Autonomous Field Robots for Precision Mechanical Weed Management in Row Crops

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ABSTRACT
Background: Weed management poses a major agronomic challenge in row crop production throughout the world, requiring a considerable amount of labor and chemicals. The shortage of workers in agriculture combined with the growing environmental awareness about herbicides makes it essential to explore new mechanical weed control methods.
Objective: The research evaluated how well the autonomous field robot equipped with advanced sensor fusion systems, artificial intelligence-based crop-weed identification technology, and automation in mechanical weeding was able to manage weeds in maize and soybeans.
Methods: Field trials were completed over three growing seasons (for the years 2022-2024) in three geographical locations. The vehicle with RTK-GNSS navigation, LiDAR and RGB cameras, and a machine learning algorithm was used to conduct inter-row and intra-row mechanical weed management. The performance of the robot was compared to the performance of hand weeding and conventional mechanical weeding with the help of randomized complete block design with six replications.
Results: The autonomous robotic system achieved a weed control efficiency of 87.3 % and a crop injury of only 2.1 % which was compared to 94.2 % of weed control efficiency and 3.8 % of crop injury for manual weeding, along with 76.5% of weed control efficiency and 8.3% of crop injury for conventional methods of mechanical weeding. The navigation precision stood at 3.2 cm in average with the application of RTK-GNSS correction. The operation of the robot resulted in a labor requirement diminished by 78%. Thus, the performance in terms of yield was equal to the results of manual weed control (9.2 t/ha for robots as compared to 9.4 t/ha for manual weed control; $p > 0.05$). The power consumption averaged 2.4 kWh/hectare while the operating costs amounted to about $87/hectare, which would lead to 34 % of the savings margin when considering the paid cost over ten years of operation.
Importance: Autonomous field robots can significantly contribute to making weed control sustainable and within the reach of labor-intensive methods applicable in row crops.

Keywords: autonomous robots, weed management, precision agriculture, artificial intelligence, mechanical control, sensor fusion, sustainable agriculture, deep learning

1. Introduction
Global agriculture is confronted by unprecedented problems associated with the management of weeds and availability of labor. Weeds are among the most economically important pests in crop production, as they reduce yields by competing for nutrients, water, and light, in addition to serving as hosts for diseases and insect pests (Zimdahl, 2018) [1]. Herbicide-based methods of weed control proved to be effective and profitable in the short term, but have become increasingly unmanageable due to the formation of weed species resistant to herbicides and due to environmental concerns associated with herbicide dependence (Heap, 2024; Powles & Yu, 2010) [2, 3]. The global market for agricultural herbicides exceeded $30 billion in 2023, but their effectiveness is decreasing due to the growing resistance (Heap, 2024; Powles & Yu, 2010) [2, 3].
Mechanical weed control through cultivation has been practiced for thousands of years and is a fundamental part of sustainable agricultural systems (Rasmussen, 2004) [4]. However, conventional mechanical methods of weeding are labor intensive, are not efficient in controlling weeds in crop rows, and may cause severe damage to the crops (Knežević *et al*., 2008; Tillett *et al*., 2008) [5, 9]. Labor shortages in agriculture are becoming critical in both developed and emerging economies, making weed control increasingly problematic using traditional manual and mechanical methods (Hennessy & Rehman, 2007) [6].
The technologies related to precision agriculture that include automated systems, real-time sensing, and analyses of data have introduced significant changes in crop production by introducing the concept of site-specific management, minimizing input of chemicals, and increasing productivity (Batte & Arnholt, 2000; Tey & Brindal, 2012) [7, 10, 22]. The combination of AI technologies, robotics, computer vision technologies, and autonomous systems for agricultural production has resulted in the emergence of the new notion of "Agriculture 4.0" or "digital agriculture." Autonomous land vehicles equipped with advanced sensing technologies and artificial intelligence allow field operations with minimal human intervention (Shamshiri *et al*., 2018; van Henten *et al*., 2019; Bergerman *et al*., 2016) [8, 16, 21].

Autonomous agricultural robots are able to eliminate present-day weaknesses of mechanical weeding techniques by several means and methods: (1) precision actuation will allow targeting single weeds and avoiding crops; (2) AI Weed-Crop discrimination will remove only those plants that are identified uniquely; (3) the absence of dependence on human labor will improve operations we can do every day; (4) real-time sensor feedback enables a precise method of management; (5) keeping records of activities will enable precision management at the plant level.

Significant progress has been made in recent years in computer vision and deep learning technology, which allows crops and weeds to be distinguished in the field. It has been found that convolutional neural networks (CNNs) trained on large annotated datasets managed to classify crops and weeds with accuracy higher than 95% under laboratory conditions (Singh *et al*., 2016) [12]. However, their performance in the field is still challenging because of varied lighting conditions, soil background, and plant growth stages. Forecasts based on recent research suggest that crop identification in the field can be achieved with 82–91% accuracy (Lobell *et al*., 2015; Salah *et al*., 2020) [13, 14].

Technologies for autonomous navigation have advanced substantially through the application of Real-Time Kinematic Global Navigation Satellite System (RTK-GNSS) (Trimble Inc., 2021) [15], which allows positioning accuracy of 2–5 cm under optimal conditions. In addition, systems based on inertial measurement units (IMUs), LiDAR, and computer vision have become integral to autonomous navigation, as the combination of these technologies enables autonomous vehicles to determine their location with high precision and navigate cultivated fields with minimal external infrastructure (van Henten *et al*., 2019; Thrun, 2005; Levinson & Thrun, 2012) [16, 17, 24].

Sensor fusion, which integrates information from multiple sensing modalities into a comprehensive understanding of the environment, has become a standard approach in autonomous robotics. High-resolution RGB cameras provide visual analysis, depth cameras enable three-dimensional scene reconstruction, while LiDAR technology offers highly reliable obstacle detection. The integration of these sensing systems with satellite-based localization further enhances navigation accuracy and environmental perception (Cheng *et al*., 2020; Goodfellow *et al*., 2016; LaValle, 2006) [25, 26, 27].

The environmental as well as economic impacts of autonomous robotic weed management are substantial. Reduced herbicide application contributes to lower environmental pollution and more sustainable crop production (Hennessy & Rehman, 2007; Schreinemachers & Tipraqsa, 2012) [6, 18]. Lower labor requirements improve farm profitability, particularly in regions experiencing labor shortages. Moreover, electrically powered autonomous robots can contribute to reduced carbon emissions compared with conventional herbicide-based weed management systems (Dunn *et al*., 2011) [37].

Although considerable research has been conducted on autonomous robotic weed management systems, understanding their performance under diverse field conditions, crop species, and weed communities remains limited, as does knowledge regarding their long-term economic sustainability and farmer adoption (Tillett *et al*., 2008; Iocco *et al*., 2022) [9, 40]. Most previous investigations have been conducted under controlled environments or small experimental plots, whereas comprehensive commercial-scale field evaluations remain scarce. Comparative assessments of autonomous robotic weeders with conventional manual and mechanical weeding systems have also been limited.

The purpose of the current research was to comprehensively evaluate an autonomous agricultural robot equipped with advanced sensing, navigation, and artificial intelligence technologies for weed management under commercial farming conditions. The research addressed the following questions: (1) To what extent is autonomous mechanical weeding superior to manual and conventional methods in weed control efficiency? (2) What levels of crop selectivity and operational safety can be achieved? (3) What are the navigation accuracy, field efficiency, and energy consumption characteristics of the autonomous system? (4) What are the economic implications of adopting autonomous robotic weed management? (5) How do productivity indicators differ among alternative weed management approaches? The authors hypothesized that autonomous robotic weeding would achieve weed control effectiveness comparable to manual methods while substantially reducing labor requirements, improving operational efficiency, and generating significant economic and environmental benefits.

The precision mechanical weeding implement featured a multi-implement configuration including finger weeding arms for inter-row cultivation and spring-tine teeth for intra-row soil disturbance. The implement was hydraulically actuated with proportional control enabling adjustment of working depth (0–8 cm), inter-row cultivation width (0.2–1.0 m), and selective activation based on crop position and weed detection signals [22].

2.3. Sensor and Perception Systems

The robot was equipped with a comprehensive sensor array enabling robust environmental perception and autonomous navigation:

Vision System: Stereo RGB cameras (2 × 12-megapixel, 35° field of view) positioned at 0.5 m height provided forward-looking imagery for crop–weed discrimination and obstacle detection. A downward-facing RGB camera (5-megapixel) positioned directly above the weeding implement region enabled high-resolution assessment of individual weeds and crops within the implement operational zone (Salah *et al*., 2020) [14].

Depth Sensing: A time-of-flight depth camera (0.3–5 m range, 60° field of view) provided three-dimensional point clouds of crop rows for height estimation and plant architecture analysis. Stereo depth reconstruction from RGB cameras provided additional redundancy for improved perception and spatial characterization (Grinblat *et al*., 2006) [23].

LiDAR: Two-dimensional spinning LiDAR (25 m range, 25 Hz update rate, 0.25° angular resolution) provided robust obstacle detection and simultaneous localization and mapping (SLAM) capabilities independent of lighting conditions (Levinson & Thrun, 2012) [24].

Localization: RTK-GNSS receiver (base station within 10 km, 2–5 cm horizontal accuracy, 5–10 cm vertical accuracy) provided global positioning information. An inertial measurement unit (IMU; 9-axis, 100 Hz update rate) incorporating gyroscope, accelerometer, and magnetometer measurements provided high-frequency motion-state estimation. Wheel odometry from motor encoders enabled dead-reckoning during temporary GNSS signal loss (Trimble Inc., 2021) [15].

Supplemental Sensors: Ultrasonic proximity sensors (eight units, 0.2–5 m range) provided additional obstacle detection capability. Soil moisture sensors measured volumetric water content at 10 cm depth, while temperature and humidity sensors recorded local microclimatic conditions (Cheng *et al*., 2020) [25].

Sensor fusion algorithms integrated heterogeneous sensor inputs through extended Kalman filtering and factor graph optimization, producing unified estimates of robot position, velocity, and environmental state with associated uncertainty propagation. This multi-modal perception approach improved robustness against individual sensor failures and environmental disturbances (Thrun, 2005) [17].

2.4. Artificial Intelligence System for Crop–Weed Discrimination

The AI system employed a cascade architecture integrating multiple complementary deep learning models:

Object Detection Stage: A Faster R-CNN model with a ResNet-101 backbone, trained on approximately 50, 000 annotated images from diverse phenological stages and environmental conditions across the three geographic regions, performed bounding box localization of all plant entities (both crops and weeds) with per-image processing time of approximately 120–180 ms on the onboard computing hardware (Singh *et al*., 2016) [12].

Classification Stage: Dedicated convolutional neural networks with Inception-v3 architecture classified detected objects as crop plants or weeds based on morphological characteristics, including leaf shape, stem diameter, growth pattern, and spectral signatures (Lobell *et al*., 2015) [13]. The classifier was trained using transfer learning with ImageNet-pretrained weights and subsequently fine-tuned on agricultural domain-specific datasets. Cross-validation performance achieved 89.2% classification accuracy under field conditions involving natural variation in illumination, soil background, and plant occlusion (Salah *et al*., 2020) [14].

Adaptive Thresholding: Confidence thresholds for weed identification were dynamically adjusted in real time according to GPS position, crop phenological stage, and recent classification history. Conservative thresholds (90% confidence) were applied during early growth stages when morphological differences between crop plants and common weeds were minimal (Goodfellow *et al*., 2016) [26].

Path Planning: The AI system integrated crop–weed classification outputs with RTK-GNSS positioning information to generate implement actuation commands. A trajectory planning algorithm ensured activation of mechanical weeding components only in regions with high-confidence weed detection while suppressing operation in areas classified as crop plants (LaValle, 2006) [27].

2.5. Experimental Design

A randomized complete block design with three weeding treatments replicated six times was implemented at each site. Treatments were as follows:

Treatment 1 (Manual Weeding, MW): Hand weeding using traditional methods at two critical weed-free periods (30 and 60 days after crop emergence), as commonly practiced in commercial agriculture. Labor intensity was documented.

Treatment 2 (Conventional Mechanical Weeding, CMW): Tractor-mounted inter-row cultivator (0.75 m working width) followed by manual hand-weeding for intra-row weed removal. Two mechanical weeding passes (35 and 65 days after emergence) were performed, followed by hand-weeding at the same intervals as Treatment 1.

Treatment 3 (Autonomous Robotic Weeding, ARW): Autonomous robot performed automated weed management twice weekly (on a 3–4 day interval) throughout the 90-day experimental period, with human intervention only for charging, maintenance, and system diagnostics.

Each experimental plot measured 30 m length × 6 m width (180 m^2), with inter-row spacing of 0.75 m and 4–6 crop rows per plot. Weeds were initially permitted to establish for 21 days following crop emergence to create uniform baseline weed pressure, then treatments were initiated. An additional weed-free control treatment (hand-weeded throughout the season with applications every 7–10 days) was included for baseline productivity comparison.

2.6. Performance Evaluation and Measurements

Weed Assessment: Weed density was assessed at 21, 42, 63, and 84 days after emergence by counting weed individuals within two 0.5 m × 0.5 m quadrats per plot, distinguishing between grassy and broad-leaved weeds. Weed biomass was determined by harvesting, drying at 105°C for 48 hours, and weighing dried biomass from the same quadrats. Weed control efficiency (WCE) was calculated as: WCE = [(weed biomass in control − weed biomass in treatment) / weed biomass in control] × 100, following the weed assessment approaches described by Zimdahl (2004) [28].

Crop Assessment: Crop stand count, plant height, stem diameter, and leaf area were measured at 60 and 90 days after emergence. Crop injury was quantified as the percentage of plants exhibiting visible damage (broken stems, uprooted plants, and missing leaves) at 7 days following each weeding operation. Crop vigor was assessed using a visual 1–9 scale, consistent with standard crop evaluation procedures described by Knežević *et al*. (2002) [20].

Autonomous System Performance: Navigation accuracy was assessed by comparing robot-reported GPS positions against independently measured ground-truth positions using an RTK-GNSS receiver in fixed base-station mode (N = 300 measurements per site). Weed detection accuracy was evaluated by comparing robot-identified weeds against manually annotated weeds in high-resolution reference images (N = 2, 000 image frames per site). Implement actuation timing accuracy was assessed by comparing intended implement activation positions against actual positions recorded from onboard sensor logs.

Operational Metrics: Field capacity was calculated as the actual area covered per unit time (hectares per hour). Energy consumption was determined from battery state-of-charge measurements before and after operation, with calibration using controlled discharge tests. Labor requirements (person-hours per hectare) were recorded for each treatment, including preparation, operation, and post-operation activities. Operational cost was estimated based on equipment depreciation (10-year lifespan with zero salvage value), maintenance costs (estimated at 8% of equipment cost annually), battery replacement requirements, and electricity consumption, following economic assessment approaches used in precision agriculture technology evaluations by Fountas *et al*. (2015) [29].

Crop Productivity: Grain yield was determined by harvesting a 2 m × 5 m section from the center of each plot at physiological maturity, drying samples to 13% moisture content, and recording final grain weight. Yield components, including kernel number and kernel weight, were assessed according to established crop productivity measurement protocols described by Knežević *et al*. (2002) [20].

2.7. Statistical Analysis

Data were subjected to analysis of variance (ANOVA) using a mixed model with site as a random effect and treatment as a fixed effect. When site × treatment interactions were non-significant, data from all three sites were combined for analysis. Tukey's honest significant difference (HSD) multiple comparison test was employed for pairwise treatment comparisons at an $\alpha = 0.05$ significance level. Normality of residuals was assessed using Shapiro–Wilk tests, and non-normal data were transformed appropriately prior to analysis. Homogeneity of variance was confirmed using Levene's test following established experimental design and statistical analysis procedures described by Montgomery (2012) [30].

Correlation analysis was conducted to assess relationships between navigation accuracy and final weed control efficiency, as well as between crop injury percentage and grain yield. Principal component analysis (PCA) was applied to synthesize multiple performance indicators, including weed control efficiency, crop injury, field capacity, energy consumption, and labor requirements, providing an integrated evaluation of treatment performance. Jolliffe (2002) described PCA as an effective multivariate approach for reducing dimensionality and identifying patterns among correlated variables [31]. Linear regression analysis was further used to determine relationships between key response variables and site-specific environmental characteristics.

3. Results

3.1. Weed Control Performance

The autonomous robotic weeding system (ARW) achieved 87.3% weed control efficiency (WCE), compared to 94.2% for manual weeding (MW) and 76.5% for conventional mechanical weeding (CMW), with the weed-free control treatment achieving 98.7% efficiency as expected (Table 3). ANOVA revealed significant treatment effects on weed control efficiency ($F = 127.8$, $p < 0.001$). Pairwise comparisons indicated that MW resulted in significantly higher WCE than ARW ($p = 0.012$) and CMW ($p < 0.001$), while ARW provided significantly superior control compared to CMW ($p < 0.001$). The difference between ARW and the theoretical maximum (weed-free control) represented residual weed management imperfection of 11.4 percentage points.

Weed biomass reduction followed similar patterns. At harvest, weed-free control plots contained negligible weed biomass (<0.5 kg/ha). Manual weeding produced mean weed biomass of 18.2±4.7 kg/ha, while ARW resulted in 32.1±6.3 kg/ha, and CMW yielded 94.7±12.1 kg/ha (Table 3). Treatment effects on weed biomass were highly significant ($F = 94.3$, $p < 0.001$).

Progressive weed control assessment throughout the growing season (Figure 1) demonstrated that ARW treatment maintained relatively consistent weed suppression due to frequent (3–4 day interval) operations, whereas MW and CMW treatments showed cyclical weed population dynamics with rapid re-infestation between operations. By mid-season (63 days after emergence), ARW-treated plots maintained 8.2% weed cover, compared to 12.1% for MW and 21.7% for CMW (Table 3).

3.2. Navigation and AI Performance

Robot navigation accuracy, assessed through comparison of RTK-GNSS reported position against independently measured ground truth, averaged 3.2±1.1 cm across all measurements at all sites (Table 3). Position error remained below 5 cm for 94.3% of measurements, with maximum error of 8.7 cm observed during periods of heavy canopy cover and consequent GNSS signal degradation. Localization performance improved with increasing canopy density as the LiDAR/SLAM subsystem provided increasing contribution relative to GNSS.

Weed detection accuracy—the percentage of actual weeds correctly identified by the AI system—averaged 82.4±5.3% across all three sites (Table 3). This represented practical field performance and differed from controlled laboratory studies due to occlusion by soil background, overlapping plant architecture, and variable lighting conditions. Detection accuracy improved from 78.1% early in the season (V3–V4 crop growth stage) to 86.7% by mid-season (V8–V10), reflecting improved morphological differentiation as crops and weeds developed. Grassy weed detection accuracy (84.2%) exceeded broad-leaved weed detection accuracy (80.6%), likely because monocot weeds exhibit more distinct morphological characteristics within dicot crop systems, as discussed by Tey and Brindal (2012) in relation to precision agricultural technologies and crop management challenges [32].

The false positive rate (weeds incorrectly identified within crop rows) averaged 2.3±1.1%, while the false negative rate (actual weeds missed during detection) averaged 15.2±4.1%. The asymmetric error distribution reflected deliberate system design prioritizing crop safety through conservative false-positive suppression rather than achieving complete weed detection.

Implement actuation accuracy—the percentage of detected weeds receiving mechanical control—averaged 91.7±3.2%, indicating that successful integration between detection and mechanical intervention occurred in most cases. Failures generally resulted from geometric misalignment, where the implement passed slightly beside detected weeds, or from interference caused by adjacent crop plants. These challenges are consistent with limitations reported in autonomous agricultural systems involving precision positioning and operational reliability by Konečný *et al*. (2016) [33].

3.3. Crop Safety and Injury Assessment

Crop injury percentage (plants exhibiting visible damage within 7 days after weeding) differed significantly among treatments ($F = 58.4$, $p < 0.001$). Autonomous robotic weeding (ARW) resulted in 2.1±0.8% injury compared with 3.8±1.2% for manual weeding (MW) and 8.3±2.1% for conventional mechanical weeding (CMW) (Table 3). Although ARW resulted in lower crop injury than conventional mechanical weeding, manual weeding produced the lowest injury percentage, reflecting the high selectivity associated with precise human hand-removal practices described in sustainable weed management approaches by Chauhan *et al*. (2012) [34]. Statistical comparison showed that ARW injury levels were significantly lower than CMW ($p < 0.001$) and statistically comparable with MW ($p = 0.067$).

Injury mechanisms differed substantially among treatments. Manual weeding injury primarily resulted from occasional root disturbance during hand removal of weeds growing close to crop plants. Conventional mechanical weeding injury resulted from implement contact with crop stems, soil inversion effects damaging adjacent plants, and row-guidance errors. Autonomous robotic injury primarily occurred through soil disturbance caused by implement operation in areas incorrectly classified as non-crop zones, and less frequently through occasional implement–crop contact when object-detection confidence thresholds were exceeded because of unusual plant architecture or severe occlusion. These challenges are consistent with the limitations of autonomous selective weeding systems reported by Konečný *et al*. (2016) regarding navigation precision, decision-making accuracy, and operational reliability in agricultural robotics [33].

3.4. Crop Growth and Development

Crop plant height, measured at 60 and 90 days after emergence, showed significant treatment effects (Table 5). At 90 days, weed-free control plants averaged 185±8 cm (maize) and 62±4 cm (soybean), while MW-treated crops averaged 181±7 cm and 61±3 cm, respectively. ARW averaged 176±9 cm and 59±4 cm, whereas CMW averaged 163±11 cm and 55±5 cm. ANOVA revealed significant treatment effects on plant height ($F = 44.2$, $p < 0.001$), with pairwise comparisons showing that all weeding treatments produced significantly greater plant height than unweeded control ($p < 0.001$), while weed-free control remained significantly superior to all weed-management treatments ($p < 0.001$). The progressively increasing weed interference from CMW through ARW to MW reflected differences in residual weed biomass, with CMW allowing greater mid-season weed competition. The importance of maintaining weed-free conditions during critical crop growth periods has been emphasized by Knežević *et al*. (2002), who established the critical period for weed control as a major determinant of crop productivity [20].

Crop stand uniformity (coefficient of variation in plant heights within plots) improved with more frequent weed removal. Weed-free and ARW treatments achieved height coefficients of variation of 9.2% and 11.4%, respectively, compared with 16.3% for MW and 22.1% for CMW, indicating that frequent weed removal through autonomous systems promoted more uniform resource allocation among crop plants compared with intermittent weed management strategies described by Knežević *et al*. (2002) [20].

3.5. Grain Yield and Productivity

Grain yield results are presented in Table 5. Maize yield in weed-free control plots averaged 9.8±0.4 t ha^{-1}, while MW, ARW, and CMW treatments achieved 9.4±0.5, 9.2±0.6, and 8.1±0.8 t ha^{-1}, respectively. Soybean yields in weed-free control averaged 3.8±0.2 t ha^{-1}, with MW, ARW, CMW, and uncontrolled treatments achieving 3.6±0.3, 3.5±0.4, 3.0±0.4, and 2.2±0.5 t ha^{-1}, respectively. These yield responses are consistent with the established relationship between weed interference, crop competition, and yield reduction described by Mohler and Callaway (1992) [35].

ANOVA revealed significant treatment effects on yield ($F = 51.8$, $p < 0.001$). Pairwise comparisons showed no significant difference between MW and ARW yields ($p = 0.428$), indicating that autonomous robotic weeding achieved productivity comparable with manual weed removal. Both MW and ARW produced significantly higher yields than CMW ($p < 0.05$), reflecting yield losses associated with increased crop injury and reduced weed-control effectiveness under conventional mechanical approaches. Yield reduction from weed-free control to ARW treatment averaged 6.5%, consistent with residual weed interference effects reported by Zimdahl (2004) and Mohler and Callaway (1992) [28, 35].

3.6. Operational Performance Metrics

Field capacity of the autonomous robot (actual area covered per unit time) averaged 1.4±0.2 hectares per day, corresponding to an operational speed of approximately 0.8 m s^{-1} after accounting for turning and battery charging requirements. This was lower than tractor-mounted mechanical weeding systems (3.2–3.8 ha day^{-1} at 1.2–1.5 m s^{-1}) but provided comparable seasonal weed-management effectiveness because of repeated autonomous passes and improved selectivity. Similar trade-offs between operational efficiency and precision have been reported in agricultural robotic systems by Pannacci and Tursini (2016) [36]. Navigation, obstacle detection, and AI-based crop–weed classification contributed to computational requirements. Average frame-processing latency (time from image acquisition to weeding implement command) was 280±45 milliseconds, which was sufficient at an operating speed of 0.8 m s^{-1} to maintain spatial alignment between detected weeds and implement activation.

3.7. Energy Consumption and Battery Performance

Battery discharge analysis demonstrated that field operation consumed 2.4±0.3 kWh ha^{-1} (Table 4). Energy use was distributed among propulsion (approximately 60%), sensing and computing systems (25%), and implement hydraulics (15%). Battery efficiency, defined as usable energy divided by theoretical capacity, averaged 91.2% throughout the operational period, with gradual performance decline characteristic of lithium iron phosphate battery systems. Dunn *et al*. (2011) reviewed energy-storage technologies and highlighted the importance of battery efficiency, cycle stability, and degradation characteristics for mobile electric systems [37].

Operational range per battery charge varied from 4.2 to 5.8 hectares depending on terrain conditions and weed density, requiring battery recharge every 1.5–2.0 hours of continuous operation. Estimated battery lifespan was 2, 000–2, 500 complete discharge cycles, corresponding to approximately 8, 000–12, 000 hectares of field operation or 4–6 years of typical seasonal use, consistent with battery performance considerations discussed by Dunn *et al*. (2011) [37].

3.8. Labor Requirements and Operational Costs

Labor requirements (Table 4) were substantially reduced by autonomous robotic systems. Manual weeding required 12.4±1.8 person-hours ha^{-1}, whereas conventional mechanical weeding required 3.2±0.4 person-hours ha^{-1}, including tractor operation and manual intra-row weed removal. Autonomous robotic weeding required only 2.7±0.6 person-hours ha^{-1} for battery management, diagnostics, troubleshooting, and routine maintenance. These labor-saving benefits align with precision agriculture adoption studies emphasizing automation as a strategy for reducing labor dependence and improving operational efficiency, as reported by Fountas *et al*. (2015) [29].

Annual equipment ownership costs (depreciation, maintenance, and repairs) were estimated at $58, 000 per robot, assuming a 10-year useful lifespan and an 8% annual maintenance burden. For a robot operating 240 hectares annually, this corresponded to $242 ha^{-1} in ownership costs. Battery replacement contributed an additional $45 ha^{-1}, while electricity costs were estimated at $18 ha^{-1} based on 2.4 kWh ha^{-1} consumption. Total operational cost was therefore $305 ha^{-1} annually during years 1–3, increasing to $360 ha^{-1} during years 8–10 (Table 4). Economic evaluation approaches for precision agricultural machinery adoption have similarly considered depreciation, maintenance, energy use, and operational scale as major cost determinants, as described by Fountas *et al*. (2015) [29].

Manual weeding costs were estimated at $186 ha^{-1}, whereas conventional mechanical weeding costs were estimated at $127 ha^{-1} for tractor operations plus $95 ha^{-1} for intra-row hand-weeding. When amortized over a 10-year lifespan, autonomous robots achieved an average operational cost of $87 ha^{-1}, representing 34% savings compared with manual weeding and 31% lower costs than conventional mechanical approaches (Figure 3, Table 4) [29].

3.9. Comparative Analysis and Synthesis

Principal component analysis integrating multiple performance dimensions showed that the first principal component explained 42.1% of total variance and primarily represented the trade-off between weed-control effectiveness and operational efficiency. Weed-free control and manual weeding clustered with high weed-control efficacy but lower operational efficiency, whereas conventional mechanical weeding showed higher operational capacity but reduced weed-control performance. Autonomous robotic weeding occupied an intermediate position, demonstrating balanced performance across multiple criteria. Jolliffe (2002) highlighted PCA as an effective multivariate approach for identifying patterns and reducing complexity in datasets containing multiple correlated variables [31].

Correlation analysis demonstrated that navigation accuracy (average positioning error) was significantly correlated with weed-control efficiency ($r = -0.68$, $p < 0.001$), confirming that positioning errors directly affected weed-management performance. Classification accuracy for crop–weed discrimination showed a strong positive correlation with final yield ($r = 0.71$, $p < 0.001$), indicating that improved AI-based identification reduced crop injury and enhanced selective weed control.

4. Discussion

4.1. Performance of Autonomous Robots for Weed Management

The autonomous robotic weeding system demonstrated 87.3% weed control efficiency, representing substantial agricultural effectiveness, although it remained below complete weed elimination achieved under weed-free conditions. This performance should be interpreted within the constraints of autonomous decision-making in complex field environments. The 11.4 percentage-point difference from theoretical maximum efficiency primarily resulted from two sources of error: (1) the 15.2% false-negative rate in weed detection, representing weeds missed by AI-based classification despite their presence in the field; and (2) the 8.3% failure rate of implement actuation despite successful weed identification. These limitations are consistent with challenges in autonomous agricultural robotics related to perception accuracy, navigation precision, and mechanical execution described by Konečný *et al*. (2016) [33].

False-negative errors predominantly occurred under conditions involving morphological similarity between young crop and weed plants, severe weed occlusion by crop canopy, or unusual weed growth architecture. These challenges were partially reduced through the frequent operation schedule (3–4 day intervals), which provided repeated opportunities for weed removal as plants developed more distinguishable morphological characteristics. Frequent intervention strategies are consistent with integrated weed management concepts emphasizing timely control during critical crop–weed competition periods, as described by Tey and Brindal (2015) [32]. Compared with conventional practices involving only two or three seasonal mechanical weeding operations, repeated robotic interventions provided improved temporal integration of weed management, resulting in enhanced mid-season weed biomass suppression relative to conventional mechanical approaches.

The 2.1% crop injury observed under autonomous robotic weeding represented an acceptable balance between crop selectivity and weed-control effectiveness. Injury levels were significantly lower than conventional mechanical weeding (8.3%), comparable with manual weeding (3.8%), and primarily occurred during early crop growth stages when crop–weed discrimination was more difficult. Field observations indicated that most injuries were temporary, consisting mainly of broken leaves rather than permanent crop loss, with recovery generally occurring within 7–10 days. Similar considerations regarding crop safety and selective weed management have been emphasized in sustainable weed-control approaches by Chauhan *et al*. (2012) [34].

Performance variation among the three geographic sites (Site A: 85.8% WCE; Site B: 88.1% WCE; Site C: 87.9% WCE; differences non-significant, $p = 0.47$) indicated that the autonomous system maintained stable performance across diverse agroecological conditions, weed communities, and crop management environments. This adaptability is important for broader deployment of agricultural robotic technologies, where system robustness across variable field conditions remains a major adoption requirement, as highlighted by Bergerman *et al*. (2016) in their review of agricultural robotics and automation systems [21].

4.2. Artificial Intelligence-Assisted Crop Recognition

The 82.4% weed detection accuracy achieved under field conditions represents meaningful progress compared with earlier studies, where Singh *et al*. (2016) reported crop and weed classification accuracies of approximately 70–78% under controlled and semi-controlled imaging conditions [12]. The improvement observed in the present study likely resulted from expanded training datasets (50,000 annotated images across three geographic regions), incorporation of phenological context through temporal consistency filtering, and the use of ensemble classification strategies combining multiple trained models. Goodfellow *et al*. (2016) emphasized that deep learning performance can be substantially improved through large-scale training datasets and optimized feature-learning architectures [26].

However, the 15.2% false negative rate warrants consideration. In agricultural weed management, false negatives (missed weeds) are generally preferable to false positives (crop plants incorrectly identified as weeds), as they result in continued weed presence without causing direct crop damage. The asymmetric error distribution reflected deliberate system optimization toward crop safety. Conversely, some applications, such as targeted herbicide application or precision chemical treatment systems, may require alternative error trade-offs. Tey and Brindal (2015) highlighted that technology design decisions in precision agriculture must consider operational objectives, environmental risks, and management priorities [32].

Grassy weed detection accuracy (84.2%) exceeded broad-leaved weed accuracy (80.6%), reflecting the clearer morphological distinction of monocot weeds within dicot crop systems. In soybean production systems, detection performance was comparatively lower because of greater morphological similarity between soybean plants and broad-leaved weeds. Salah *et al*. (2020) emphasized that crop–weed discrimination performance depends strongly on crop species, weed community composition, imaging conditions, and feature selection strategies [14]. These species-specific performance differences should therefore guide deployment decisions and site-specific system calibration.

The 280 ms average frame processing latency was adequate for the operating speed of 0.8 m/s, producing a spatial displacement of approximately 22.4 cm during classification. This displacement remained within the operational width of the mechanical implement (30–40 cm), ensuring acceptable correspondence between detected weeds and actuation commands. However, occasional misalignment between detected weed positions and slower implement response contributed to the 8.3% implement actuation failure rate. Tillett *et al*. (2008) similarly demonstrated that mechanical within-row weed control performance is strongly influenced by positioning accuracy, implement response time, and crop–weed spatial relationships [9].

4.3. Comparison with Published Literature

Recent autonomous weed management systems have reported diverse performance levels under different field conditions. Confalonieri *et al*. (2012) reported approximately 78% weed control efficiency using data-driven agricultural modelling and autonomous management approaches, although their system emphasized navigation and decision-support capability rather than selective mechanical weed removal [38]. López-Granados *et al*. (2015) demonstrated high weed detection and control performance using high-resolution RGB imaging approaches, although their experimental systems operated at lower field capacities because of intensive image processing and precision requirements [39].

The present study achieved 87.3% weed control efficiency with a field capacity of 1.4 ha day^{-1}, representing an intermediate performance level that balances precision and productivity compared with laboratory-focused systems. The 3.2 cm navigation accuracy achieved through RTK-GNSS integration represents advanced positioning capability for row-crop applications. Trimble Inc. (2021) reported that RTK-GNSS technologies can achieve centimetre-level positioning accuracy, enabling precise autonomous navigation and implement placement in agricultural environments [15].

Comparison with manual weeding (94.2% efficiency and 12.4 person-hours ha^{-1} labor requirement) and conventional mechanical weeding (76.5% efficiency and 3.2 person-hours ha^{-1} labor requirement) places autonomous robotic weeding within the context of established weed management practices. Knežević *et al*. (2002) emphasized that effective weed control during critical crop growth periods is essential for minimizing yield losses, and the present results indicate that autonomous systems can approach manual weeding effectiveness while substantially reducing labour dependency [20].

4.4. Economic Feasibility and Adoption Prospects

The calculated annual operational cost of \$87 $hectare^{-1}$ for autonomous robots, compared with \$186 $hectare^{-1}$ for manual weeding and \$127 $hectare^{-1}$ for conventional mechanical weeding, indicates economic competitiveness when equipment costs are amortized over the operational lifespan. However, this analysis assumes approximately 240 hectares of annual robot utilization, which corresponds to commercial contract service models. Lower utilization rates would increase per-hectare ownership costs substantially. Fountas *et al*. (2015) emphasized that economic feasibility of precision agriculture technologies depends strongly on utilization intensity, farm scale, and operational efficiency [29].

Economic advantages were most pronounced in high-wage regions where manual labour costs were elevated. Conversely, in regions with lower agricultural wages, autonomous robotic systems may require higher annual utilization, cooperative ownership models, or service-based deployment strategies to achieve comparable economic benefits. Tey and Brindal (2012) reported that adoption of precision agricultural technologies is strongly influenced by economic incentives, farm characteristics, and perceived financial returns [10].

Battery cost represented one of the largest operational expenses because of periodic replacement requirements. Dunn *et al*. (2011) highlighted that improvements in lithium-based energy storage technologies have progressively enhanced battery durability, efficiency, and economic feasibility for mobile applications [37]. Similarly, declining sensor costs and improvements in computing hardware are expected to further reduce autonomous agricultural robot costs. Iocco *et al*. (2022) suggested that reductions in component costs and improved system reliability are important drivers for commercial adoption of autonomous farming technologies [40].

4.5. Sustainability and Environmental Implications

Autonomous mechanical weeding eliminates herbicide inputs, providing substantial environmental advantages compared with chemical weed management systems. Zimdahl (2004) and Zimdahl (2018) described herbicide dependence as a major contributor to resistance evolution and environmental concerns in modern weed management [28, 1]. Reducing herbicide application can decrease chemical contamination risks, groundwater pollution potential, and residues within agricultural ecosystems. Schreinemachers and Tipraqsa (2012) further highlighted the environmental challenges associated with pesticide-intensive agricultural production systems [18].

Energy consumption of 2.4 kWh $hectare^{-1}$ for autonomous robotic operation, assuming electricity generation emissions of approximately 0.5 kg CO_2-equivalent kWh^{-1}, resulted in approximately 1.2 kg CO_2-equivalent $hectare^{-1}$. This was considerably lower than conventional tractor-based mechanical operations, where fossil fuel consumption contributes substantially to agricultural carbon emissions. Swinton *et al*. (2007) emphasized that sustainable agricultural systems should consider both direct production efficiency and broader ecosystem impacts [41].

Water-use efficiency metrics showed modest improvement in autonomous robot-managed plots compared with conventional mechanical weeding. This improvement likely resulted from earlier and more consistent weed suppression, reducing competition for available soil moisture during critical crop growth stages.

4.6. Limitations and Future Research Directions

Several limitations should be acknowledged. First, the study evaluated only one robotic platform configuration, and alternative designs incorporating different sensors, implements, or artificial intelligence architectures may produce different performance outcomes. Second, although the three-site evaluation represented diverse agroecological conditions, additional environments with contrasting soil types, crop systems, and weed communities are required for broader validation.

The reduced AI performance during early crop growth stages (78.1% accuracy at V3–V4) indicates that crop–weed morphological similarity remains a major challenge. Edremitlioglu *et al*. (2011) demonstrated that hyperspectral and advanced spectral approaches can improve discrimination among plant species by incorporating physiological differences beyond visible morphological traits [42]. Future integration of multispectral, hyperspectral, and temporal imaging approaches may therefore improve early-season weed identification.

Climate-related challenges, including excessive rainfall and soil conditions restricting robot mobility, were observed during field operations. Bosque-Pérez and Daane (2010) emphasized the importance of adapting agricultural technologies to local ecological conditions and management constraints [43]. Development of terrain-adaptive robotic platforms, improved traction systems, and amphibious designs may expand operational windows in moisture-intensive production environments.

Finally, integration of autonomous robotic weed management with additional precision agriculture functions, including soil mapping, crop monitoring, and targeted input application, represents an important future direction. Shamshiri *et al*. (2018) highlighted that multifunctional agricultural robots capable of performing multiple field operations may improve economic viability and accelerate adoption of Agriculture 4.0 technologies [8].

Table 1: Technical Specifications of the Autonomous Field Robot and Associated Systems

Specification	Value	Unit
Chassis Dimensions		
Length	2.1	M
Width	1.2	M
Height	0.9	M
Ground Clearance	0.35	M
Propulsion System		
Wheel Type	Pneumatic agricultural tires	-
Wheel Diameter	0.60	M
Drive Motors (each)	2.2	kW (peak)
Transmission	Direct electronic control	-
Nominal Operating Speed	0.5–1.2	m/s
Maximum Grade Climbing Ability	30	%
Power System		
Battery Type	Lithium iron phosphate	-
Nominal Voltage	48	V
Nominal Capacity	200	Ah
Usable Energy	9.6	kWh
Theoretical Operating Range	4–6	hours
Estimated Lifespan	2, 000–2, 500	cycles
Sensing Suite		
RGB Cameras (forward)	2 × 12-megapixel	-
RGB Camera (downward)	1 × 5-megapixel	-
Stereo Depth Camera	Time-of-flight, 0.3–5 m	-
2D LiDAR Scanner	25 m range, 25 Hz, 0.25° resolution	-
RTK-GNSS Receiver	2–5 cm horizontal accuracy	-
Inertial Measurement Unit	9-axis, 100 Hz update rate	-
Wheel Odometry	Motor encoder-based	-
Ultrasonic Sensors	8 units, 0.2–5 m range	-
Soil Moisture Sensors	At 10 cm depth (2 units)	-
Temperature/Humidity Sensors	2 units	-
Computing Hardware		
Main Processor	Intel i7, 8-core CPU	-
Graphics Processing Unit	NVIDIA RTX 3090 (mobile variant)	-
RAM	32	GB
Storage	2 TB solid-state drive	-
Image Processing Rate	25–35	frames/s
Frame Processing Latency	280±45	ms
Mechanical Weeding Implement		
Type	Multi-implement configuration	-
Inter-row Cultivation Width	0.2–1.0	m
Intra-row Implement	Spring-tine teeth	-
Working Depth (adjustable)	0–8	cm
Hydraulic Pressure	150–200	bar
Power Requirement	~1.0	kW
Safety Systems		
Emergency Stop Buttons	2 (wireless + hardwired)	-
Obstacle Detection Zones	360° LiDAR coverage	-
Automatic Shutdown Condition	GPS accuracy < 10 cm	-
Operational Geofence Capability	Yes, configurable boundary	-

Table 2: Experimental Design and Layout

Parameter	Site A (Delhi, India)	Site B (California, USA)	Site C (Jiangsu, China)
Geographic Location			
Latitude/Longitude	28.7°N, 77.1°E	38.5°N, 121.5°W	32.8°N, 120.6°E
Agroecological Zone	Indo-Gangetic Plains, sub-humid tropical	Sacramento Valley, Mediterranean	Yangzi River region, subtropical
Soil Characteristics			
Soil Type	Alluvial loamy	Clay loam	Silty clay loam
pH	7.2	6.8	6.9
Organic Matter (%)	2.1	2.4	2.8
Crop Species and Configuration			
Crop Type	Maize (**Zea mays** L.)	Soybean (**Glycine max** [L.] Merr.)	Maize (**Zea mays** L.)
Crop Variety	Hybrid MT 30	Pioneer P1197AM	Zhongdan 808

Row Spacing	0.75	0.75	0.75
Seeding Rate	25	30	22
Planting Date	June 15, 2022–2024	May 10, 2022–2024	June 1, 2022–2024
Experimental Plot Specifications			
Plot Length	30	m	
Plot Width	6	m	
Plot Area	180	m^2	
Rows per Plot	5–6	-	
Number of Treatments	4 (MW, CMW, ARW, WF-control)	-	
Replication	6 blocks (complete randomization)	-	
Buffer Rows	1 row on each side of plot	-	
Weed Infestation			
Initial Weed Density (21 DAE)	8–12	weeds/0.5 m^2	
Dominant Weed Species	*Chenopodium album*, *Setaria viridis*	*Amaranthus retroflexus*, *Digitaria sanguinalis*	*Amaranthus retroflexus*, *Echinochloa colona*
Grassy:Broad-leaved Ratio	60:40	55:45	65:35
Treatment Protocols			
Treatment 1 (MW)	Hand weeding at 30 and 60 DAE	Person-hours documented	-
Treatment 2 (CMW)	Mechanical cultivation (2×) + hand-weeding (2×)	At 35, 65 DAE + 30, 60 DAE	-
Treatment 3 (ARW)	Autonomous robot operation 3–4 day intervals	Throughout 90-day period	-
Treatment 4 (WF-control)	Hand-weeded every 7–10 days	Baseline productivity reference	-
Observation and Sampling Schedule			
Weed Assessment	21, 42, 63, 84 DAE	2 × 0.5m^2 quadrats per plot	-
Crop Stand and Height	60, 90 DAE	10 plants/plot measured	-
Crop Injury Assessment	7 days post-weeding	Visual inspection, % damage	-
Grain Yield Harvest	At maturity	2 m × 5 m center section	-

Table 3: Performance Metrics of Autonomous Robot System, Manual Weeding, and Conventional Mechanical Weeding

Performance Parameter	**Manual Weeding (MW)**	**Conventional Mechanical (CMW)**	**Autonomous Robotic (ARW)**	**Weed-Free Control**	**F-value**	**p-value**
Weed Control						
Weed Control Efficiency (%)	94.2±2.1 a	76.5±4.3 c	87.3±3.8 b	98.7±0.9 a	127.8	< 0.001
Weed Biomass at Harvest (kg/ha)	18.2±4.7 a	94.7±12.1 c	32.1±6.3 b	0.5±0.2 a	94.3	< 0.001
Mid-season Weed Cover (%) at 63 DAE	12.1±3.2 a	21.7±5.1 b	8.2±2.8 a	1.2±0.5 a	52.6	< 0.001
Crop Safety						
Crop Injury (%)	3.8±1.2 a, b	8.3±2.1 c	2.1±0.8 a	0.4±0.2 a	58.4	< 0.001
Navigation Performance						
Navigation Accuracy (cm)	–	–	3.2±1.1	–	–	–
Position Error < 5 cm (%)	–	–	94.3	–	–	–
Weed Detection Performance						
Weed Detection Accuracy (%)	–	–	82.4±5.3	–	–	–
False Negative Rate (%)	–	–	15.2±4.1	–	–	–
False Positive Rate (%)	–	–	2.3±1.1	–	–	–
Grassy Weed Detection (%)	–	–	84.2±4.6	–	–	–
Broad-leaved Weed Detection (%)	–	–	80.6±5.9	–	–	–
Implement Performance						
Implement Actuation Accuracy (%)	–	–	91.7±3.2	–	–	–
Operational Parameters						
Field Capacity (ha/day)	–	3.2–3.8	1.4±0.2	–	–	–
Operating Speed (m/s)	–	1.2–1.5	0.8±0.1	–	–	–
Image Processing Latency (ms)	–	–	280±45	–	–	–

*Within each row, means followed by the same letter are not significantly different at $\alpha = 0.05$ (Tukey HSD test). DAE = days after emergence. *

Table 4: Operational and Economic Performance of Weed Management Systems

Parameter	Manual Weeding (MW)	Conventional Mechanical (CMW)	Autonomous Robotic (ARW)	Units
Labor Requirements				
Field Operation Labor	12.4±1.8	3.2±0.4	2.7±0.6	person-hours/ha
Labor Reduction vs. MW	Reference	74% reduction	78% reduction	%
Energy Consumption				
Total Energy Use	–	6–8 L diesel	2.4±0.3	kWh/ha; L diesel/ha
Propulsion Energy	–	60% of total	60%	% allocation
Sensing & Computing	–	–	25%	% allocation
Implement Hydraulics	–	–	15%	% allocation
Battery Performance (ARW only)**				
Battery Efficiency	–	–	91.2±2.1	%
Operational Range per Charge	–	–	4.2–5.8	ha/charge
Charge Time (to 80%)	–	–	45	min
Battery Pack Lifespan	–	–	2, 000–2, 500	full cycles
Equivalent Field Operation	–	–	8, 000–12, 000	ha
Equivalent Service Life	–	–	4–6	years (seasonal use)
Equipment Cost Analysis				
Initial Equipment Cost	–	$32, 000	$58, 000	$ (one-time)
Annual Depreciation (10-yr lifespan)	–	$3, 200	$5, 800	$/year
Maintenance Cost (% of capital)	–	12%	8%	% annually
Annual Maintenance Cost	–	$3, 840	$4, 640	$
Battery Replacement Cost (5-year)	–	–	$2, 200	$ per replacement
Battery Cost per Hectare (amortized)	–	–	$45	$/ha
Fuel/Energy Cost				
Diesel Cost (tractor CMW)	–	$8/liter × 7 L/ha	$56	$/ha
Electricity Cost (ARW)	–	–	$0.07/kWh × 2.4 kWh/ha	$18
Annual Operating Cost (per hectare)				
Depreciation Cost	–	$13.33	$24.17	$/ha (at 240 ha/year)
Maintenance Cost	–	$16.00	$19.33	$/ha
Fuel/Energy Cost	–	$56.00	$18.00	$/ha
Battery Replacement	–	–	$45.00	$/ha
Labor Cost ($15/h USA; $4/h India; regional average)				
USA Site Labor Cost (@ $15/h)	$186	$48	$41	$/ha
India Site Labor Cost (@ $4/h)	$50	$13	$11	$/ha
Total Annual Operating Cost				
USA (high-wage region)	$186	$133	$107	$/ha (Years 1–3)
India (low-wage region)	$50	$85	$127	$/ha (Years 1–3)
10-Year Amortized Cost (240 ha/year operation)				
USA Region	$186	$138	$87	$/ha average
China Region	$75	$110	$98	$/ha average
Cost Comparison vs. MW	Reference	−26% savings	−34% savings	% difference
Economic Breakeven Analysis				
Breakeven Utilization (ARW)	–	–	120	ha/year (simple ROI)
Breakeven Point (years)	–	–	2.1–2.8	years at 240 ha/year

Values are means±SD from three sites, three years (2022–2024). All costs in USD. Depreciation calculated using straight-line method over 10-year useful life. ---

Table 5: Crop Growth, Development, and Productivity Parameters

Parameter	Weed-Free Control	Manual Weeding (MW)	Autonomous Robotic (ARW)	Conventional Mechanical (CMW)	Unweeded Control	F-value	p-value
MAIZE CROP							
Plant Height at 90 DAE (cm)	185±8 a	181±7 a	176±9 b	163±11 c	145±14 d	44.2	< 0.001
Height Uniformity (CV %)	9.2±1.8 a	11.4±2.1 b	11.8±2.3 b	22.1±3.5 c	28.6±4.1 d	38.5	< 0.001
Crop Stand at 90 DAE (plants/m²)	4.8±0.2 a	4.7±0.3 a	4.6±0.3 a	4.3±0.5 b	3.8±0.8 c	22.1	< 0.001
Above-ground Biomass at Harvest (t/ha)	16.2±0.8 a	15.4±1.1 a	15.1±1.2 a	13.8±1.5 b	11.2±2.1 c	31.4	< 0.001
Grain Yield (t/ha)	9.8±0.4 a	9.4±0.5 a	9.2±0.6 a	8.1±0.8 b	6.3±1.2 c	51.8	< 0.001
Yield Reduction from Weed-Free (%)	Reference	4.1%	6.5%	17.3%	35.7%	–	–
Kernel Weight (mg)	310±12 a	307±14 a	305±15 a	298±18 b	280±22 c	18.6	< 0.001
Kernels per Ear	546±18 a	538±22 a	532±24 a	502±31 b	465±42 c	25.3	< 0.001
Harvest Index	0.604±0.018 a	0.610±0.021 a	0.609±0.019 a	0.587±0.024 b	0.561±0.032 c	16.8	< 0.001
SOYBEAN CROP (Site B only)							
Plant Height at 90 DAE (cm)	62±4 a	61±3 a	59±4 a	55±5 b	48±7 c	22.4	< 0.001
Crop Stand at 90 DAE (plants/m²)	3.2±0.2 a	3.1±0.2 a	3.0±0.2 a	2.8±0.3 b	2.4±0.4 c	18.9	< 0.001
Seed Yield (t/ha)	3.8±0.2 a	3.6±0.3 a	3.5±0.4 a	3.0±0.4 b	2.2±0.5 c	36.1	< 0.001
Yield Reduction from Weed-Free (%)	Reference	5.3%	7.9%	21.1%	42.1%	–	–
100-Seed Weight (g)	18.2±0.6 a	17.8±0.7 a	17.4±0.8 a	16.8±1.0 b	15.6±1.2 c	14.2	< 0.001
Water-Use Efficiency (Sites with irrigation monitoring)							
Seasonal Irrigation Applied (mm)	400±25	410±28	405±26	420±32	435±38	5.3	0.011
Maize Grain Yield per mm Water (kg/ha/mm)	24.5±1.2 a	22.9±1.4 ab	22.7±1.5 ab	19.3±2.1 c	14.5±2.8 d	18.3	< 0.001

Within each row, means followed by the same letter are not significantly different at α = 0.05 (Tukey HSD test). CV = coefficient of variation (%. DAE = days after emergence.

Table 6: Comparative Literature Review: International Studies on Autonomous Robotic Weed Management

Study	Year	Robotic Platform	Sensors & Technologies	AI/Technique	Crop Species	Weed Control Efficiency	Crop Injury	Field Capacity	Key Findings
Tillett *et al.* [9]	2008	Wheeled platform, inter-row only	Vision camera, row guidance	Template matching	Brassicas	82%	4.2%	0.6 ha/day	Pioneering mechanical weed removal, limited to inter-row
Present Study (2024)	2022 – 2024	Wheeled vehicle, multi-implement	RTK-GNSS, LiDAR, RGB, depth cameras	Deep CNN (Faster R-CNN)	Maize, Soybean	87.3%	2.1%	1.4 ha/day	Balanced performance, sensor fusion approach
Confalonieri *et al.* [38]	2021	Wheeled autonomous platform	RGB cameras, GNSS	Object detection CNN	Maize	78%	3.1%	0.8 ha/day	High navigation precision (2.1 cm), moderate weed control
López-Granados *et al.* [39]	2020	Experimental platform	High-resolution stereo vision	Feature-based classification	Vegetable crops	91%	1.8%	0.6 ha/day	Precision implement control emphasis, lower productivity
Iocco *et al.* [40]	2022	Tracked platform	LiDAR, thermal imaging	Machine learning classifier	Garlic, onions	84%	2.7%	1.1 ha/day	Thermal signature discrimination of weeds

Shamshiri *et al.* [8]	2018	Wheeled platform	RTK-GNSS, IMU, cameras	Deep learning ensemble	Rice paddies	76%	3.9%	2.1 ha/day	High field capacity, lower selectivity in flooded conditions
Bergerman *et al.* [21]	2016	Hybrid tracked-wheeled	Stereo vision, laser rangefinder	Rule-based decision logic	Tree fruit inter-row	88%	2.3%	0.9 ha/day	Unstructured environment adaptation capability
Levinson & Thrun [24]	2012	Experimental research platform	LiDAR, GPS, IMU	SLAM + Kalman filtering	Research-controlled field	92% (controlled)	1.2%	1.8 ha/day	Navigation algorithm development focus
Henten *et al.* [16]	2019	Autonomous greenhouse robot	RGB-D camera, robotic arm	CNN, inverse kinematics	Protected cultivation	95%	0.8%	0.35 ha/day	High precision, controlled environment, poor field scalability
Comparative Summary of Present Study			RTK-GNSS + LiDAR + multi-spectral fusion	Deep CNN cascade + adaptive thresholding	Major row crops	87.3% (field practical)	2.1% (competitive)	1.4 ha/day (practical)	Balanced efficacy-productivity trade-off; field validation across 3 sites; economic analysis; practical commercialization readiness

Weed Control Efficiency (WCE) calculated as [(weed biomass control − weed biomass treatment)/weed biomass control] × 100. Crop injury measured as percentage of plants with visible damage. Field capacity in hectares of field actually weeded per day (accounting for non-productive time). SLAM = simultaneous localization and mapping; CNN = convolutional neural network.

5. Conclusion

1. As demonstrated by the present investigation, autonomous field robots fitted with sophisticated sensor-fusion, machine-learning based crop-weed differentiation, and targeted mechanical action can serve as practical substitutes to hand and traditional mechanical weed control in row-crop agriculture. The most important findings of the investigation can be summarized as follows:
2. **Weed Management Efficacy:** Autonomous robotic systems achieved 87.3% weed control efficiency, approaching manual weeding performance (94.2%) while substantially exceeding conventional mechanical weeding (76.5%), with progressive improvement through the growing season reflecting frequent operation protocols.
3. **Selectivity and Safety:** Crop injury from autonomous robotic operations (2.1%) was significantly lower than conventional mechanical weeding (8.3%) and comparable to manual weeding (3.8%), indicating that precision AI-assisted control provides sufficient selectivity for practical implementation.
4. **Operational Efficiency:** While field capacity of autonomous robots (1.4 ha/day) was lower than tractor-mounted systems (3.2–3.8 ha/day), the frequent operation protocol and high selectivity produced superior integrated season-long weed suppression, with no significant yield penalty compared to manual weeding.
5. **Labor Reduction:** Autonomous systems reduced labor requirements by 78% compared to manual weeding (2.7 vs 12.4 person-hours/hectare), addressing critical agricultural labor shortage constraints.
6. **Economic Feasibility:** At typical operational capacity (240 ha/year), autonomous systems achieved $87/hectare annual cost, representing 34% savings compared to manual weeding and comparable cost to conventional mechanical weeding, with improving economics projected as battery and computing costs decline.
7. **Environmental Sustainability:** Elimination of herbicide inputs and relatively low energy consumption (2.4 kWh/ha) position autonomous mechanical weeding as an environmentally sustainable alternative to chemical weed control, particularly valuable in regions emphasizing organic or pesticide-minimization production models.
8. **Agronomic Performance:** Grain yield from autonomous robot weeding (9.2 t/ha maize, 3.5 t/ha soybean) was equivalent to manual weeding and significantly higher than conventional mechanical weeding, confirming that improved weed selectivity preserved crop productivity despite lower absolute weed control efficiency.

These findings suggest that autonomous agricultural robots are now a mature technology getting close to commercialization. Future advances should focus on improving the quality of the AI models for better differentiation between crops and weeds under varying environmental conditions, cutting down on hardware prices to boost profits and combining the technology with other precision agriculture activities to achieve larger farm efficiency. The shift from manual weeding and weed management involving the use of pesticides to the use of autonomous mechanical systems is an important step on the way to sustainable agriculture worldwide, which will allow keeping the productivity of agriculture while minimizing negative environmental impact and solving the issue of labor shortages in agriculture. Investing in autonomous agricultural robot research and development should remain a priority, especially for regions suffering from labor shortages and having environmental concerns regarding the use of chemical pesticides.

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