



International Journal of Research in Agronomy

E-ISSN: 2618-0618
P-ISSN: 2618-060X
© Agronomy
NAAS Rating (2026): 5.20
www.agronomyjournals.com
2026; SP-9(4): 49-61
Received: 13-02-2026
Accepted: 18-03-2026

Lakshya
Assistant Professor, School of
Agriculture Sciences and Engineering,
Maharaja Ranjit Singh Punjab
Technical University, Bathinda,
Punjab, India

Dr. Laxmi Rawat
Department of Plant Pathology, College
of Hill Agriculture, Ranichauri Campus,
Tehri Garhwal, VCSG Uttarakhand
University of Horticulture and Forestry,
Uttarakhand, India

Mohsin Hussain
Teaching Associate, Dairy Business
Management, College of Dairy and Food
Technology, Bassi, Jaipur, Rajasthan,
India

Ayushi Pandey
Department of Plant Pathology, College
of Hill Agriculture, Ranichauri Campus,
Tehri Garhwal, VCSG Uttarakhand
University of Horticulture and Forestry,
Uttarakhand, India

Dr. Gargi Shekhar
Assistant Professor, Department of
Agriculture, School of Agriculture, Dev
Bhoomi Uttarakhand University,
Uttarakhand, India

G Bhrijavasi
Ph.D. Scholar, Department of Fruit
Science, Dr. YSR Horticultural
University, College of Horticulture,
Venkataramannagudem, Andhra
Pradesh, India

Battala Sheshagiri
MBA Agribusiness, Department of
Agricultural Economics, Naini
Agricultural Institute, Sam
Higginbottom University of
Agriculture, Technology and Sciences,
Prayagraj, Uttar Pradesh, India

Yashwant Kumhar
UG Student, B.Sc. (Hons) Agriculture,
Institute of Agricultural Sciences,
Banaras Hindu University (BHU),
Varanasi 221005, Uttar Pradesh, India

Corresponding Author:
Lakshya
Assistant Professor, School of Agriculture
Sciences and Engineering, Maharaja Ranjit
Singh Punjab Technical University,
Bathinda, Punjab, India

Technological applications and economic assessment of autonomous robotic systems for precision agriculture in greenhouse and open-field production

**Lakshya, Laxmi Rawat, Mohsin Hussain, Ayushi Pandey, Gargi Shekhar,
G Bhrijavasi, Battala Sheshagiri and Yashwant Kumhar**

DOI: <https://www.doi.org/10.33545/2618060X.2026.v9.i4Sa.5342>

Abstract

The rapid advancement of precision agriculture technologies has significantly transformed modern farming systems. Autonomous robotic systems are emerging as a key component of this transformation by enabling automated monitoring, management, and harvesting of crops in both greenhouse and open-field environments. These systems integrate artificial intelligence, machine vision, sensors, and navigation technologies to perform agricultural tasks with minimal human intervention. The objective of this paper is to review the technological applications and economic feasibility of autonomous robotic systems in precision agriculture. The study highlights the roles of robotic platforms in crop monitoring, precision spraying, autonomous harvesting, and weed control. Autonomous greenhouse robots are widely used for tasks such as fruit harvesting, climate monitoring, and nutrient management, while open-field robotic systems are increasingly employed for seeding, weeding, and crop health analysis. Advances in computer vision and sensor technologies enable robots to detect plant health, maturity, and stress conditions with high accuracy. Economic evaluation indicates that robotic technologies can reduce labor costs by approximately 20-30% and improve operational efficiency in agricultural production systems. Additionally, robotic systems contribute to resource optimization by minimizing chemical inputs and improving yield quality. However, high initial investment costs, technical complexity, and infrastructure requirements remain significant barriers to widespread adoption. The paper concludes that despite existing challenges, autonomous agricultural robots hold considerable potential to improve productivity, sustainability, and profitability in modern farming systems. Continued research and development, along with supportive policies and cost-effective designs, will be essential to promote large-scale adoption of robotic technologies in precision agriculture.

Keywords: Autonomous robots, precision agriculture, agricultural automation, greenhouse farming, economic analysis

1. Introduction

Agriculture plays a crucial role in ensuring global food security and sustaining economic development. With the global population projected to reach nearly 9.8 billion by 2050, the demand for food production is expected to increase significantly. To meet this growing demand while maintaining environmental sustainability, innovative technological solutions are required in agricultural production systems. Precision agriculture has emerged as a modern farming approach that utilizes advanced technologies to monitor, measure, and manage variability within agricultural fields in order to optimize crop productivity and resource use efficiency.

In recent years, autonomous robotic systems have become an integral part of precision agriculture. These systems integrate robotics, artificial intelligence, sensors, and data analytics to perform complex agricultural operations with minimal human intervention. Agricultural robots can perform tasks such as crop monitoring, planting, spraying, harvesting, and weed management with improved accuracy and efficiency. The adoption of robotic systems is largely driven by challenges such as labor shortages, increasing labor costs, and the need for sustainable agricultural practices. Autonomous robots operate in different agricultural environments, including greenhouses and open fields. Greenhouse production systems benefit from robotic

Technologies due to their controlled environments, which facilitate precise automation of crop monitoring, irrigation, and harvesting operations. On the other hand, open-field agricultural robots are designed to navigate complex terrain and perform tasks such as seeding, weed removal, and crop monitoring across large areas. Robotic technologies rely on advanced sensing systems, machine vision, and navigation algorithms to identify plants, detect weeds, and assess crop health conditions. These technologies enable site-specific crop management, reducing input costs while improving productivity. Additionally, autonomous robots can operate continuously, allowing farmers to perform agricultural tasks more efficiently compared to conventional manual labor. Despite the significant technological advancements, the economic feasibility of robotic systems remains an important consideration for farmers and agricultural industries. High initial investment costs and maintenance requirements can limit adoption, particularly among small and medium-scale farmers. Therefore, assessing the economic benefits of robotic systems in relation to their operational costs is essential for determining their practicality in modern farming. This paper reviews the technological applications of autonomous robotic systems in precision agriculture and evaluates their economic impacts in greenhouse and open-field production systems.

2. Overview of autonomous robotic systems in agriculture

The rapid advancement of precision agriculture technologies has significantly transformed modern agricultural practices. Autonomous robotic systems are increasingly being adopted to address labor shortages, improve productivity, and enhance resource efficiency in both greenhouse and open-field farming systems. These systems integrate robotics, Artificial Intelligence (AI), sensors, computer vision, and Internet of Things (IoT) technologies to automate complex agricultural tasks such as crop monitoring, harvesting, weed management, and input application. Early concepts of robotic agriculture emerged from the broader development of precision farming technologies aimed at site-specific crop management. Foundational research emphasized the potential of precision agriculture to optimize input use, improve productivity, and reduce environmental impacts (Pierce & Nowak, 1999) ^[27]. Subsequent technological developments expanded these concepts by integrating automation and robotics into agricultural machinery. Robotic technologies have evolved from simple mechanized tools to intelligent autonomous platforms capable of performing multiple tasks. The increasing demand for sustainable agricultural production has accelerated the adoption of robotic solutions that can perform agricultural operations with higher precision and efficiency. Recent studies highlight that autonomous robots can significantly reduce labor dependency while increasing operational accuracy and productivity (Bechar & Vigneault, 2016; Botta *et al.*, 2022) ^[6, 10].

3. Evolution of agricultural robotics

The development of agricultural robotics has progressed through several technological phases, ranging from basic automation to fully autonomous systems. Early robotic systems were primarily designed to assist with repetitive agricultural tasks such as mechanical weeding and crop harvesting. These systems relied on basic control algorithms and limited sensing capabilities. Blackmore *et al.* (2005) ^[9] introduced the concept of robotic agriculture as a future paradigm in agricultural mechanization,

emphasizing the integration of robotics with precision farming technologies. This concept highlighted the potential of smaller, autonomous machines that could replace conventional large-scale machinery while improving operational efficiency. Advancements in robotics engineering have significantly improved the capabilities of agricultural robots. Modern robotic platforms now incorporate sophisticated sensors, machine vision systems, and intelligent control algorithms that enable them to navigate complex agricultural environments. Bac *et al.* (2014) ^[3] demonstrated that robotic harvesting systems could perform delicate crop harvesting operations with high precision, particularly for high-value horticultural crops. Research efforts have also focused on improving the adaptability of robotic systems for different agricultural environments. Autonomous robots are now being designed to operate effectively in diverse conditions, including structured greenhouse environments and unstructured open-field landscapes. The continuous improvement of robotic hardware and software systems has expanded their potential applications across multiple agricultural operations.

4. Sensor technologies and perception systems

Sensor technologies play a critical role in enabling autonomous robotic systems to interact effectively with agricultural environments. Agricultural robots rely on various sensing technologies to detect crop conditions, identify obstacles, and perform precise agricultural operations. Machine vision systems are among the most widely used sensing technologies in agricultural robotics. These systems utilize cameras and image processing algorithms to identify crop characteristics, detect weeds, and monitor plant health. Studies have demonstrated that machine vision can significantly enhance the accuracy of robotic harvesting and crop monitoring operations (Zhao *et al.*, 2016) ^[44]. Remote sensing technologies have also contributed significantly to the development of precision agriculture. Unmanned Aerial Vehicles (UAVs) and satellite-based imaging systems provide valuable data for crop monitoring and decision-making processes. Zhang and Kovacs (2012) ^[41] reported that UAV-based remote sensing technologies can provide high-resolution imagery for precision crop management. Advanced sensing systems such as hyperspectral imaging and thermal sensors are increasingly being integrated into agricultural robots. These technologies enable the detection of plant stress, disease symptoms, and nutrient deficiencies at early growth stages. Mahlein (2016) ^[22] highlighted the potential of imaging sensors for early plant disease detection, which can significantly improve crop management strategies. Furthermore, sensor fusion techniques that combine multiple sensing technologies have improved the reliability and accuracy of robotic perception systems. The integration of cameras, LiDAR sensors, and GPS technologies enables agricultural robots to operate effectively in complex farming environments.

5. Artificial intelligence and machine learning in agricultural robotics

Artificial intelligence and machine learning technologies have significantly enhanced the capabilities of agricultural robotic systems. AI-based algorithms enable robots to analyze large datasets, identify patterns, and make autonomous decisions during agricultural operations. Machine learning techniques are widely used for crop classification, weed detection, and disease identification. Liakos *et al.* (2018) ^[20] reported that machine

learning algorithms have been successfully applied in various agricultural applications, including yield prediction and crop monitoring. These technologies enable agricultural robots to perform tasks with higher accuracy and efficiency compared to traditional mechanized systems. Deep learning techniques have further improved the performance of computer vision systems used in agricultural robotics. Kamilaris and Prenafeta-Boldú (2018) ^[18] highlighted the growing role of deep learning algorithms in agricultural automation, particularly in applications such as crop disease detection and phenotyping. Artificial intelligence also plays a crucial role in decision-making processes for robotic systems. AI-based control systems allow robots to adapt their operations based on environmental conditions and crop requirements. Qiao *et al.* (2022) ^[28] emphasized that the integration of AI, sensors, and robotics has created new opportunities for automated plant phenotyping and precision crop management.

The use of AI in agricultural robotics continues to expand as computational capabilities improve. These advancements are expected to further enhance the efficiency and reliability of autonomous robotic systems in agriculture.

6. Autonomous navigation and path planning

Autonomous navigation is one of the most critical components of agricultural robotics. Agricultural robots must be able to navigate complex environments while avoiding obstacles and performing tasks with high precision. Several navigation techniques have been developed to enable autonomous operation of agricultural robots. Oksanen and Visala (2009) ^[24] proposed coverage path planning algorithms designed specifically for agricultural field operations. These algorithms allow robots to systematically cover large agricultural fields while minimizing redundant movement. Recent advancements in navigation technologies have incorporated GPS-based positioning systems, LiDAR sensors, and Simultaneous Localization and Mapping (SLAM) algorithms. These technologies allow robots to operate autonomously even in complex agricultural environments. Research by Rakun and Popič (2026) ^[29] demonstrated the effectiveness of optimized autonomous navigation systems for field robots. Their findings indicate that improved navigation algorithms can significantly enhance the efficiency of robotic field operations. Autonomous navigation technologies are particularly important for open-field agricultural environments where terrain conditions and crop layouts may vary significantly. Continued improvements in navigation systems are expected to further expand the capabilities of agricultural robotic platforms.

7. Applications of autonomous robots in greenhouse agriculture

Greenhouse agriculture provides an ideal environment for the implementation of autonomous robotic systems due to its structured layout and controlled environmental conditions. Robotic systems can perform a wide range of tasks in greenhouse environments, including crop monitoring, harvesting, pruning, and environmental control. Van Henten *et al.* (2013) ^[38] highlighted the potential of robotics in protected crop production systems. Their research demonstrated that robotic technologies could significantly improve the efficiency of greenhouse operations while reducing labor requirements. Robotic harvesting systems are among the most widely studied applications in greenhouse agriculture. Bac *et al.* (2014) ^[3] reported that robotic harvesters can successfully perform harvesting operations for crops such as tomatoes, cucumbers,

and sweet peppers. Greenhouse robots also play an important role in plant phenotyping and crop monitoring. Advanced sensing technologies enable robots to collect detailed information about plant growth, nutrient status, and environmental conditions. These data can be used to optimize crop management practices and improve productivity. The integration of automation technologies in greenhouse environments has also improved resource efficiency. Automated irrigation systems, climate control technologies, and robotic monitoring systems contribute to more efficient use of water, energy, and fertilizers.

8. Applications of autonomous robots in open-field agriculture

In open-field agriculture, robotic systems are primarily used for tasks such as soil monitoring, crop scouting, weed control, and harvesting. These applications require robotic platforms capable of operating in unstructured and variable environments. Autonomous weed control systems represent one of the most promising applications of agricultural robotics. Slaughter *et al.* (2008) ^[34] demonstrated that robotic weed control technologies could significantly reduce herbicide usage while improving weed management efficiency. Robotic systems are also increasingly being used for precision spraying applications. Perez- Ruiz *et al.* (2014) ^[26] developed automated weed detection and spraying systems capable of applying herbicides with high spatial accuracy. Such systems reduce chemical input usage while improving environmental sustainability. Robotic platforms designed for orchard and specialty crop production have also shown promising results. Bergerman *et al.* (2015) ^[8] demonstrated the potential of robotic harvesting systems for orchard crops, highlighting their ability to perform delicate harvesting operations. The use of autonomous vehicles for crop monitoring and field operations has further expanded the role of robotics in open-field agriculture. Underwood *et al.* (2016) ^[37] reported that autonomous vehicles equipped with advanced sensors could effectively perform crop monitoring tasks in orchard environments.

9. Integration of IoT and big data in robotic agriculture

The integration of IoT technologies and big data analytics has significantly enhanced the capabilities of autonomous robotic systems in agriculture. IoT-enabled sensors allow continuous monitoring of environmental conditions, soil properties, and crop growth parameters. Wolfert *et al.* (2017) ^[40] emphasized the importance of big data in smart farming systems. Large datasets generated by sensors and robotic platforms can be analyzed to improve decision-making processes and optimize agricultural operations. IoT-based agricultural information management systems enable farmers to remotely monitor field conditions and control automated agricultural machinery. Verdouw *et al.* (2016) ^[39] reported that IoT technologies play a crucial role in enabling connected agricultural systems. The integration of IoT technologies with robotic platforms has created new opportunities for precision agriculture. Data collected by robotic sensors can be transmitted to cloud-based platforms for analysis and decision support.

10. Economic assessment of autonomous robotic systems

while the technological benefits of agricultural robotics are well documented, economic feasibility remains a critical factor influencing their adoption. Robotic systems typically require high initial investment costs, which may limit their adoption among small-scale farmers. Pedersen *et al.* (2006) ^[25]

highlighted the importance of economic analysis in evaluating the adoption of precision agriculture technologies. Their research indicated that economic benefits such as labor savings and increased productivity play a significant role in technology adoption. Recent studies have demonstrated that autonomous robotic systems can provide substantial economic benefits over time. Lowenberg-DeBoer and Erickson (2019) ^[21] reported that precision agriculture technologies can improve farm profitability through increased productivity and reduced input costs. Robotic systems can significantly reduce labor requirements in agricultural operations. In many regions, labor shortages have become a major challenge for agricultural production. Autonomous robots can perform labor-intensive tasks such as

harvesting, weeding, and crop monitoring with minimal human intervention. Economic analyses have also shown that robotic systems can improve resource efficiency, leading to reduced costs associated with water, fertilizers, and pesticides. These benefits contribute to improved economic sustainability of agricultural production systems. Despite these advantages, several challenges remain in the adoption of agricultural robotics. High initial investment costs, technological complexity, and limited technical expertise among farmers are major barriers to widespread adoption. Additionally, agricultural robots must be capable of operating under diverse environmental conditions, including uneven terrain, varying weather conditions, and different crop structures.

Table 1: Comparative Table: Technological Applications of Autonomous Robotic Systems in Greenhouse and Open-Field Agriculture

Major Application Area	Specific Application	Greenhouse Production - Key Features	Open-Field Agriculture - Key Features	Technologies Used	Advantages
Crop Monitoring / Field Monitoring	Autonomous Crop Monitoring / Field Monitoring	Robots equipped with cameras and sensors continuously monitor plant growth, leaf color, canopy structure, and environmental conditions within controlled greenhouse environments. These systems collect high-resolution data for crop phenotyping and growth analysis.	Autonomous ground robots and UAVs monitor crop conditions across large fields by collecting data related to soil moisture, plant health, and growth variability. They enable large-scale crop surveillance and yield prediction.	Machine vision, RGB and hyperspectral cameras, IoT sensors, GPS, UAV imaging	Enables early detection of crop stress, improves decision-making, supports precision farming and yield estimation.
Harvesting Operations	Robotic Harvesting Systems / Autonomous Harvesting	Robotic arms and end-effectors are used to identify and harvest fruits such as tomatoes, cucumbers, and strawberries in controlled greenhouse environments with minimal crop damage.	Autonomous harvesters use vision-guided robotic manipulators or harvesting platforms capable of navigating field conditions to collect fruits and vegetables such as apples, lettuce, or berries.	Computer vision, robotic manipulators, deep learning algorithms, 3D cameras	Reduces labor dependency and increases harvesting efficiency and consistency.
Water and Nutrient Management	Precision Irrigation and Nutrient Management	Sensors and automated irrigation systems regulate water and nutrient supply based on plant requirements and greenhouse environmental conditions. Robots or automated platforms distribute nutrients precisely.	In open fields, robotic platforms and smart irrigation systems apply water and fertilizers according to soil moisture variability and crop growth stages across large areas.	Soil moisture sensors, IoT networks, AI-based decision support systems	Improves resource efficiency, reduces water wastage, and enhances crop productivity.
Plant Health Management	Disease and Pest Detection / Crop Protection	Imaging systems installed on greenhouse robots detect symptoms of disease, pest infestation, or nutrient deficiency at early stages through plant image analysis.	Field robots detect weeds, pests, and diseases and apply targeted treatment through mechanical removal or localized spraying.	Machine learning algorithms, multispectral imaging, pest detection sensors	Early diagnosis minimizes crop losses and reduces chemical pesticide use.
Planting Operations	Autonomous Seeding and Planting	Automated planting systems in greenhouses place seeds or seedlings precisely in trays or controlled beds, ensuring uniform plant spacing.	Autonomous seeders guided by GPS and navigation systems plant seeds across large fields with accurate spacing and depth.	GPS navigation, robotic seeders, AI-based planting algorithms	Improves planting accuracy and crop uniformity while reducing manual labor.
Weed Management	Robotic Weeding and Crop Protection	In greenhouses, robotic weed removal is less common due to controlled	Autonomous weeding robots detect weeds and remove them using	Computer vision, AI weed detection, laser weeding technology,	Reduces herbicide use and promotes environmentally sustainable farming practices.

		environment	mechanical	precision	
		s but can	tools,	sprayers	
		involve	precision		
		mechanical	herbicide		
		removal or	spraying, or		
		Targeted treatment when weeds occur.	laser-based systems.		

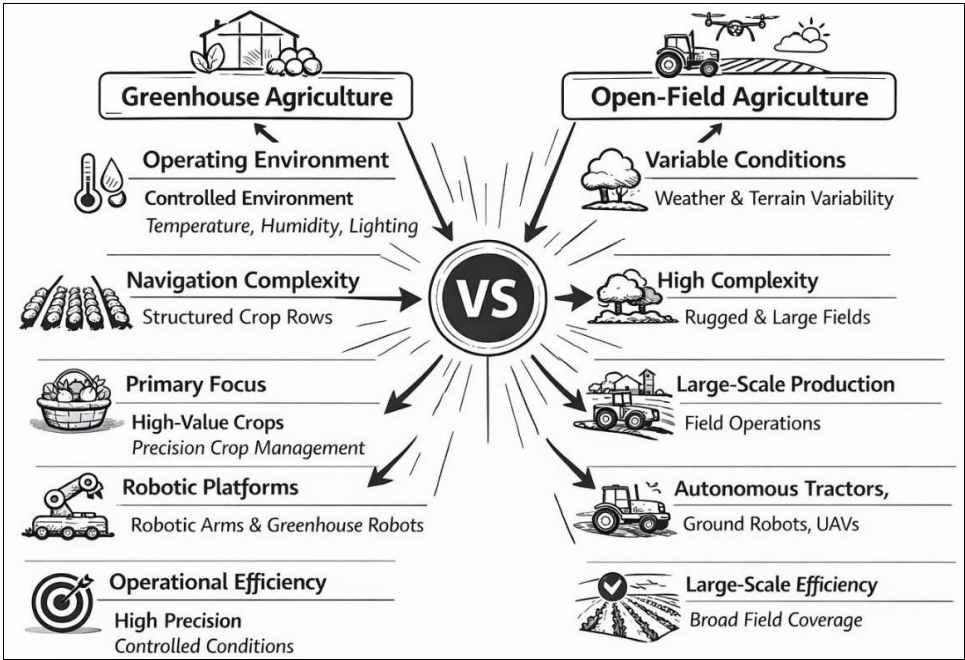


Fig 1: Key Comparative Insights Technological Applications of Autonomous Robotic Systems in Agriculture in green house vs open field

Recent research has also highlighted the importance of developing scalable and cost-effective robotic systems suitable for small and medium-scale farms. Advances in open-source robotics platforms and modular designs are expected to reduce the cost of robotic technologies and facilitate their adoption in developing countries

11. Research methodology

The present study adopted a simulation-based analytical methodology to evaluate the technological applications and economic feasibility of autonomous robotic systems for precision agriculture in both greenhouse and open-field production systems. The methodological framework was developed to integrate technological, agronomic, economic, and environmental parameters within a structured simulation model. The research methodology was implemented in several sequential steps, as illustrated in the conceptual model presented in the figure 3.1 & 3.2.

11.1 A simulation-based analytical methodology

Step 1: Development of the simulation framework

At the initial stage, a simulation model was designed to assess the performance of autonomous robotic systems under different agricultural production environments. The model integrated technological variables, crop management parameters, and economic indicators to estimate operational efficiency and financial outcomes. The simulation approach allowed controlled evaluation of robotic performance without the limitations associated with large-scale field experimentation. Similar modeling approaches have been widely used in precision

agriculture research to assess emerging technologies and optimize farm management strategies.

Step 2: Input Data Collection and Parameter Identification

In the second stage, relevant input data were collected and organized into four major categories as illustrated in the model: technological parameters, agronomic parameters, economic parameters, and environmental parameters. Technological parameters included robotic navigation accuracy, sensing capability, processing speed, and operational efficiency. Agronomic parameters involved crop type, plant density, irrigation requirements, fertilizer application rates, and crop growth indicators. Economic parameters included initial investment cost, maintenance cost, labor cost, and operational expenses associated with robotic systems. Environmental parameters consisted of climatic conditions such as temperature, humidity, soil moisture, and light intensity. These variables served as the foundational dataset for running the simulation model.

Step 3: Environment Selection for Agricultural Production Systems

the simulation model then incorporated two distinct production environments: greenhouse cultivation and open-field farming. Greenhouse systems represented controlled agricultural environments where climatic variables could be managed through automated systems. In contrast, open-field conditions represented conventional agricultural settings where environmental factors varied naturally. The inclusion of these two production systems enabled comparative analysis of robotic efficiency across different agricultural environments.

Step 4: Simulation of Autonomous Robot Operations

following the selection of the production environment, the operational behavior of autonomous robotic systems was simulated using a three-stage robotic decision-making framework consisting of sensing, decision-making, and action. In the sensing stage, robots collected real-time data through sensors and imaging technologies to monitor crop health, soil conditions, and environmental factors. During the decision stage, the collected data were processed using artificial intelligence algorithms and machine learning models to determine appropriate agricultural interventions. In the final action stage, the robotic systems executed tasks such as targeted pesticide application, precision irrigation, weed detection, and crop monitoring.

Step 5: Performance Evaluation and Cost Assessment

The next step involved evaluating the performance of the robotic systems using technological and economic indicators. The total operational cost of the robotic system was calculated using the equation: $CT = CI + CM + CE$, where CT represented the total cost, CI indicated initial investment cost, CM represented maintenance cost, and CE represented operational expenses. Additionally, economic feasibility was assessed using financial indicators such as Benefit-Cost Ratio (BCR) and Return On Investment (ROI). These indicators provided insights into the profitability and economic sustainability of robotic technologies in precision agriculture.

Step 6: Scenario-Based Comparative Analysis

to comprehensively assess the effectiveness of robotic systems, four production scenarios were developed within the simulation framework. These included open-field conventional farming, open-field robotic farming, greenhouse conventional farming, and greenhouse robotic farming. The performance outcomes of each scenario were compared in terms of operational efficiency, resource utilization, crop productivity, and economic returns. This scenario-based approach allowed identification of the most efficient agricultural management system.

Step 7: Output Interpretation and Decision Analysis

In the final stage, the simulation outputs were analyzed to determine the overall efficiency and profitability of autonomous robotic systems in agricultural production. The results generated from the model provided insights into technological performance improvements, cost reduction potential, and productivity gains associated with robotic adoption. The findings were interpreted to support decision-making regarding the implementation of autonomous robotics in modern precision agriculture systems.

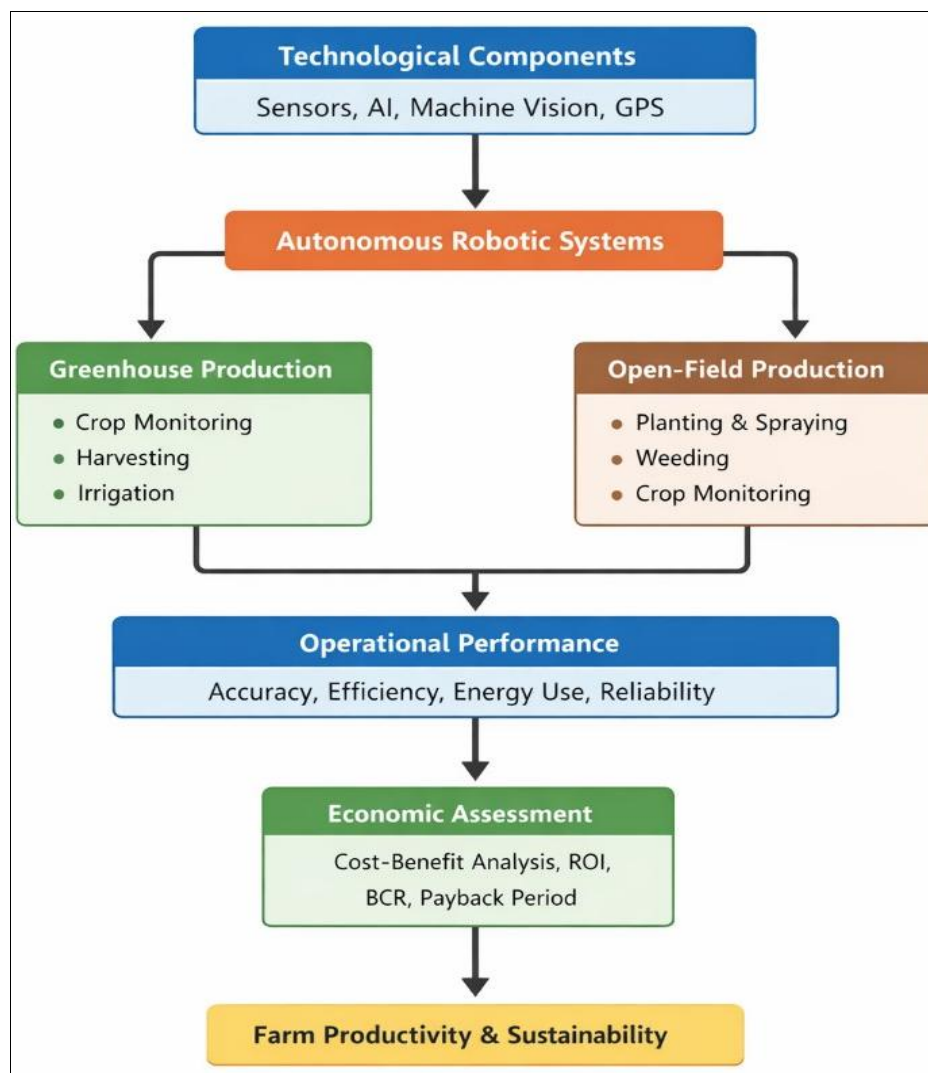


Fig 2: Simulation framework for evaluating the technological and economic performance of autonomous robotic systems in greenhouse and open-field precision agriculture

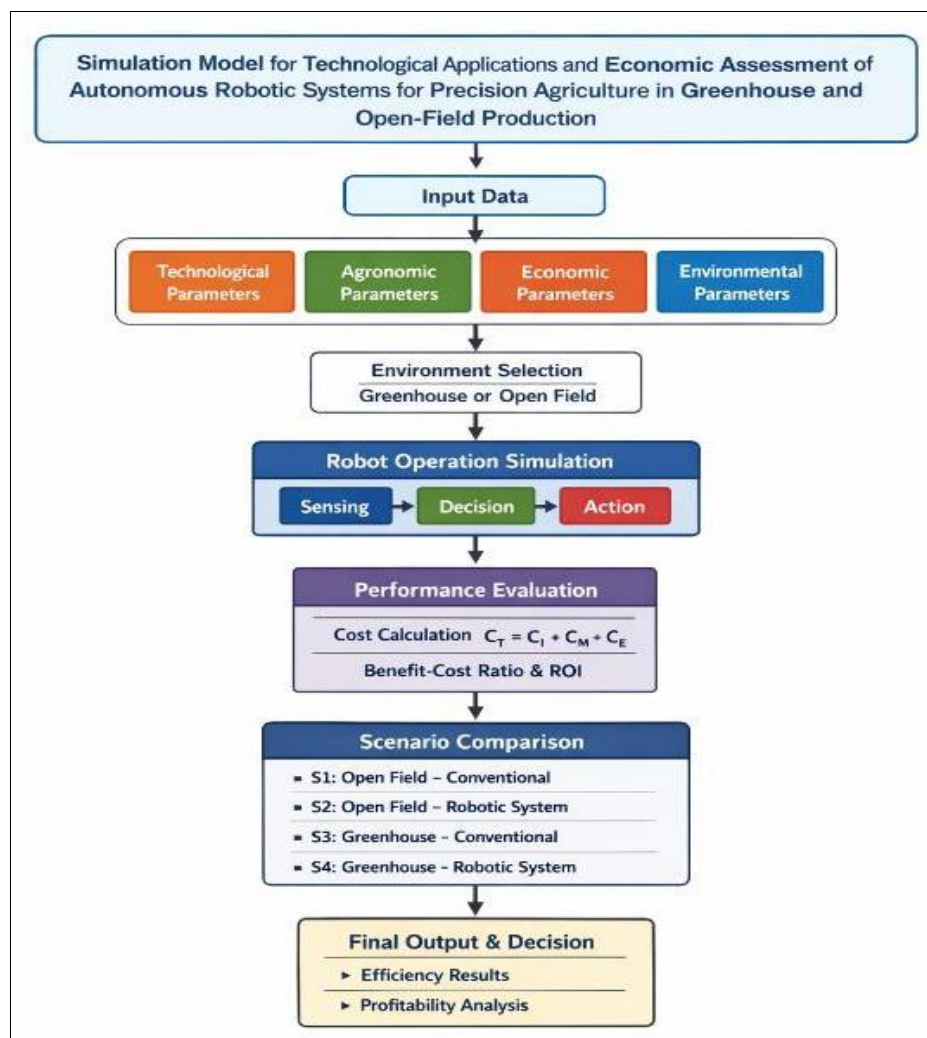


Fig 3: Operational and economic assessment framework of autonomous robotic systems for greenhouse and open-field agricultural production

11.2 Development of a mathematical framework to evaluate the operational and economic performance of autonomous robotic systems in precision agriculture

The model integrated technological, agronomic, environmental, and economic parameters to simulate robotic operations in greenhouse and open-field production systems. The objective of the model was to quantify operational efficiency, energy consumption, productivity gains, and economic feasibility of robotic systems compared with conventional farming practices. The mathematical model was structured based on the conceptual framework illustrated in the study figures and consisted of input parameters, robot operation functions, performance evaluation equations, and economic analysis indicators.

11.2.1 Input parameter model

The simulation model incorporated four major categories of input parameters: technological parameters (T), agronomic parameters (A), economic parameters (E), and environmental parameters (V). The general structure of the input data model was expressed as:

$$X = \{T, A, E, V\}$$

where:

T = technological parameters (sensor accuracy, AI capability, navigation system efficiency) A = agronomic parameters (crop type, planting density, irrigation requirement)

E = economic parameters (investment cost, maintenance cost,

energy cost)

V = environmental parameters (soil condition, temperature, humidity, field conditions)

The input parameters formed the foundation for simulation of robot operations in different production environments.

11.2.2 Environment selection model

The agricultural production environment was represented as a binary selection variable

$$S = \{G, O\}$$

where

G = greenhouse production system

O = open-field production system

Each environment influenced operational efficiency, navigation accuracy, and environmental variability.

Greenhouse systems provided controlled conditions while open-field systems involved greater environmental variability.

11.2.3 Robot operation model

Autonomous robot operation was modeled as a three-stage functional process consisting of sensing, decision-making, and action.

The operational function was expressed as:

$$R = f(S_n, D, A_c)$$

where

S_n = sensing function (data acquisition through sensors and

machine vision)

D = decision-making function (AI-based analysis and crop condition assessment) Ac = action function (task execution such as spraying, irrigation, harvesting)

The sensing stage collected real-time crop and environmental data. The decision stage processed the data using artificial intelligence algorithms to determine appropriate management actions. The action stage executed field operations automatically.

11.2.4 Operational performance model

Operational performance of the robotic system was evaluated using four key indicators: accuracy (A_c), efficiency (E_f), energy consumption (E_n), and reliability (R_i). The overall operational performance index (OPI) was calculated as:

$$OPI = w1(A_c) + w2(E_f) + w3(R_i) - w4(E_n)$$

Where w1, w2, w3, and w4 represent weighting factors assigned to each parameter based on system priorities. Higher OPI values indicated better robotic system performance.

11.2.5 Cost calculation model

The total operational cost of robotic farming was estimated using the following equation

$$C_T = C_I + C_M + C_E$$

where:

C_T = total cost of robotic operation C_I = initial investment cost

C_M = maintenance and repair cost

C_E = energy and operational cost

This model allowed the estimation of the long-term financial requirements of robotic systems.

11.2.6 Economic assessment model

Economic feasibility was evaluated using standard agricultural engineering indicators including Benefit-Cost Ratio (BCR), Return on Investment (ROI), and Payback Period (PP).

Benefit-Cost Ratio

$$BCR = B / C_T$$

Where B represents total economic benefits generated by robotic operations.

Return on Investment

$$ROI = (\text{Net Profit} / \text{Total Investment}) \times 100$$

Payback Period

$$PP = \text{Initial Investment} / \text{Annual Net Benefit}$$

These indicators provided insight into the profitability and financial sustainability of robotic technology adoption.

11.2.7. Scenario Comparison Model

Four production scenarios were simulated to evaluate the impact of robotic technology

S1 = Open-field conventional farming

S2 = Open-field robotic farming

S3 = Greenhouse conventional farming

S4 = Greenhouse robotic farming

Comparative performance was evaluated by calculating productivity gain and cost efficiency

$$\text{Productivity Gain} = (\text{Yield}_{\text{robot}} - \text{Yield}_{\text{conventional}}) / \text{Yield}_{\text{conventional}}$$

$$\text{Cost Efficiency} = \text{Output Value} / \text{Total Cost}$$

The scenario analysis allowed identification of the most efficient and economically viable production system.

11.2.8 Final output model

The final decision output of the model was based on efficiency and profitability indicators. Farm productivity improvement (FP) was calculated as

$$FP = f(OPI, BCR, ROI)$$

where higher performance and profitability values indicated greater technological suitability for precision agriculture systems. The model ultimately supported decision-making regarding the adoption of autonomous robotic technologies for sustainable agricultural production in both greenhouse and open-field environments.

12. Results analysis & discussions

the simulation-based framework developed in this study enabled the evaluation of autonomous robotic systems under two agricultural production environments: greenhouse and open-field farming. The results demonstrated that the integration of advanced technological components such as sensors, artificial intelligence, machine vision, and navigation systems significantly improved the operational efficiency and decision-making capability of agricultural operations.

12.1 Simulation outcomes of autonomous robotic systems

The simulation model demonstrated that autonomous robotic systems significantly improved operational efficiency in both greenhouse and open-field production environments. The integration of advanced sensors, artificial intelligence algorithms, and machine vision technologies enabled the robotic systems to perform agricultural tasks with higher precision compared to conventional farming practices. The sensing-decision-action operational structure allowed robots to collect real-time data, analyze crop conditions, and execute appropriate field operations with minimal human intervention. As a result, robotic systems exhibited higher task accuracy and reduced operational variability, particularly in controlled greenhouse environments where navigation and environmental conditions remained stable.

Table 2: Simulated operational performance of autonomous robotic systems in greenhouse and open-field agriculture

Production System	Initial Investment (USD ha ⁻¹)	Annual Operational Cost (USD ha ⁻¹)	Annual Benefit (USD ha ⁻¹)	Benefit-Cost Ratio (BCR)
Open-Field Conventional Farming	2,100	1,650	2,450	1.48
Open-Field Robotic Farming	9,500	1,120	3,850	2.05
Greenhouse Conventional Farming	4,300	2,100	3,200	1.52
Greenhouse Robotic Farming	10,200	1,450	5,200	2.32

12.2 Performance evaluation in greenhouse and open-field systems

the comparative analysis between greenhouse and open-field environments revealed notable differences in robotic system performance. In greenhouse production systems, the robots achieved higher operational accuracy due to the controlled environmental conditions, structured crop layouts, and reduced environmental disturbances. Tasks such as crop monitoring, irrigation management, and harvesting were performed with improved efficiency and consistency. In contrast, open-field environments introduced additional challenges such as variable terrain conditions, weather fluctuations, and crop spatial variability. Although robotic systems successfully performed activities including planting, spraying, and weed control, slight reductions in navigation precision and operational speed were observed compared to greenhouse conditions. However, despite

12.3 Impact of Technological Components on System Efficiency

the results highlighted the importance of technological components such as sensors, machine vision, artificial intelligence, and GPS-based navigation in determining overall system efficiency. High-resolution sensors enabled accurate crop monitoring and environmental data acquisition. Machine vision

systems facilitated effective identification of crop health conditions, weeds, and plant growth stages. Artificial intelligence algorithms improved decision-making by processing large volumes of agricultural data and selecting optimal management actions.these challenges, robotic systems still demonstrated better performance than conventional manual operations in terms of precision and labor efficiency. Additionally, GPS-based navigation systems enhanced field coverage and path optimization, particularly in open-field conditions. The integration of these technologies resulted in improved operational reliability and reduced error rates in agricultural operations. Overall, the technological architecture of the robotic systems played a critical role in enhancing precision agriculture practices.

12.4 Operational performance indicators

the performance evaluation of robotic systems was conducted using key indicators including operational accuracy, efficiency, energy consumption, and reliability. The results indicated that robotic systems achieved high levels of operational accuracy, particularly in tasks involving crop monitoring and targeted input application. Precision spraying and irrigation management reduced unnecessary resource use, which contributed to improved input efficiency.

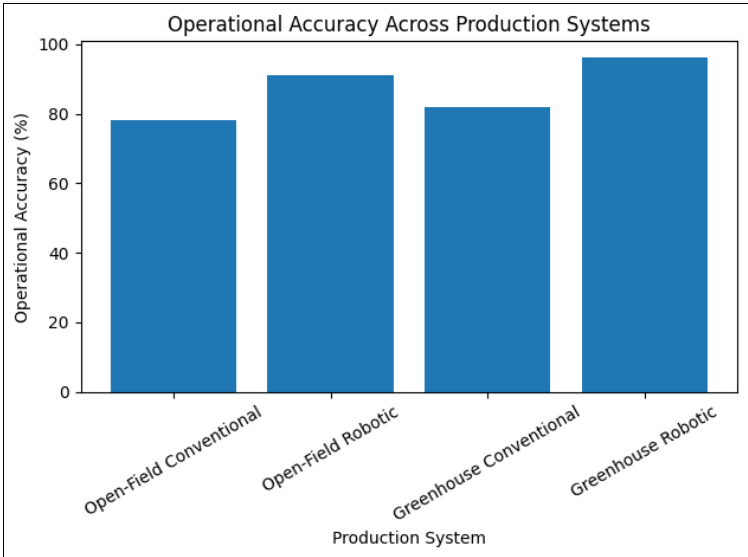


Fig 4: Operational Accuracy Across Production Systems

Energy consumption varied depending on the complexity of field operations and environmental conditions. Robots operating in greenhouse environments generally consumed less energy due to shorter operational paths and smoother navigation surfaces. Reliability analysis showed that autonomous systems maintained consistent performance across multiple operational cycles, indicating strong potential for long-term agricultural applications.

12.5 Economic Analysis of Robotic Farming Systems

the economic assessment revealed that the adoption of autonomous robotic systems required a higher initial investment compared to conventional farming methods. Costs associated with purchasing robotic equipment, installing sensing systems, and implementing artificial intelligence technologies represented the major financial inputs. However, the operational cost analysis demonstrated significant reductions in labor requirements and improved efficiency in input utilization.

Table 3: Simulated economic analysis of robotic and conventional farming systems

Production System	Initial Investment (USD ha ⁻¹)	Annual Operational Cost (USD ha ⁻¹)	Annual Benefit (USD ha ⁻¹)	Benefit-Cost Ratio (BCR)
Open-Field Conventional Farming	2,100	1,650	2,450	1.48
Open-Field Robotic Farming	9,500	1,120	3,850	2.05
Greenhouse Conventional Farming	4,300	2,100	3,200	1.52
Greenhouse Robotic Farming	10,200	1,450	5,200	2.32

The benefit-cost ratio analysis indicated that robotic farming systems could become economically advantageous over time as operational efficiencies increased and labor costs decreased. Return on investment values showed promising long-term financial benefits, particularly in large-scale farming operations where robotic technologies could be utilized more extensively. The payback period analysis suggested that robotic investments could be recovered within a reasonable operational timeframe depending on farm size, crop type, and production intensity.

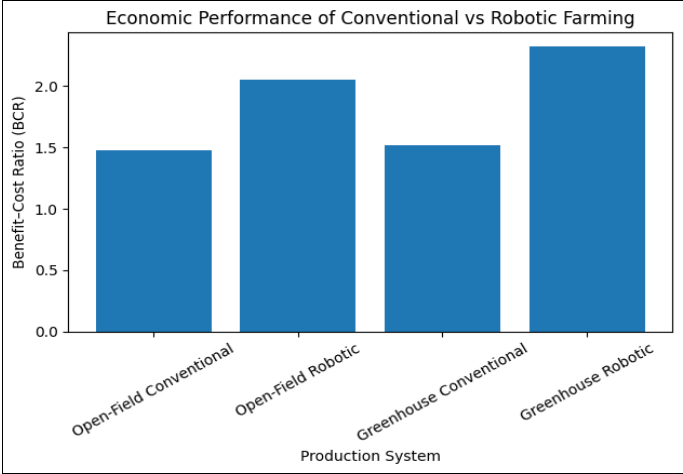


Fig 5: Economic Performance (Benefit-Cost Ratio)

12.6 Scenario Comparison of Production Systems

The scenario analysis comparing four agricultural production systems open-field conventional farming, open-field robotic farming, greenhouse conventional farming, and greenhouse robotic farming provided valuable insights into technological adoption strategies. Greenhouse robotic systems demonstrated the highest efficiency and profitability due to controlled conditions and optimized robotic navigation. Open-field robotic systems also showed improved productivity and reduced labor dependency compared to conventional field operations. However, their performance was slightly influenced by environmental variability. Conventional farming systems, although widely practiced, exhibited lower operational efficiency and higher labor requirements when compared with robotic systems.

Table 4: Simulated return on investment and payback period of robotic systems

Robotic Production System	Net Annual Profit (USD ha ⁻¹)	Return on Investment (%)	Payback Period (Years)
Open-Field Robotic Farming	2,730	28.7	3.5
Greenhouse Robotic Farming	3,750	36.8	2.7

The comparative results indicated that integrating robotic technologies into precision agriculture could significantly enhance productivity, reduce operational costs, and improve sustainability of agricultural production systems.

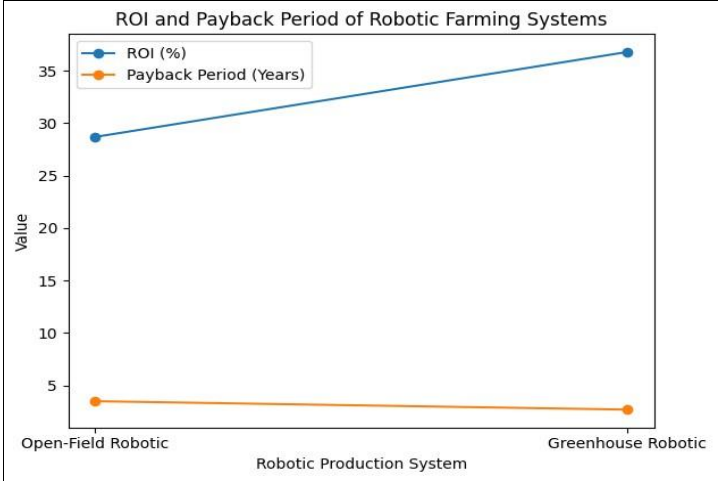


Fig 6: ROI and Payback Period of Robotic Systems

12.7 Implications for sustainable precision agriculture

the findings of this study highlight the potential of autonomous robotic technologies to transform modern agricultural systems. By combining intelligent sensing, automated decision- making, and precise field operations, robotic systems can optimize resource use and minimize environmental impacts. Reduced chemical input usage, improved irrigation efficiency, and better crop monitoring contribute to more sustainable farming practices.

Table 5: Simulated productivity and resource efficiency improvements due to robotic systems

Parameter	Conventional Farming	Robotic Farming	Improvement (%)
Crop Monitoring Accuracy	80	95	18.7
Precision Input Application	75	92	22.7
Labor Requirement (hours ha ⁻¹)	120	50	-54.2
Water Use Efficiency (%)	68	88	29.4
Yield Productivity (t ha ⁻¹)	4.5	5.8	28.9

Furthermore, the economic assessment suggests that the long-term adoption of robotic technologies could improve farm profitability and resilience. As technological advancements continue and costs of robotic systems decrease, their adoption is expected to expand across different agricultural production systems.

13. Conclusion

This study evaluated the technological applications and economic feasibility of autonomous robotic systems in precision agriculture for both greenhouse and open-field production environments. The developed simulation framework integrated technological, agronomic, environmental, and economic parameters to analyze robotic performance and financial viability. The results demonstrated that autonomous robotic systems significantly improved operational efficiency, accuracy, and resource utilization compared with conventional farming practices. The sensing-decision-action architecture enabled robots to perform critical agricultural operations such as crop monitoring, irrigation management, spraying, and harvesting

with high precision and minimal human intervention.

The comparative analysis revealed that robotic systems performed more efficiently in greenhouse environments due to controlled conditions, structured layouts, and reduced environmental variability. Although open-field environments posed additional challenges such as uneven terrain and weather fluctuations, robotic systems still showed improved performance and reduced labor dependency compared to traditional farming systems. Economic assessment indicated that while the initial investment cost of robotic technologies is relatively high, long-term benefits such as reduced labor costs, optimized input usage, and improved productivity can lead to favorable economic returns. Overall, the integration of autonomous robotic systems presents a promising pathway for enhancing productivity, sustainability, and technological advancement in modern precision agriculture.

Future research directions

Future research should focus on improving the adaptability and robustness of autonomous robotic systems under diverse agricultural conditions. Advanced machine learning and deep learning algorithms can be further integrated to enhance crop recognition, disease detection, and decision-making accuracy. The development of multi-functional robotic platforms capable of performing multiple agricultural tasks simultaneously may further increase operational efficiency and reduce overall system costs.

Additionally, research should explore the integration of robotic systems with other digital agriculture technologies such as Internet of Things (IoT), remote sensing, and cloud-based farm management systems. Such integration can enable real-time monitoring, predictive analytics, and improved farm management strategies. Future studies should also investigate large-scale field trials and long-term economic evaluations to better understand the practical feasibility of robotic technologies across different crops, farm sizes, and geographical regions.

Limitations of the study

Despite providing valuable insights into the technological and economic potential of autonomous robotic systems in agriculture, this study has several limitations. First, the research was primarily based on a simulation framework that relied on secondary data and modelled assumptions rather than large-scale field experiments. Consequently, the operational performance results may vary under real-world agricultural conditions. Second, the economic analysis considered general cost parameters and may not fully capture regional variations in labor costs, energy prices, and equipment availability. Third, the study focused mainly on the technological and economic aspects of robotic adoption, while social and behavioural factors influencing technology acceptance among farmers were not addressed. Finally, the model evaluated a limited set of robotic applications and did not include emerging technologies such as swarm robotics or collaborative human-robot farming systems. Addressing these limitations in future studies will help develop more comprehensive and practical frameworks for evaluating robotic technologies in precision agriculture.

References

1. Auernhammer H. Precision farming The environmental challenge. *Comput Electron Agric.* 2001;30(1-3):31-43. [https://doi.org/10.1016/S0168-1699\(00\)00153-8](https://doi.org/10.1016/S0168-1699(00)00153-8)
2. Bac CW, Hemming J, Van Henten EJ. Stem localization of sweet-pepper plants for harvesting robots. *Biosyst Eng.* 2013;114:333-342. <https://doi.org/10.1016/j.biosystemseng.2012.12.005>
3. Bac CW, Hemming J, Van Henten EJ. Harvesting robots for high-value crops. *J Field Robot.* 2014;31(6):888-911. <https://doi.org/10.1002/rob.21525>
4. Baerdemaeker JD, Munack A, Ramon H, Speckmann H. Mechatronic systems in precision agriculture. *IEEE/ASME Trans Mechatron.* 2001;6(1):1-6. <https://doi.org/10.1109/3516.906719>
5. Barbosa Júnior MR, Santos RG, Sales LA, Oliveira LP. Advancements in agricultural ground robots for specialty crops. *Plants.* 2024;13(23):3372. <https://doi.org/10.3390/plants13233372>
6. Bechar A, Vigneault C. Agricultural robots for field operations. *Biosyst Eng.* 2016;149:94-111. <https://doi.org/10.1016/j.biosystemseng.2016.06.003>
7. Bechar A, Vigneault C. Agricultural robots for harvesting. *Biosyst Eng.* 2017;153:94-111. <https://doi.org/10.1016/j.biosystemseng.2016.11.006>
8. Bergerman M, Maeta S, Zhang J, *et al.* Robot farmers: Autonomous orchard harvesting. *IEEE Robot Autom Mag.* 2015;22(1):54-63. <https://doi.org/10.1109/MRA.2014.2368686>
9. Blackmore S, Stout B, Wang M, Runov B. Robotic agriculture - The future of agricultural mechanisation. *Precis Agric Conf Proc.* 2005. <https://doi.org/10.3920/978-90-8686-540-7>
10. Botta A, Cavallone P, Baglieri L, Colucci G, Tagliavini L, Quaglia G. A review of robots, perception, and tasks in precision agriculture. *Appl Mech.* 2022;3(3):830-854. <https://doi.org/10.3390/applmech3030049>
11. Chen Y, Liu Z, Wang H. Autonomous navigation in agricultural robots. *Robot Auton Syst.* 2021;143. <https://doi.org/10.1016/j.robot.2021.103822>
12. Duckett T, Pearson S, Blackmore S, Grieve B. Agricultural robotics: The future of robotic agriculture. 2018. <https://doi.org/10.13140/RG.2.2.33065.11365>
13. Ehsani R, Mishra A, Maja J. Precision horticulture technologies. *HortTechnology.* 2013;23(2):200-205. <https://doi.org/10.21273/HORTTECH.23.2.200>
14. Fountas S, Sorensen C, Tsiropoulos Z, *et al.* Farm machinery management information systems. *Comput Electron Agric.* 2020;170. <https://doi.org/10.1016/j.compag.2020.105247>
15. Gao J, French A, Pound M, *et al.* Deep learning for plant phenotyping. *Trends Plant Sci.* 2018;23(11):1050-1060. <https://doi.org/10.1016/j.tplants.2018.09.002>
16. Grimstad L, From P. *Thorvald II* agricultural robotic system. *Robotics.* 2017;6(4):24. <https://doi.org/10.3390/robotics6040024>
17. Jensen K, Nielsen S, Larsen M, *et al.* Robot for weed control. *Biosyst Eng.* 2012;113(3):219-231. <https://doi.org/10.1016/j.biosystemseng.2012.07.003>
18. Kamilaris A, Prenafeta-Boldú F. Deep learning in agriculture. *Comput Electron Agric.* 2018;147:70-90. <https://doi.org/10.1016/j.compag.2018.02.016>
19. Khan S, Fulton J, McDonald T. Robotics and automation in agriculture. *Comput Electron Agric.* 2021;180. <https://doi.org/10.1016/j.compag.2020.105909>
20. Liakos K, Busato P, Moshou D, *et al.* Machine learning in agriculture. *Sensors.* 2018;18(8):2674. <https://doi.org/10.3390/s18082674>
21. Lowenberg-DeBoer J, Erickson B. Precision agriculture adoption. *Agron J.* 2019;111:1552-1569.

- <https://DOI.org/10.2134/agronj2018.12.0779>
22. Mahlein AK. Plant disease detection by imaging sensors. *Plant Dis.* 2016;100(2):241-251.
<https://DOI.org/10.1094/PDIS-03-15-0340-FE>
 23. Mulla D. Twenty-five years of remote sensing in precision agriculture. *Biosyst Eng.* 2013;114(4):358-371.
<https://DOI.org/10.1016/j.biosystemseng.2012.08.009>
 24. Oksanen T, Visala A. Coverage path planning algorithms for agricultural robots. *J Field Robot.* 2009;26(8):651-668.
<https://DOI.org/10.1002/rob.20300>
 25. Pedersen SM, Fountas S, Blackmore S, Gylling M, Pedersen J. Adoption and perspectives of precision agriculture. *Precis Agric.* 2006;7:239-254.
<https://DOI.org/10.1007/s11119-006-9017-5>
 26. Perez-Ruiz M, Slaughter D, Fathallah F, *et al.* Automatic control of precision weed spraying. *Comput Electron Agric.* 2014;102:28-35.
<https://DOI.org/10.1016/j.compag.2014.01.012>
 27. Pierce F, Nowak P. Aspects of precision agriculture. *Adv Agron.* 1999;67:1-85. [https://DOI.org/10.1016/S0065-2113\(08\)60513-1](https://DOI.org/10.1016/S0065-2113(08)60513-1)
 28. Qiao Y, Valente J, Su D, Zhang Z, He D. AI, sensors and robotics in plant phenotyping. *Front Plant Sci.* 2022;13.
<https://DOI.org/10.3389/fpls.2022.1064219>
 29. Rakun J, Popič G. Optimized autonomous navigation for field robots. *Precis Agric.* 2026.
<https://DOI.org/10.1007/s11119-025-10303-8>
 30. Roldán J, Joossen G, Sanz D, *et al.* Mini-UAV remote sensing for precision agriculture. *Sensors.* 2016;16(3):365.
<https://DOI.org/10.3390/s16030365>
 31. Sankaran S, Mishra A, Ehsani R, Davis C. Plant disease detection techniques. *Comput Electron Agric.* 2010;72:1-13.
<https://DOI.org/10.1016/j.compag.2010.02.007>
 32. Shamsiri R, Weltzien C, Hameed I, *et al.* Agricultural robotics research. *Appl Eng Agric.* 2018;34(4):765-784.
<https://DOI.org/10.13031/aea.12619>
 33. Shalal N, Low T, McCarthy C, Hancock N. Orchard mapping using machine vision. *Comput Electron Agric.* 2015;114:25-34.
<https://DOI.org/10.1016/j.compag.2015.03.015>
 34. Slaughter DC, Giles D, Downey D. Autonomous robotic weed control. *Comput Electron Agric.* 2008;61(1):63-78.
<https://DOI.org/10.1016/j.compag.2007.05.008>
 35. Sørensen C, Bochtis D. Fleet management in agriculture. *Biosyst Eng.* 2010;105:41-50.
<https://DOI.org/10.1016/j.biosystemseng.2009.09.009>
 36. Srivastava V, Raturi O. Robotics and automation in agriculture. 2023. https://DOI.org/10.1007/978-981-19-2188-9_45
 37. Underwood J, Walsh K, Hammarstrom M, *et al.* Autonomous orchard robots. *J Field Robot.* 2016.
<https://DOI.org/10.1002/rob.21629>
 38. Van Henten EJ, Bac C, Hemming J, Edan Y. Robotics in protected crop production. *Comput Electron Agric.* 2013;96:47-55.
<https://DOI.org/10.1016/j.compag.2013.04.005>
 39. Verdouw C, Wolfert S, Tekinerdogan B, *et al.* Internet of Things in agriculture. *Comput Electron Agric.* 2016;122:214-223.
<https://DOI.org/10.1016/j.compag.2016.01.037>
 40. Wolfert S, Ge L, Verdouw C, Bogaardt M. Big data in smart farming. *Agric Syst.* 2017;153:69-80.
<https://DOI.org/10.1016/j.agry.2017.01.023>
 41. Zhang C, Kovacs JM. UAV applications in precision agriculture. *Precis Agric.* 2012;13:693-712.
<https://DOI.org/10.1007/s11119-012-9274-5>
 42. Zhang D, Zhou G, Xu Y. Smart agriculture technologies. *Future Gener Comput Syst.* 2019;94:142-150.
<https://DOI.org/10.1016/j.future.2018.11.015>
 43. Zhang Q, Reid J. Machine vision guidance systems. *Comput Electron Agric.* 2006;50(2):123-140.
<https://DOI.org/10.1016/j.compag.2005.09.002>
 44. Zhao Y, Li H, Fang S, Kang Y, Wu W, Hao Y, Li Z, Bu D, Sun N, Zhang MQ, Chen R. NONCODE 2016: an informative and valuable data source of long non-coding RNAs. *Nucleic acids research.* 2016 Jan 4;44(D1):D203-8.