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Review article

Reconfigurable agricultural robotics: Control strategies, communication, and applications

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ABSTRACT

Over the past decade, the integration of robotic systems into agricultural tasks has catalyzed a transformation in food production processes, spanning from planting to harvesting stages. The precision and efficiency of robotic technology enable advanced crop management applications, including plant disease detection, optimized water and nutrient usage, and continuous monitoring of environmental and soil conditions. The adoption of robotics in agriculture, driven by intelligent automation, not only enhances crop yields but also reduces environmental impacts, thereby addressing key challenges such as climate change and population growth in pursuit of sustainable food security.

This article provides a comprehensive review of the state of the art in modular robotic systems and their agricultural applications. Modular robots offer reconfigurability and adaptability, supporting versatile, task-specific solutions that are essential for the evolving demands of the agricultural sector. These solutions are largely contingent upon the robot's control architecture, which can be classified as centralized, decentralized, or hybrid. Centralized control facilitates unified management and precise coordination for high-accuracy tasks, while decentralized systems offer flexibility and resilience in dynamic environments that demand adaptability. Hybrid control approaches, which combine elements of both centralized and decentralized methods, aim to balance control with autonomy, enhancing efficiency and effectiveness in real-world applications.

In some scenarios, bio-inspired motion control techniques are embedded into control systems to emulate natural behaviors and enhance a robot's adaptability for specific tasks. For example, bio-inspired models such as chemosynthesis — a process in which bacteria transform inorganic compounds into energy — have been adapted for individual robots to support autonomous exploration and navigation. Consequently, this article discusses the convergence of modular robotics, bio-inspired control strategies, and their potential as sustainable solutions to contemporary agro-industrial challenges.

Contents

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1. Introduction

The projected increase in the world population to 11.2 billion by 2100 will impact agricultural resource management and food production. Meeting this demand requires optimizing agricultural processes and implementing technologies that enhance productivity and resource efficiency (United Nations, 2022).

Agricultural robotics enables the automation of tasks such as planting, monitoring, and harvesting. These systems facilitate precise resource utilization, reduce reliance on manual labor, and support large-scale food production.

In this context, robotics, as a branch of engineering focused on designing, manufacturing, and operating robots, provides advanced technological tools that enhance agricultural management capabilities. Equipped with sensors and artificial intelligence, robots can optimize water and fertilizer use, execute planting tasks, and manage crop maintenance and harvesting. For instance, computer vision systems enable the automated detection and harvesting of ripe peppers (Cortez et al., 2023).

Agrotechnology combines robotics and automation with agricultural practices, transforming traditional methods at various stages of production. Specifically, autonomous systems for planting adapt to diverse environmental conditions, ensuring consistent seed spacing and depth, which maximizes crop yield by controlling plant growth (Zhang et al., 2019). This advancement has enabled the deployment of multi-robot systems or robot swarms that perform tasks simultaneously across different field areas, increasing coverage and efficiency. For example, swarms of drones can be used for crop monitoring and spraying (Hafeez et al., 2023).

Among multi-robot systems, reconfigurable robots stand out for their ability to adapt to various tasks and environments, allowing a single robotic unit to perform multiple functions by adjusting its structure or modules according to specific needs (Seo et al., 2019). These systems can be applied in agriculture for tasks such as pesticide spraying, data collection, and precision farming. Their adaptability and reconfigurability contribute to improving operational efficiency, reducing the need for multiple specialized machines, which optimizes both costs and space utilization.

The performance of these multi-robot systems is largely determined by their control strategies. Centralized approaches enable precise coordination for specific tasks, while distributed systems offer greater flexibility and robustness in dynamic environments. Hybrid control systems, which combine both strategies, aim to balance precision and adaptability in agricultural applications (Kvalsund et al., 2022). Additionally, the integration of bio-inspired control techniques has enhanced the autonomy and capability of these systems to operate in unstructured environments, facilitating their interaction with crops and variable conditions (Zhang et al., 2020).

Furthermore, communication between modules and among multiple robots is essential for coordination and scalability in agricultural tasks. Different communication architectures optimize collaboration in robotic teams, facilitating the efficient execution of field tasks. These communication and control technologies are key in the evolution of multi-robot systems and reconfigurable robots, expanding their applications in agricultural automation and improving crop management.

The objective of this review is to analyze the state of the art in communication and control strategies in multi-robot systems and reconfigurable robots for agriculture, identifying recent advances in control architectures, communication systems, and bio-inspired approaches. This study aims to highlight the advantages and limitations of these systems, as well as their applications in the agricultural context, providing a foundation for future research and developments in the field.

This article examines the role of communication and control in multi-robot systems and reconfigurable robots applied to agriculture. The following section presents the methodology used for the literature review, followed by an exploration of agricultural robot development, from individual applications to multi-robot systems. Finally, the conclusions discuss the potential of these systems to address current agricultural challenges and enhance production efficiency.

2. Methodology

The topic covers multiple fronts, detailed in the following sections. For each main theme, different search strategies were applied to gather the most relevant information. The research initially focuses on agriculture-related topics and automation methods. It then shifts towards multi-robot systems and control strategies. Lastly, it narrows down to specialized areas concerning modular robots, multicellular robots, and swarm sensing, as outlined below. Out of an initial selection of 120 sources, 93 were chosen based on their relevance, recent publication dates, and alignment with the research objectives, ensuring a thorough and focused examination of the subject.

- **Agriculture and automation:**
  - `Agricultural robotics AND agriculture AND emerging technologies`
  - `Robotic systems AND crops AND environmental sustainability in agriculture`
  - `Automation technologies AND agricultural practices`
  - `Trends in modular robotics AND agriculture`
- **Multi-robot systems and control forms:**
  - `Autonomous robotic systems AND precision agriculture`
  - `Synthetic biology AND modular robots AND agricultural optimization`
  - `Bio-inspired robotics AND motion control`
- **Modular robots, Multicellular robots, and Swarm Sensing:**
  - `Modular robots AND multicellular robots`
  - `Swarm sensing AND robots`
  - `Synthetic biology AND modular robots AND agricultural optimization`

The consulted databases and information sources encompass studies, articles, and reports from researchers, students, and organizations to quantify and understand the technological trends in modular robotics. Searches were conducted on platforms like IEEE Xplore, Web of Science, Scopus, Springer, and Google Scholar, as well as through technical reports, conference proceedings, and relevant theses to provide a comprehensive overview of the current state and future directions of modular robotics in agricultural applications. This review primarily focuses on identifying and analyzing recent advancements and potential uses of modular robots in agriculture. However, it is

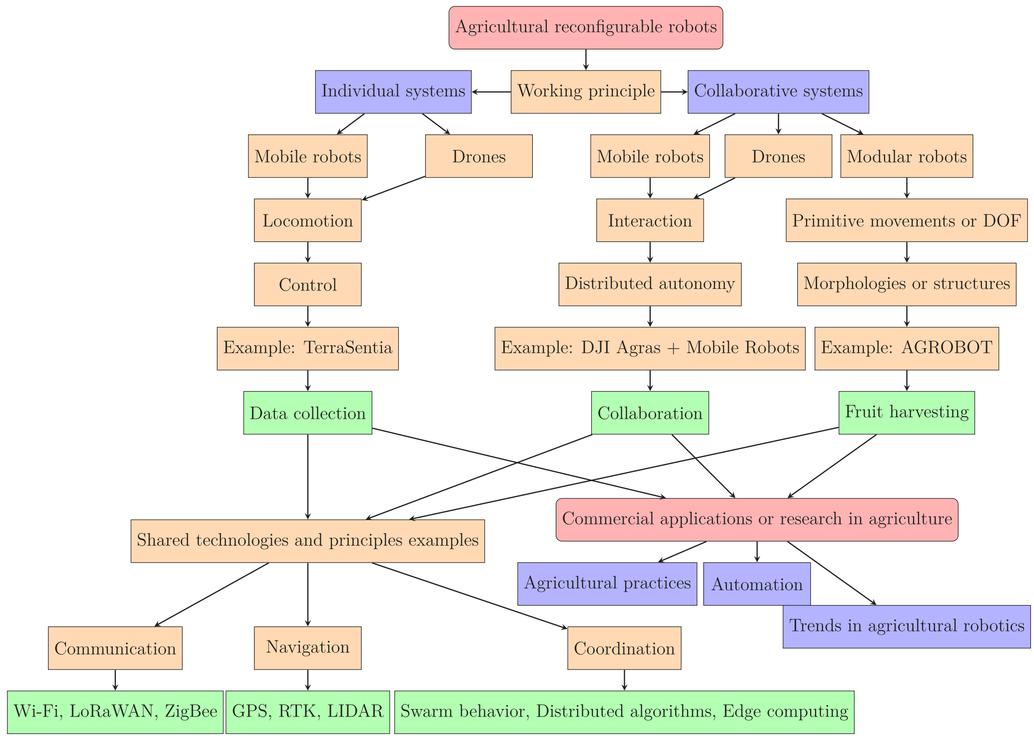


Fig. 1. Correlation of Terms in Modular Robotics with Shared Technologies, Examples, and Applications.

worth noting that the rapid progression of robotics may result in the exclusion of some very recent developments, as illustrated in Fig. 1.

The figure presents a correlation of terms in modular robotics, highlighting how shared technologies and application examples are interconnected. The structure shows that modular robotics in agriculture includes key elements such as drones, mobile robots, and modular robots, which are interconnected in various application areas, from data collection to fruit harvesting. Additionally, communication technologies, such as Wi-Fi and LoRaWAN, and navigation technologies, such as GPS and RTK, are essential for the efficient coordination of robots in agricultural environments.

At the bottom of the figure, application examples such as the TerraSentia robot and AGROBOT are highlighted, which are used for data collection and fruit harvesting, respectively. These examples illustrate how modular robot systems collaborate to optimize agricultural tasks, such as data collection and crop monitoring. Furthermore, the figure also emphasizes the importance of distributed autonomy, robot collaboration, and the use of distributed algorithms and swarm behavior to improve the efficiency of executing agricultural tasks.

3. Classification of robotics in agriculture

Agriculture is among the sectors transformed by the adaptability of robotics. Robots in this field are categorized in multiple ways, considering factors like functionality, control methods, types of actuators, and other characteristics. Broadly, robotic systems are divided into two main categories: individual robotic systems and multi-robot systems (Dorigo et al., 2021).

An individual robotic system is designed to autonomously perform specific tasks. These robots are equipped with sensors, communication modules, and control mechanisms that enable them to carry out activities such as land preparation, crop treatment, planting, agronomic data collection, and harvesting (Oliveira et al., 2021). In contrast, a multi-robot system consists of multiple robots working together on one or more tasks within the same agricultural environment. These robots share information, make decisions based on collective data, and can cover expansive areas efficiently.

Agriculture robotics has seen significant advancements, and robotic systems are classified into different categories based on their functionality and adaptability. This section explores individual robotic systems (Section 3.1), which are robots designed to autonomously perform agricultural tasks such as planting, irrigation, and harvesting. Section 3.2 analyzes modular robotics, which stands out for its reconfigurability to perform various agricultural tasks, providing flexibility in its application. Section 3.3 delves into the technical details of modular robots, explaining how their modules are assembled and adjusted to meet different field functions. Section 3.4 discusses control systems and path planning, which are essential for the precise coordination of robots in agricultural tasks. Finally, Section 3.5 addresses multicellular robots, which function as collaborative units and optimize performance by working together on complex tasks in agriculture. This classification is summarized in Table 1 and further elaborated upon in this section.

3.1. Individual robotic system

Individual agricultural robots are equipped with various sensors, actuators, and communication systems to enhance farmers' productivity in specific tasks. First, these robots utilize imaging, environmental, and soil sensors to analyze, visualize, and collect environmental data, supporting activities like planting, fertilization, and pest control. Second, they incorporate locomotion systems — such as wheels, tracks, propellers, or legs — that enable mobility across different terrains. Third, their communication systems employ wireless technologies like Wi-Fi, Bluetooth, LoRaWAN, NB-IoT, and GSM, allowing integration into smart agricultural systems and enabling remote operation (Dyshekov et al., 2023; Pincheira et al., 2023).

Another distinguishing feature of these robots is their diverse sizes and designs, ranging from compact autonomous devices to large, complex systems. Smaller robots are generally deployed for simpler tasks such as weeding or crop monitoring, as their agility allows them to navigate easily between crop rows. Larger robots, on the other hand, are commonly used for tasks like planting, fertilization, and harvesting, where extensive coverage and higher power are essential (Joseph

Table 1
Comparison between an individual robotic system and a multi-robot system in agriculture.

Category	Basic characteristics	Applications	Advantages	Disadvantages
Individual robot (Fernandes et al., 2020)	Capable of performing tasks autonomously or through remote operation.	Used in automated planting and harvesting, monitoring, and fertilization of crops.	Adaptability to different types of crops.	Limited in the variety of tasks they perform, high implementation and maintenance costs.
Multiple robots (Chitre et al., 2023)	A group of robots working coordinately through a system of communication and collaboration among them.	Ideal for supervision and management of large crop areas and integrated weed control.	Increases the farmer's reach and coverage in large expanses of land.	Coordination of individual robots is non-trivial and requires robust control methods to achieve effective interaction among them.

(a) CropScout (Design, 2023)

(b) WeedBot (Tran et al., 2023)

(c) GrapeBot (Peng et al., 2022)

Fig. 2. Example of individual robotic systems.

et al., 2022; Zhang et al., 2023b). Below are several examples that illustrate the core functionalities of these robots, with an overview provided in Table 2, summarizing their key characteristics, benefits, and limitations.

- **CropScout** (Fig. 2(a)) is a robot designed for crop inspection and analysis, equipped with multispectral cameras and sensors for temperature and humidity to monitor crop health and growth. It transmits data in real-time using Wi-Fi to a central database, where the information is analyzed to provide insights into crop conditions. CropScout navigates fields autonomously with wheels designed to adapt to various agricultural terrains (Design, 2023).
- **WeedBot** (Fig. 2(b)) is designed to identify and mechanically remove weeds among crops using cameras and computer vision, eliminating the need for herbicides. It communicates via Wi-Fi for updates and data sharing with operators, and its compact design allows it to maneuver efficiently between crops (Tran et al., 2023).
- **GrapeBot** (Fig. 2(c)) is specialized for viticulture, equipped with sensors to assess grape maturity and environmental conditions, and is capable of autonomous harvesting. GrapeBot communicates with operators via Wi-Fi, makes autonomous decisions based on collected data, and features a modular design that adapts to various grape varieties and cultivation techniques (Peng et al., 2022).

3.2. Multi-robot systems

Individual robotic systems initiated a transformation in the agricultural sector by demonstrating their capability to perform tasks like planting, irrigation, and harvesting, thus reducing reliance on manual labor. However, many of these systems have since evolved into multi-robot systems. This shift is defined by the coordinated collaboration among multiple robots, working as a synchronized fleet to enhance the capabilities of each individual unit.

For instance, *SwarmFarm Robotics* are modular robots designed for tasks such as planting, spraying, and weeding under controlled conditions. Their modular design enables reconfiguration for various tasks. Similarly, fleets of *DJI Agricultural Drones* (model *DJI Agras MG-1*) are used for spraying and aerial monitoring, allowing for rapid fumigation over extensive land areas to increase crop yields by effectively controlling pests (Farm, 2024; DJI, 2024).

Other examples of multi-robot systems, such as *AgEagle Aerial Systems* and *Harvest Automation HV-100*, utilize the specialization of each robot to collaboratively solve tasks. *AgEagle* drones perform aerial mapping and spraying, while *Harvest Automation HV-100* robots are designed for greenhouse logistics. Each of these robotic systems is redefining agricultural practices, with some examples summarized in Table 3 below.

Agriculture has integrated technologies like drones and mobile robots to optimize crop management. Drones provide aerial data using multispectral sensors, while mobile robots perform specific field tasks. The synergy between these technologies enables large-area monitoring and automation of tasks such as harvesting and weed control. Drones collect crop condition data, and mobile robots act on the identified areas.

For weed or pest control, drones identify zones with excessive unwanted plant growth, while mobile robots remove weeds through mechanical cutting or targeted herbicide applications. Mobile robots navigate autonomously, adapting to the terrain and adjusting their paths based on field conditions, increasing task efficiency. This technology reduces indiscriminate chemical use by applying treatments only in specific areas detected by drones (Moshayedi and Yang, 2024).

For example, the *Agrobot* is a mobile robot specifically designed for automated strawberry harvesting, a crop requiring delicate handling to avoid damage. This system combines drones' capability to monitor crop maturity from the air with the precision of mobile robots for harvesting. Drones equipped with multispectral cameras fly over strawberry fields, identifying ripe areas by assessing fruit color and maturity.

Once the drone identifies optimal harvesting zones, the *Agrobot* takes action. This mobile robot has flexible mechanical arms that individually pick strawberries without harming the plants. Unlike manual harvesting, this automated process reduces time and minimizes crop waste. The *Agrobot*'s arms adapt to each strawberry's shape and size, ensuring precise harvesting even in challenging terrain.

This system has been implemented on farms where manual strawberry harvesting is costly and labor-intensive. The technology not only boosts efficiency but also ensures strawberries are harvested at peak ripeness, enhancing final product quality. This integration of

Table 2
Comparison of individual robotic systems with agricultural applications.

	Name	Application	Loco-motion	Functional advantages	User interface
Land Preparation	John Deere Autonomous Tractor (John Deere US, 2024)	Commercial	4WD	– High traction on rough terrains. – Reduces operator fatigue.	Cabin control panel, mobile app
	Kubota X Tractor (KUBOTA, 2024)	Commercial	4WS	– High-efficiency electric vehicle. – Reduces environmental impact and saves energy.	Mobile app, touch control panel
	Agrobot SW6010 (AGROBOT, 2024)	Commercial	2WS	– Stability on uneven terrains. – Minimizes soil compaction.	Remote control, mobile app
	SoilAnalyzer (Rao and Krishna, 2024)	Research	4WD	– Adaptable to various soil types. – Analyzes soil composition.	Mobile app, web interface
Plant Treatment	Ecorobotix ARA (Ecorobotix ARA, 2024)	Commercial	4WD	Uses solar energy for mobility. Reduces the use of chemicals or fertilizers.	Mobile app, touch control panel
	Dino (Technologies, 2024)	Commercial	4WS	Maneuverability in tight spaces. Controlled weeding in vegetable crops.	Cabin control panel, mobile app
	DJI Agras T20 (DJI, 2024)	Commercial	UAV	Aerial access for precise spraying. Improves spraying efficiency.	Remote control, mobile app
	PlantHealth (Rizk and Habib, 2018)	Research	4WS	Precision in soil treatment application. Diagnosis and treatment of plant diseases.	Mobile app, web interface
Sowing	Rowbot (Mansur et al., 2022)	Commercial	4WD	Quickly fertilizes row crops. Reduces excessive seed expenditure.	Mobile app, web interface
	AgriBots (Adetunji et al., 2022)	Research	4WD	Precision and reduction in seeding waste.	Control panel, mobile app
	SeedMaster (SeedMaster, 2024)	Research	4WD	Precision seeding efficiency. Reduces variability in seeding.	Mobile app, web interface
	PlantingDrone (Mohan et al., 2021)	Research	UAV	Aerial seeding in inaccessible terrains. Expands the reach of seeding.	Remote control, mobile app
Harvesting	Harvest CROO Robotics (Karkee and Silwal, 2022)	Commercial	4WD	Increases productivity in harvesting.	Cabin control panel, mobile app
	AppleHarvester AI (advancedfarm, 2024)	Research	4WD	AI-based smart harvesting. Reduces damage and improves fruit selection.	Control panel, mobile app
	TerraSentia (Kayacan and Chowdhary, 2019)	Research	4WD	Mobility in high-density crops. Detailed monitoring and crop performance improvement.	Mobile app, web interface
	SoilScan AI (Liu et al., 2023)	Research	UAV	Real-time soil analysis. Soil fertility optimization and nutrient detection.	Mobile app, web interface

Table 3
Comparison of commercial multi-robot systems with agricultural applications.

Name	Application	Locomotion	Functional advantages	User interface
SwarmFarm robots (Farm, 2024)	Agricultural tasks	4WS	Modularity and adaptability for various agricultural tasks	Centralized control panel
DJI agricultural drones (DJI, 2024)	Crop fumigation	UAV	Quickly fumigates large crop areas	Radio signals
Harvest automation HV-100 robots (Harvest, 2024)	Nurseries and garden centers	4WS	Space optimization and efficiency in nurseries and garden centers	Radio signals and Wi-Fi
Agrobotix harvest robots (Henríquez et al., 2019)	Harvesting crops	UAV	Autonomous harvesting for various types of crops	Radio signals

Note: *WS (Wheel Steering), UAV (Unmanned Aerial Vehicle).

drones and mobile robots optimizes the entire harvesting process, reducing human intervention and supporting sustainable, scalable operations (Oliveira et al., 2021).

Similarly, drones equipped with moisture sensors collect data on crops' water needs, allowing mobile robots to adjust irrigation systems and distribute water precisely where it is needed (Moshayedi and Yang, 2024). In applications like strawberry and grape cultivation, drones survey fields to identify areas requiring intervention, while mobile robots with mechanical arms perform precision harvesting, minimizing crop damage (Qu et al., 2022).

In rice cultivation, drones monitor soil conditions and plant maturity, while mobile robots handle seedling transplantation and adjust irrigation based on drone data. This process improves water distribution, ensuring optimal plant growth (Shamshiri et al., 2024). Additionally, drones equipped with nutrient sensors enhance fertilization systems,

Table 4
Comparison of drone systems: characteristics, advantages, and disadvantages.

Characteristics	Advantages	Disadvantages	Integrated technology	Communication modules
Aerial monitoring with multispectral cameras (Moshayedi and Yang, 2024)	Fast coverage of large areas	Requires advanced technology and training	Multispectral cameras, thermal sensors	Wi-Fi, LoRa, LTE
Real-time data capture (Qu et al., 2022)	Accurate and real-time data	Dependence on favorable weather conditions	Real-time data transmission systems	Wi-Fi, Bluetooth
Ability to cover large areas (Xie et al., 2022)	Allows identification of specific areas for intervention	High initial costs	Electric motors and autonomous flight control	Wi-Fi, radio frequency
Detection of pests and nutrient deficiencies (Shamshiri et al., 2024)	Reduced indiscriminate use of pesticides and fertilizers	Limited battery life	Optical and temperature sensors	Wi-Fi, integrated sensors
Compatibility with mobile robots for joint actions (Moshayedi and Yang, 2024)	Optimization of agricultural tasks when combined with mobile robots	Constant equipment and software maintenance	Navigation and communication systems between devices	Wi-Fi, Bluetooth, RTK

allowing mobile robots to apply fertilizers precisely, reducing environmental impact and excessive chemical use (Moshayedi and Yang, 2024). Detailed information is summarized in Table 4.

In this context, *Wi-Fi* (Wireless Fidelity), *LoRa* (Long Range), *LTE* (Long-Term Evolution), and *RTK* (Real-Time Kinematic) are communication technologies that enhance the integration and functionality of drones and robots in agricultural and industrial environments. Wi-Fi is commonly used for short-range, high-speed data transmission, enabling real-time communication between robots and control systems. In agriculture, Wi-Fi facilitates the rapid transfer of data from drones monitoring crops to ground-based robots, supporting coordinated tasks such as irrigation or pest control (Oliveira et al., 2021).

LoRa, by contrast, is a long-range, low-power communication technology well-suited for large outdoor environments, such as fields or farms. Its low data rate is ideal for transmitting sensor data over extended distances, making it valuable for applications requiring sustained connectivity across wide areas without high data demand Moshayedi and Yang (2024) and Jiang et al. (2021).

LTE and RTK provide more advanced capabilities for drones and robots. LTE, a mobile broadband standard, enables connectivity in areas lacking Wi-Fi coverage, ensuring continuous communication and data transfer (Xie et al., 2022). This is particularly useful for remote monitoring and operations in agricultural or industrial settings where infrastructure may be limited. RTK provides precision positioning for tasks requiring accurate navigation, such as robotic movement over uneven terrain or precision seeding and planting. Through real-time positioning corrections, RTK enables drones and robots to perform tasks with high accuracy, supporting synchronized operations in large-scale farming and industrial applications (Qu et al., 2022) (see Fig. 3).

Nonetheless, these prototypes exhibit certain limitations, as illustrated in case studies of UAVs in agricultural applications, where tests have been conducted to evaluate drone performance under various environmental conditions. For instance, wind speed was observed to significantly impact UAV mission duration. Under wind speeds below 5 mph, UAVs achieved 19% greater flight autonomy compared to those operating in winds above 10 mph. This is because drones must expend additional energy to stabilize and counteract wind forces during crop monitoring missions (Qu et al., 2022; Jiang et al., 2021; Delavarpour et al., 2021).

Temperature was another critical factor. At temperatures exceeding 90° F, 51% of missions failed due to equipment overheating, affecting both UAVs and ground communication devices. These failures included data transmission errors and battery malfunctions. Conversely, at temperatures below 80° F, only 5% of missions encountered technical issues. Additionally, lighting conditions played a significant role in the quality of captured images; incorrect predictions were recorded in 50% of missions conducted during early morning hours due to long shadows and low sunlight (Puente-Castro et al., 2022).

In this context, a predictive model was employed to enhance communication efficiency and video transmission quality between drones and ground base stations. Regression models such as KRR and GPR demonstrated good performance in network precision (goodput), achieving a value of 4.9 Mbps with a 95% confidence interval. However, real-world experiments produced a slightly lower value of 3.7 Mbps, highlighting the need to adjust these models for more realistic conditions (Qu et al., 2022).

In field tests conducted on a soybean crop, lightweight UAVs (L-UAVs) demonstrated an average flight time of around 25 min, using a combination of RGB, multispectral, and thermal cameras to gather crop data. The multispectral imagery enabled the identification of vegetation indices, such as the NDVI, while thermal cameras tracked canopy temperature, a critical marker of water stress in plants. Findings showed that to produce accurate crop defoliation maps with 80% precision, only 43% of the field area needed to be surveyed when employing a reinforcement learning model integrated with a fleet computer. This approach substantially reduced the time and energy required for the missions, in contrast to conventional "lawnmower scouting" methods, which necessitated covering 70% of the field (Qu et al., 2022) (see Fig. 4).

3.3. Modular robots

Recent advancements in research and the development of functional modular robot prototypes have shown promising potential in agriculture. Although these technologies are not yet widely adopted, ongoing experiments and field trials suggest they could become essential for enhancing efficiency and sustainability in crop management.

While modular robots are still in the early stages of commercialization, examples like the Agrobot SW6010 and Thorvald II illustrate progress that emphasizes their adaptability across diverse tasks and their precision in operations such as harvesting and crop monitoring. Agrobot SW6010, for instance, has been tested for strawberry harvesting, demonstrating its ability to autonomously identify and collect ripe fruit using a modular arm system. Thorvald II, on the other hand, has been deployed for autonomous crop monitoring and disease detection, offering a scalable solution for precision agriculture (Oliveira et al., 2021; Qu et al., 2022).

Despite these advancements, modular robots still face challenges related to cost, scalability, and integration with existing agricultural systems. The high initial investment and the need for advanced computational models for decision-making hinder widespread adoption. Additionally, ensuring interoperability with conventional farming equipment and adapting to diverse environmental conditions remain critical

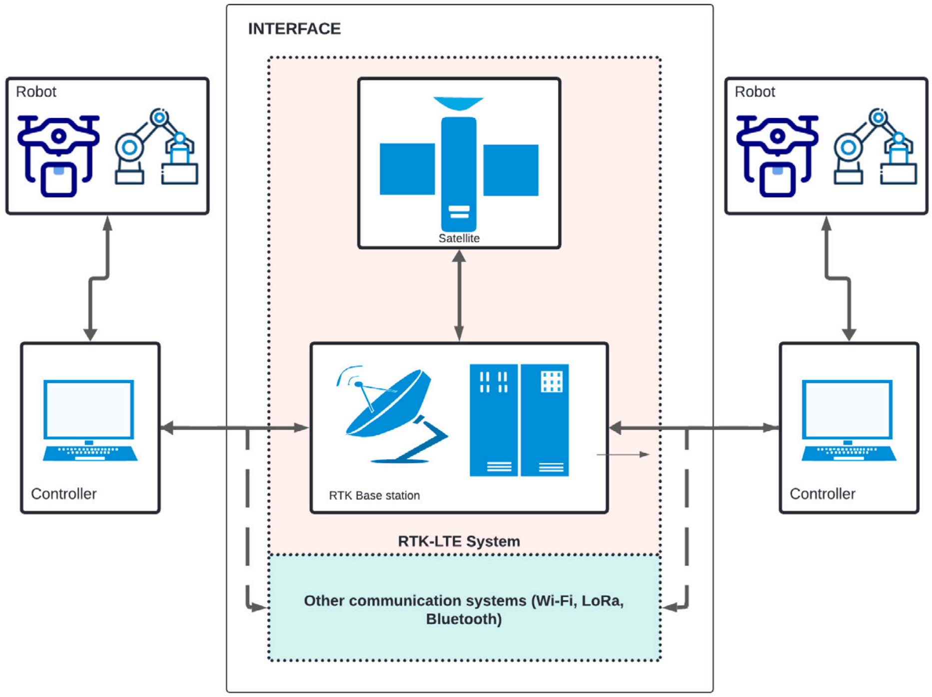
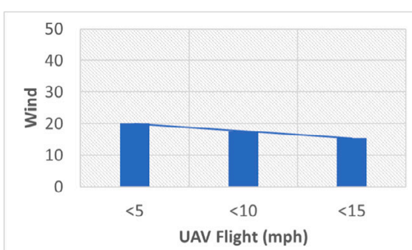
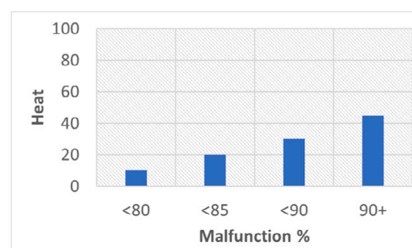


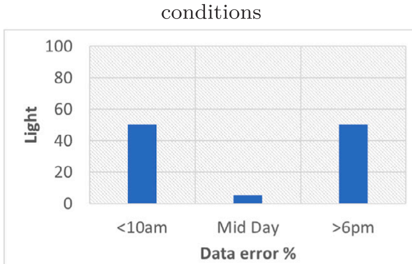
Fig. 3. Communication systems in the integration of drones and robots.



(a) Fly in stable or calm weather conditions



(b) Protect equipment from shade



(c) Fly at midday

Fig. 4. Recommendations based on the measurements reported by Qu et al. (2022).

research areas. However, ongoing developments in artificial intelligence, energy-efficient actuators, and adaptive control algorithms suggest that modular robotics could soon become a viable solution for autonomous, reconfigurable, and efficient agricultural systems.

In the context of multi-robot systems, modular robots (Fig. 5) are distinguished by their design, comprising articulated blocks, standardized components, or modules. Unlike traditional robots, these modules enable the robot to reconfigure itself, creating various morphologies to tackle different tasks. These configurations can be predefined or flexible. On the one hand, modules can be assembled in a specific, orderly manner, while on the other, they offer diverse connection forms, allowing the creation of multiple structure types (Ning et al., 2024; Martínez et al., 2022).

The modules of a modular robot can be reconfigured either manually, with user assistance, or autonomously, where the robot independently manages its individual modules. Module control can be achieved through various approaches: centralized, where a single controller within a module or an external device coordinates the robot's movements; decentralized, with two or more modules sharing control responsibilities; or hybrid, combining centralized coordination with decentralized autonomy. The interchangeable nature of modular robot components makes decentralized control systems advantageous, as they

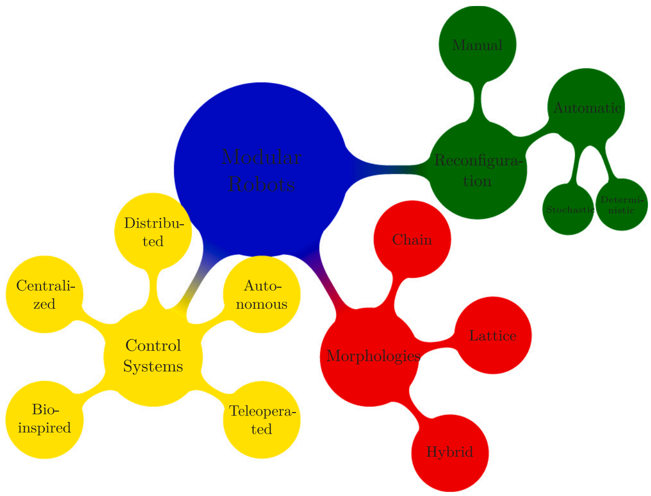


Fig. 5. Basic characteristics of modular robots.

can lower the unit cost of each module by enabling mass production (Liu et al., 2020; Tian and Zhan, 2021).

Control defines the intelligence of each module based on its ability to interact with the environment. Consequently, some researchers include local sensors and actuators in each module to allow responsive interactions with external stimuli, such as heat, light, electricity, and moisture. This approach suggests that module design should address at least three key stages: defining the architecture to identify functional modules and feasible configurations; optimizing system configuration tasks for efficient assembly; and establishing control methods to coordinate the movement of the assembled robotic structure. Modular robots are generally classified into three categories: chain, lattice, and hybrids. Chain-type modular robots consist of sequentially connected modules forming kinematic chains in two (2D) or three (3D) dimensions. Lattice-type modular robots create geometric structures resembling a prism, while hybrid robots integrate characteristics of both chain and lattice types, allowing modules to form linear chains or regular geometric patterns (Gerbl and Gerstmayr, 2022; Liu et al., 2020).

The mechanisms used for module coupling are essential, as they enable reconfiguration and facilitate the transfer of mechanical force, energy, heat, or data. The shape and design of the module's faces impact the movement and load capacity of the assembled robot. These faces can feature connectors such as male, female, hermaphroditic, or gender-neutral types. Male and female connectors fit together mechanically or electromechanically, while hermaphroditic connectors combine both male and female elements on each face, enabling flexible positioning. Gender-neutral connectors are typically electromagnetic, requiring no mechanical coupling (Freeman et al., 2023; Martínez et al., 2022).

A specific example of a chain-type modular robot is the *EMeRGE* modular robot, which has four faces, three with female connectors and one with a male connector. Magnetic elements on these faces allow quick module coupling (see Fig. 6a). Another example is the lattice-type modular robot *ElectroVoxel*, which employs electromagnetically actuated pivoting mechanisms to enable self-reconfiguration. This system leverages embedded electro-permanent magnets to create flexible structures that can adapt to various environments without requiring complex mechanical components (see Fig. 6b). Additionally, the hybrid modular robot *HyMod* features modules with three degrees of freedom and hermaphroditic connectors, enabling it to form diverse structures and manipulate objects with user-activated tools via an application (see Fig. 6c).

While most studies take the load capacity of the mechanism into account during the design phase, it is not necessarily a decisive factor in determining whether reliable connections can be achieved in module assemblies. The limited load capacity and movement capabilities of many of these robots indicate that they are still in early development stages, lacking a defined commercial application. Each connection mechanism has its own advantages and disadvantages; for instance, connectors facilitate quick coupling and decoupling of modules, which enables self-repair capabilities. This allows the robot to replace faulty modules with functional ones while carrying out a task, making self-repair a specific case of self-reconfiguration (Peck et al., 2022; Nokhanji and Santoro, 2021).

Recent research by Peck et al. Peck et al. (2022) explores self-assembly and self-repair mechanisms in modular robots. These techniques allow robots to replace defective modules while in motion, reducing downtime and maintaining task execution. Unlike previous methods requiring complete system shutdowns, this approach facilitates real-time module replacement. Experimental validation has been conducted in simulation and physical prototypes, but further research is needed for large-scale implementation in agricultural environments.

Another focus within modular robotics is the enumeration of modules in the robot's configuration, though this does not yield information about performance in specific tasks (Feng and Liu, 2022). Artificial evolution has been proposed as a method for discovering effective combinations of morphologies and controllers. Luo et al. and Shin et al. explored the concept of evolving morphologies and controllers simultaneously to create virtual creatures, though physical construction proved challenging. Similar techniques have been applied to modular robots, which can be easily assembled from modules, simplifying their adaptation to various applications and tasks (Shin et al., 2023; Luo and Lam, 2023).

This implies that the design of robot controllers must be highly sophisticated, along with the techniques used for control. Therefore, the following sections of this article will describe the controllers used for these robots and their methods of information transmission.

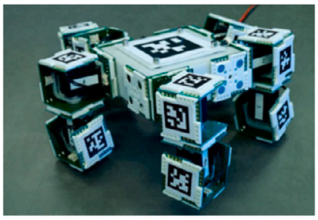
3.4. Control systems and path planning

Control systems for modular robots include centralized, distributed, and hybrid models, each with specific characteristics depending on the robot's design and purpose. Centralized control relies on a single controller that manages decision-making and coordinates actions across all modules. This approach enables task synchronization and coordinated management of multiple units. However, if the central controller fails, the entire system may be affected. This type of control has been applied in harvesting robots such as Agrobot SW6010 and RoboFruit, which require precise management to prevent crop damage and optimize the harvesting process (Kvalsund et al., 2022).

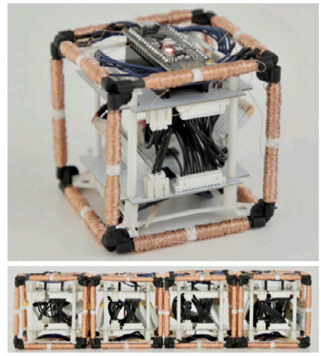
Distributed control equips each module with an independent controller, allowing local decision-making and inter-module communication. This approach enables system operation in variable environments with dynamic conditions. In irrigation robots, distributed control has been implemented to adjust water distribution based on soil moisture levels, optimizing resource use (Moreno and Faiña, 2021). Each robot analyzes its environment and executes actions autonomously, reducing the need for centralized supervision and improving responsiveness to changing conditions.

An analysis of the relationship between control architecture and modular robot morphology is presented in the study by Kvalsund et al. (2022), which evaluated the impact of centralized and distributed models on the adaptability of these systems. The findings indicate that distributed control offers scalability and flexibility when optimized alongside the robot's morphology (Kvalsund et al., 2022). In agricultural applications, this approach allows robots to operate over large areas without relying on continuous communication infrastructure.

Hybrid systems combine elements of centralized and distributed control, enabling general task planning while allowing individual robots



(a) EMeRGE (Moreno and Faiña, 2021)



(b) ElectroVoxel (Nisser et al., 2022)

(c) HyMod (Parrott and Dodd, 2018)

Fig. 6. Examples of modular robots and their morphologies See Moreno and Faiña (2021), Nisser et al. (2022), Parrott and Dodd (2018).

Table 5
Comparison of path planning methods for modular robots.

Method	Advantages	Disadvantages	How it works	Performance (Error/Time)
Ant Colony Algorithm (ACA) (Harshavardhan et al., 2024)	Adaptable to dynamic environments. Fast in local optimization and flexible in reconfiguration.	Requires fine-tuning of parameters such as pheromone decay rate. Can take longer for global optimization.	Uses virtual pheromones to guide modular robots by allowing each module to explore and optimize paths iteratively.	Error margin: 5%–8% Avg. time: 3–4 s for a medium-size field (100 × 100 m).
Particle Swarm Optimization (PSO) (Rossides et al., 2021)	Efficient in global search. Scalable for large areas.	May get stuck in local minima, requiring re-initialization.	Simulates the behavior of swarms (particles) that communicate and adjust their trajectories based on personal and global bests.	Error margin: 4%–6% Avg. time: 2–3 s for a 100 × 100 m area.
Genetic Algorithm (GA) (Sun et al., 2022)	Good for optimization across multiple criteria. Can handle complex terrain and multi-objective tasks.	High computational cost and longer processing times compared to others.	Uses selection, crossover, and mutation to iteratively improve path planning for modular robot configurations.	Error margin: 3%–5% Avg. time: 6–8 s for a medium-size field (100 × 100 m).
Rapidly-Exploring Random Tree (RRT) (Zhang et al., 2023a)	Fast exploration of unknown spaces. Good for navigating dynamic obstacles.	Can generate paths that are not always optimal.	Builds a tree structure by exploring random points and connecting them, expanding the robot's route in an unstructured environment.	Error margin: 7%–10% Avg. time: 2–5 s depending on terrain complexity.
Potential Field-Based Planning (Lee et al., 2024)	Simple and computationally light. Good for obstacle avoidance.	Prone to getting stuck in local minima. Less effective in complex environments.	Represents the environment as a field where the robot is attracted to the goal and repelled from obstacles.	Error margin: 6%–9% Avg. time: 1–2 s for real-time avoidance in a 100 × 100 m area.

Note: A medium-size field refers to an area of approximately 100 × 100 meters. A large-size field typically refers to an area exceeding 200 × 200 meters.

to make local decisions. In agricultural scenarios, this type of control has been implemented in Thorvald II, a modular robot designed for crop monitoring and input application. This approach allows the system to adapt to different conditions without compromising overall coordination (Stroppa et al., 2023).

Bioinspired control has been explored in modular robotics with techniques based on collective behaviors observed in natural organisms. Algorithms inspired by ant colonies and neural networks have been applied in robots such as SwarmBot, where multiple units collaborate to perform sowing and harvesting tasks. These approaches have been used to improve navigation and decision-making in agricultural environments, reducing human intervention and facilitating deployment across large cultivation areas (Seo et al., 2019).

Distributed control allows each module to operate independently while coordinating complex movements with other modules. This structure enhances overall robustness, as a single module's failure does not incapacitate the entire robot. Additionally, distributed control allows for real-time reconfiguration, which is essential for adapting to changing environments (Cortez et al., 2023).

Other advanced control forms include bio-inspired and autonomous control. Bio-inspired control takes cues from natural behaviors, allowing robots to respond to environmental changes by mimicking biological processes for improved efficiency. Autonomous control, on the other hand, enables robots to function independently, using sensors and algorithms for self-directed decision-making. Moreover, remote and hybrid control systems allow for human oversight in hazardous conditions or combine multiple control strategies to balance efficiency and adaptability based on task requirements (Cortez et al., 2023; Stroppa et al., 2023).

For instance, the *ATRON* robot employs a distributed control system that integrates Artificial Neural Networks (ANN) for local decision-making in self-reconfiguration tasks, using genetic algorithms to optimize ANN weights. This blend of bio-inspired and autonomous control allows ATRON to operate without direct human input, making decisions locally and coordinating movements for self-repair. Similarly, the *Molecubes* robot utilizes a bio-inspired approach, employing a genetic algorithm to evolve the control of its modular neural network, thus generating behaviors suited to specific tasks (Parada et al., 2021).

Table 6
Comparison of self-reconfigurable modular robots.

Robot name	Degrees of Freedom per module (DOF)	Actuator type	Self-reconfigurable	Control type	Scalability	Potential applications
ElectroVoxel (Deng et al., 2022)	3	Electromagnets	Yes	Distributed	High	Space exploration, self-assembling structures
Module-W (Koh et al., 2022)	2	Flexible actuators	Yes	Distributed	High	Conformal structure formation, soft robotics
ReBiS (Li et al., 2023)	1	Electric motors	Yes	Centralized	Medium	Rough terrain exploration, search and rescue
Soft Mod. Rob. Cubes (Zhao et al., 2023)	3	Soft actuators	Yes	Distributed	High	Unstructured environment navigation, soft robotics
Omni-Pi-tent (Gao et al., 2023)	3	Electric motors	Yes	Distributed	High	Industrial applications, object manipulation

Note: This table summarizes the characteristics and applications of various self-reconfigurable modular robots based on recent research.

Path planning, or route determination, plays an important role in modular robotics because the reconfigurable nature of these robots allows them to adapt to environments that can vary, such as agricultural fields. Path planning algorithms enable modular robots to navigate autonomously and complete tasks.

The selection of a control approach typically depends on the robot's operational environment. Centralized control might be suitable for controlled settings, while distributed control is advantageous in unpredictable or risky environments due to its resilience and adaptability.

In modular robot path planning, algorithms inspired by nature, such as the Ant Colony Algorithm (ACA) and Particle Swarm Optimization (PSO), have proven effective in dynamic environments, providing flexibility and robustness for applications in agriculture and beyond. Table 5 summarizes several path planning strategies used in modular robotics.

3.5. Multicellular robots

3.6. Multicellular robots and ant colony optimization in agriculture

Control system models conceptualize these robots as multicellular entities, designed to emulate the organization and functions found in living organisms. Similar to how cells in a biological organism specialize and collaborate to accomplish complex objectives, multicellular robots utilize control systems — such as distributed or bio-inspired approaches — to self-organize, adapt, and navigate dynamic environments (Parada et al., 2021; Moreno and Faiña, 2021; Freeman et al., 2023).

This interdisciplinary connection between biology and robotics represents a paradigm where engineering principles intersect with biological insights. For example, research by Satoshi et al. in synthetic biology demonstrates how cellular signaling through platforms like synNotch can program cells to undergo specific morphological transformations and achieve spatial organization (Kuzuya et al., 2023; Yoo et al., 2018).

Among bio-inspired control strategies, **Ant Colony Optimization (ACO)** has been widely studied in agricultural robotics due to its decentralized nature and adaptability to dynamic environments. ACO mimics the behavior of ants foraging for food, where each individual follows simple rules while collectively optimizing routes and decision-making. In agricultural applications, ACO has been implemented for **autonomous path planning, resource allocation, and multi-robot coordination**, allowing modular robotic swarms to efficiently navigate crop fields, optimize spraying routes, and dynamically adapt to terrain variations (Liu and Wang, 2023).

To quantify the effect of ACO in agricultural robots, recent studies have evaluated its performance based on key **efficiency indicators**:

- **Path optimization efficiency**: Measured as the reduction in total travel distance compared to traditional heuristic methods. Recent experiments have shown an average **distance reduction of 18–25%** when using ACO for navigation tasks in agricultural environments (Roberts and Kim, 2023).
- **Computational efficiency**: The convergence rate of the algorithm, assessed by the number of iterations required to find an optimal solution. Studies report that ACO-based routing algorithms **reach near-optimal paths within 30–50 iterations**, significantly faster than genetic algorithms in similar applications (Fernandez and Torres, 2023).
- **Task completion time**: ACO-controlled agricultural robots complete designated field operations **15%–22% faster** than traditional control strategies by dynamically adapting to obstacles and terrain conditions (Gupta and Zhang, 2024).

These results highlight the potential of ACO to enhance the efficiency of modular robots in agricultural environments, particularly in large-scale precision farming applications. Future research should focus on integrating real-time sensor feedback to further optimize decision-making processes and reduce energy consumption in robotic swarms.

Such studies underscore the capacity of biological systems to self-organize into intricate multicellular formations via cellular interactions. Cells communicate and alter their behavior in response to particular signals, paralleling how robotic modules use control systems to adapt to environmental stimuli. These artificial genetic programs facilitate the assembly of cellular structures with natural developmental traits, such as resilient self-organization, sequenced assembly, type differentiation, symmetry breaking, and regenerative capabilities following damage (Tissera et al., 2019).

In robotics, multicellular robots are modular systems comprised of multiple autonomous units, often called modules or robotic cells, that collaborate to achieve shared goals. These modules can self-organize and adapt in a manner akin to biological cells forming tissues and organs. Key concepts essential for understanding multicellular robotics include (Liu et al., 2020):

- **Modularity**: Multicellular systems have a modular framework, where each unit or module fulfills specific roles.
- **Self-organization**: These robots form complex structures or behaviors autonomously, mirroring biological processes like tissue development or morphogenesis.
- **Adaptability**: They respond to environmental shifts or task changes by autonomously reconfiguring their structure or modifying their actions.
- **Communication**: Robotic modules often interact via physical connections or wireless signals, enabling coordination and cooperation among them.

Examples of multicellular robots inspired by biological systems include *RoboBees*, swarm robots, and robots modeled after marine organisms, which demonstrate collective intelligence similar to natural systems. *RoboBees*, for instance, are small flying robots designed to operate in swarms, performing tasks such as crop pollination and search-and-rescue missions in areas difficult for humans to access. Equipped with sensors, flight mechanisms, and communication abilities, these robots coordinate to mimic bee-like behaviors, gathering data and pollinating crops across extensive areas autonomously (Harvard University, 2024).

Each *RoboBee* communicates with its counterparts to optimize flight paths and prevent collisions, enabling efficient coverage of expansive areas. This capability is especially valuable in crop pollination, where rapid and precise action is required. Additionally, these robots can modify their behavior in response to environmental changes, making them well-suited for agricultural settings with uneven terrain or varying weather conditions (Harvard University, 2024).

Swarm robots, which consist of numerous small units, coordinate to form structures or patterns, allowing them to explore new environments or transport objects collaboratively (Harvard University, 2024). There are also robots inspired by marine life, designed to mimic the collective behavior of fish schools or jellyfish colonies, with applications in marine environmental monitoring or oil spill response. Table 6 provides a summary of different modular robot types and their respective applications.

Conclusions

- Modular robots are characterized by their reconfigurability, which allows them to adapt to different tasks within the agricultural field. This reconfiguration can be manual or automatic, depending on the specific task requirements. Section 3 describes different types of configurations, such as *chain*, *lattice*, and *hybrid* modular robots. These configurations enable robots to perform various functions such as planting, monitoring, harvesting, and crop treatment. For example, *chain* robots are assembled in linear sequences, making them suitable for tasks that require straight or precise movements, while *lattice* robots are able to form geometric structures, which are useful for tasks requiring stability and load-bearing capabilities. Additionally, *hybrid* robots combine the features of both types to offer greater versatility. Table 6 details the types of modular robots, their characteristics, and potential applications, emphasizing how each type of configuration addresses specific needs in agricultural environments. This adaptability is crucial in agriculture since robots must adjust to varying field conditions such as uneven terrain, crop variability, and changing weather.
- The efficient operation of modular robots in an agricultural environment significantly depends on the control and communication systems used for their coordination. In Section 3.4, various control approaches applied to these robots are detailed: centralized, distributed, and hybrid. Centralized control is more suitable for controlled environments where a single command center can precisely and efficiently coordinate the actions of robots. However, in more dynamic or unstructured environments like agricultural fields, distributed control proves more effective since it allows each module to operate autonomously, making local decisions based on the data it collects from its immediate surroundings. This is essential for handling changing conditions without relying on a centralized system that might fail. Table 5 shows several examples of control systems applied to modular robots, highlighting how distributed control offers advantages in terms of flexibility and robustness in variable agricultural environments. Communication between robot modules and between robots and base stations also plays a crucial role, as it enables collaboration and task execution in a coordinated manner. Advances in communication technologies like Wi-Fi, LoRa, and LTE, discussed in Section 3.5 and Table 4, allow modular robots to work efficiently over large areas, which is fundamental in precision agriculture, where coverage and real-time communication are essential for tasks like spraying, monitoring, and resource management.
- Modular robots have the potential to be a key tool in modern agriculture, not only due to their ability to perform tasks autonomously and precisely but also because of their contribution to sustainability in food production. In Sections 3.2 and 3.3, specific applications of modular robots such as the *Agrobot SW6010*, used for strawberry harvesting, and *Thorvald II*, employed for crop monitoring, are described. These modular robots are designed to operate in complex agricultural environments, with different crop types and soil conditions, allowing them to optimize agricultural practices. For example, the *Agrobot SW6010* is equipped with modular arms that allow it to perform harvesting tasks precisely, minimizing damage to crops and improving the efficiency of fruit collection. These robots contribute to reducing waste and optimizing resource use by performing specific tasks more efficiently than traditional methods. Table 2 offers additional examples of robots used in different stages of the agricultural process, such as planting, monitoring, and harvesting, highlighting how these robots, through their reconfigurability, can adapt to the specific needs of each task. In terms of sustainability, modular robots enable more efficient management of water, fertilizers, and pesticides by applying these resources only where and when needed, reducing environmental impact and improving crop efficiency. Moreover, automating tasks like harvesting and monitoring can reduce the reliance on labor in rural areas, which is especially relevant given the increasing labor shortages in many agricultural regions.

CRediT authorship contribution statement

Henry Alberto Hernández: Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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