, navigation, dynamic targeting, servo control, and safety protection. The technical barrier has shifted from single-point algorithm optimisation towards whole-machine closed-loop operational capability.

Laser weeding robots must therefore be regarded as complete agricultural cyber-physical systems rather than as standalone visual models or isolated actuators. Their success should be judged by whether the robot can maintain accurate target localisation, stable platform motion, sufficiently low control latency, and safe and reliable laser energy delivery in dynamic field environments, and ultimately achieve high weed control efficacy, low crop damage, and sustainable field operation. This system-level perspective can serve as the core theoretical basis for subsequent prototype design, field validation, and industrial deployment.

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