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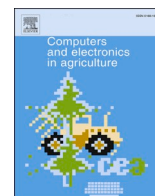
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## Review Article

# Advancing agroecology and sustainability with agricultural robots at field level: A scoping review

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## ABSTRACT

Agricultural robots show a growing potential to improve resource management and reduce the environmental impacts of farming. However, the evaluation of robots' contribution to support sustainable farming is still lacking. This study specifically reviewed the operationalization of four agroecological principles at the field level: recycling, soil health, biodiversity and synergy. To this aim, a scoping review was conducted on the Scopus database, with a query within titles, abstracts, and author keywords mentioning robots, and agroecology or sustainability. The body of literature was screened to include only open field robots. The resulting 78 documents were coded inductively on three macro areas: (1) academic background, (2) robot operations, (3) contribution to agroecology principles, whether explicitly or implicitly mentioned. The results highlight that robots operationalize agroecology principles through non-chemical and selective weeding to preserve diversity and soil health, lighter designs that reduce soil compaction, and advanced data collection systems to optimize resource use and synergy. Solar-powered robots represent early steps toward recycling, but this principle remains understudied. The discussion expands on the potential of robotics in other innovative approaches for sustainable agriculture, such as agroforestry, conservation agriculture, and novel farming system design. Key challenges include ensuring farmers are enabled to master data collection and management, as well as integrating high-tech robotics with low-tech solutions. These efforts are critical for leveraging agricultural robotics to advance agroecology and sustainability across diverse farming systems.

## 1. Introduction

Agroecology is defined as an “integrated approach that simultaneously applies ecological and social concepts and principles to the design and management of food and agricultural systems. It seeks to optimize the interactions between plants, animals, humans, and the environment while taking into consideration the social aspects that need to be addressed for a sustainable and fair food system” (FAO, 2018). It encompasses multiple elements (Wezel et al., 2014), further articulated into 13 principles by the High Level Panel of Experts (2019), which identify distinct levels of operationalization, including the field, farm, agroecosystem, and food system. Notably, the field is the level where agricultural practices are designed and realized by farmers, then observed, and refined by agronomy (Maat, 2011) and related disciplines (Deffontaines, 1993). Historically, agroecology has been originally developed at the field level too, though other levels have gained attention lately (Wezel and Soldat, 2009). The field level remains particularly relevant for analysing

interactions between data-driven machines and agroecological principles, as it provides a tangible context for evaluating the direct impact of technology on farming practices, environmental resources, and socio-technical management systems.

The integration of agricultural machinery with information and communication technologies is expected to contribute to the transition toward agroecology (Bellon Maurel and Huyghe, 2017) and more sustainable agricultural practices (Gusev, 2020; Rains et al., 2011). Technological advances have consistently influenced the evolution of agriculture, constantly renewing the promise of improved efficiency, productivity, and sustainability (Pedersen et al., 2019; Schulze-Lammers et al., 2016). However, these promises derive often from a technocentric perspective (Rizzo et al., 2022; Salembier et al., 2020), highlighting the critical role of machinery and technology in mediating between farming practices and their environment outcomes (Huttunen, 2019; Sigaut, 1975).

Scientific literature supports the potential of innovations in

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agricultural technologies, particularly those involving data-driven management, to enable precise monitoring and optimize the use of farming inputs (Sassenrath et al., 2008; Therond et al., 2017). Yet, the role of these technologies in advancing agroecological transitions remains controversial, with concerns about their compatibility with agroecological principles and their broader implications for farming systems (Gkisakis and Damianakis, 2020). The growing body of literature on data-driven agriculture and agricultural robotics often claims its potential role in supporting agroecological transition. However, a comprehensive analysis of how agricultural robots contribute to agroecological principles is lacking. Such an analysis is relevant for defining evaluation criteria and informing the redesign of cropping systems to integrate these technologies effectively. Indeed, agroecology challenges robotics to operate in unstructured and dynamic environments while meeting the demand for higher frequency and precision of farming practices—a need also relevant to conventional machinery development.

While several studies have addressed farmers and societal acceptability of robots (Caffaro et al., 2020; Nordell, 2024; Spykman et al., 2021; Zeddies et al., 2024) or detailed their technical capabilities for specific tasks (Fountas et al., 2020; Liu et al., 2024), the agronomic suitability of agricultural robots in the context of agroecological principles remains understudied. Understanding farmers' perspectives is critical, but agricultural robots can be more simply addressed as additional tools within the broader technological evolution of farming to focus on their agronomical role first. In this regard, over-mechanization of agriculture has historically led to negative externalities (Pretty, 2008), even though improved design and development of agricultural robots could mitigate these effects by enhancing resource use efficiency (Pretty et al., 2018). This perspective shifts the focus from the development of automation technologies themselves (Bazargani and Deemyad, 2024) to their role in operationalizing agricultural evolutions and agroecology (Ditzler and Driessen, 2022). For example, the French government allocated €21 million in 2023 to support the agroecological transition specifically through agricultural robotics under the program named "Grand Défi Robotique Agricole" – Great Challenge Agricultural Robotics (Martin et al., 2024).

This paper focuses on agricultural robots as a frontier in technological innovation for agroecological transitions. The scientific concept of "robot" refers to a machine capable of executing physical tasks with versatility (i.e., the ability to execute different tasks) and/or self-adaptability to its working environment (Coiffet, 2007). For this study, agricultural robots are defined as data-driven, self-propelled machines equipped with implements to execute agricultural tasks (Daum 2021). This definition is broadened to include also unmanned aerial vehicles (UAVs), and robotic platforms, such as automated tools mounted on tractors, which manufacturers sometimes provide as lower cost alternatives to their self-propelled models.

This study aims to evaluate the potential of robots to operationalize the transition toward agroecology. Indeed, agricultural robots are often presented as solutions to various agricultural issues thanks to their precise and data-driven operations (Fountas et al., 2020; Lenain et al., 2019; Moshayedi et al., 2024). By reviewing of research focused on this topic, the study analyses how specific contributions of these technologies—such as their role in automating and optimizing farming tasks like planting, weeding, and crop monitoring—are in line with key agroecological principles at the field level.

## 2. Methodology

This study was based on a scoping review of scientific literature at the intersection of robotics and agroecology. Scoping reviews adopt a more flexible approach than systematic reviews, with broader inclusion criteria and less stringent quality assessments, aiming to provide a comprehensive overview of the literature on emerging topics (Arksey and O'Malley, 2005). The review process was reported according to the dedicated PRISMA-ScR guidelines (McGowan et al., 2020). A set of

inclusion and exclusion criteria, detailed below, guided the composition of the final body of literature. Each selected document was coded to analyse how the operations executed by robots, as reported, enable to operationalize specific agroecological principles.

### 2.1. Review approach and search strategy

A document search was conducted using the Scopus database, including publications up to March 2024. Scopus was selected for its extensive coverage of peer-reviewed research across various disciplines, including a broader range of proceedings and book sections compared to other databases (Singh et al., 2021). Proceedings and books were considered relevant to intercept emerging results on the rapidly evolving domain of agricultural robotics, beyond conventional journal articles.

The search query was designed on three key components: (i) robots, including alternative spellings; (ii) agriculture or farming; (iii) agroecology or sustainability. The search was limited to document titles, abstracts, and author keywords. Search in generic keywords was deliberately excluded to avoid terms attributed by Scopus based on controlled external thesauri (e.g. MeSH, Emtree) to harmonize their database, which may not directly appear in the documents themselves. The final search query was structured as follows: TITLE-ABS ((agrobot\* OR robot\*) AND (farm\* OR agricultur\*) AND (sustainab\* OR \*ecolog\*)) OR AUTHKEY (\*robot\* AND (farm\* OR agricultur\*) AND (sustainab\* OR \*ecolog\*)) AND ORIG-LOAD-DATE < 20240314. Notably, initial searches using "agroecology" alone retrieved only 15 papers, prompting the inclusion of "sustainability" as a related concept, to ensure a more comprehensive review.

### 2.2. Eligibility criteria

We retained all the document types (i.e. journal articles, conferences papers, and book chapters) and subject areas included in the Scopus database. The rationale was to refine the selection upon thematic criteria and to maintain the focus on open field robotics. Accordingly, we excluded documents related to three topics: (1) controlled environments, such as vertical farming, hydroponic systems, greenhouses, and similar indoor settings; (2) animal husbandry and aquaculture; (3) technical specifications, industrial settings, or cybersecurity. Finally, we excluded non-English documents due to potential language barriers that may hinder accurate assessment.

### 2.3. Coding process and analysis

To ensure a thorough analysis of the full text contents, we adopted a deductive coding approach with reference to three macro topics: contextual information, agricultural operations, and field level agroecological principles (Fig. 1). In qualitative data analysis, inductive coding is used to explore trends where no objective predefined codes are available while remaining fully consistent with the sources (Skjott Linneberg and Korsgaard, 2019). Each of the three macro topics was further refined as described here after (Fig. 2).

#### 2.3.1. Sample characterization

Each document was contextualized using four descriptors to describe key academic background. (1) *Demographic trends*: the authors' countries' affiliation and publication years were mapped to provide a baseline description of academic interest in robotics and agroecology or sustainability. (2) *Keywords analysis*: using VOSviewer software (version 1.6.20), the network of co-occurrence of authors' keywords was mapped and classified into four clusters based on the association strength (van Eck and Waltman, 2009, Equation 6). (3) *Crop studied*: the coding distinguished between crops actually assessed or hypothetically mentioned, providing insight into the applicability and effectiveness of agricultural robots. (4) *Type of research*: studies were coded as field tests, laboratory tests (e.g. prototypes), or reviews, to account for robustness

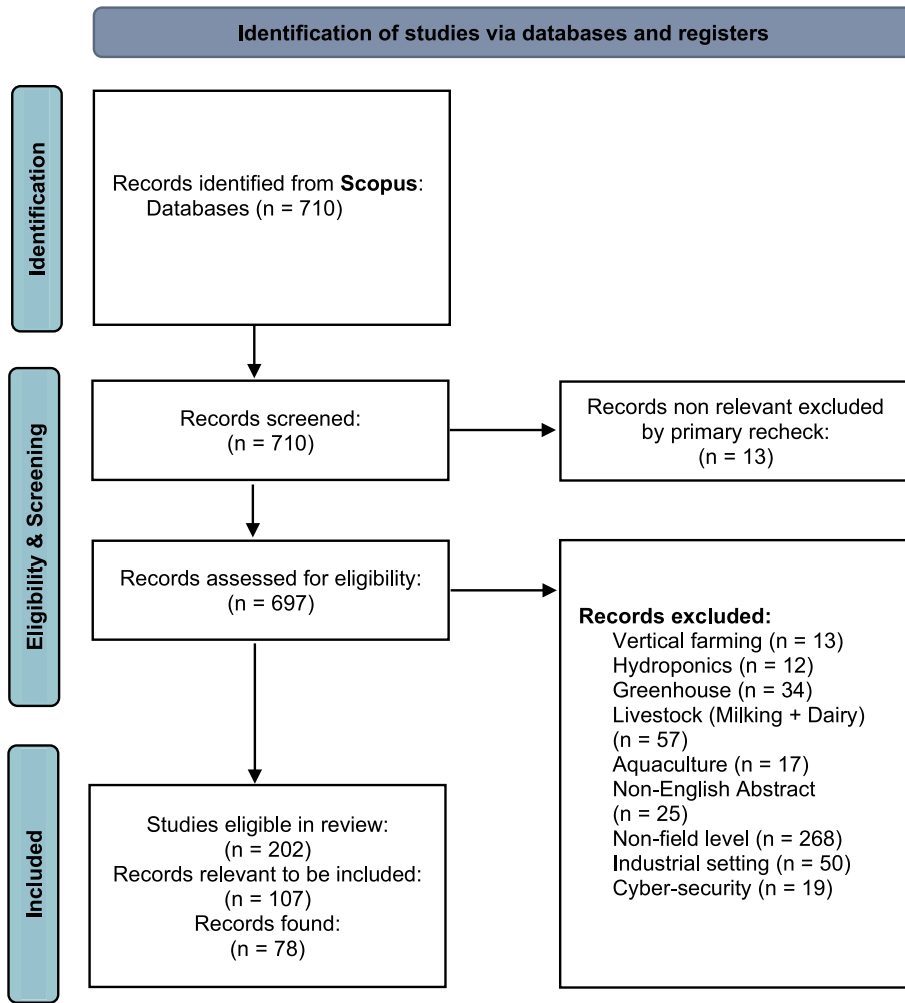


Fig. 1. PRISMA-ScR flowchart describing the selection process of the reviewed documents.

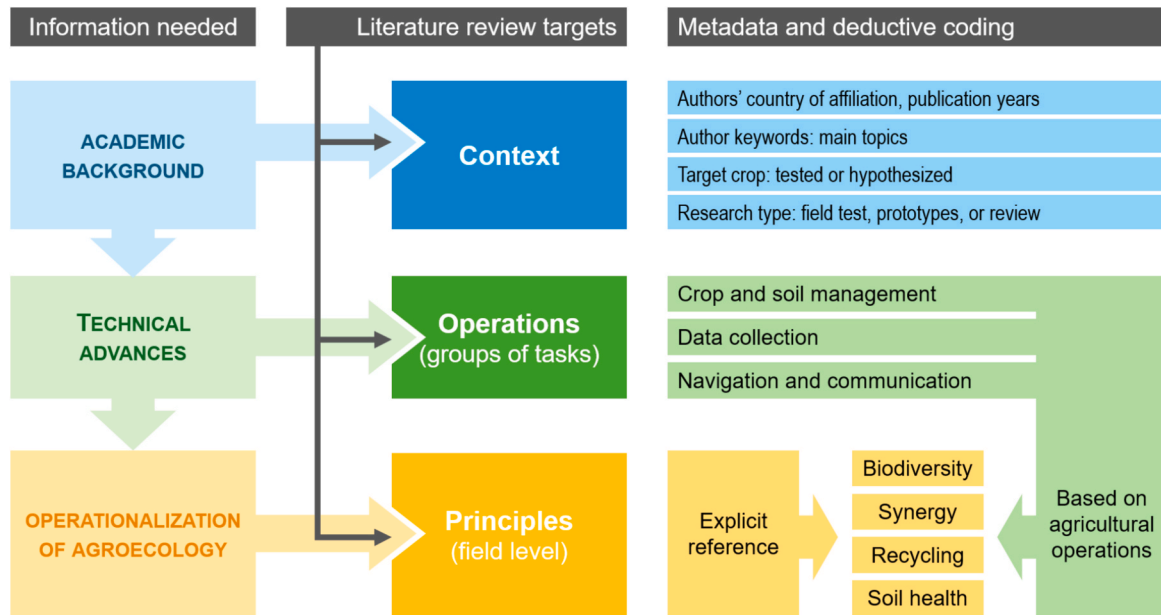


Fig. 2. Schematic representation of the methodology to retrieve the needed information through the deductive coding of the literature body on three areas: context, operations and principles.

and comparability of the evidence. The dataset is available in the following repository: [doi: 10.5281/zenodo.14652720](https://doi.org/10.5281/zenodo.14652720).

The geographical distribution of authors' countries of affiliation closely follows the world machinery market. The United States of America, Germany, and Italy together account for one third of all affiliations (Fig. 3). Other significant contributions come from India, China, Japan, and Spain, while other countries are less represented. Temporal trends indicate an increased interest in robotics and agroecology after 2020, with a consistent presence of conference papers since 2019 (Fig. 4).

A total of 598 unique author keywords were identified across the analysed documents, with only 28 occurring more than four times (Fig. 6). The keywords include variations such as "robotics", "robot", and "robots", resulting in some redundancy and ambiguity. Among agricultural tasks, weed control was the only explicitly mentioned, highlighting its importance in the context of agricultural robotics and agroecology. The technologies mentioned in the documents cluster around two main areas: (1) precision farming, automation, and artificial intelligence; and (2) computer vision, image processing, and related technologies. These clusters illustrate the multidisciplinary nature of agricultural robotic research related to agroecology, with specific advances in data collection operations playing a relevant role (Fig. 5).

Only 28 documents explicitly mentioned a crop, most of which related to field studies. Sugar beet and rice were the most frequently mentioned crops, followed by a wide range of annual and specialty crops. The documents are almost equally divided among field studies (37) and reviews (30), followed by laboratory studies (10), part of which also included some field tests (6 out of 10); finally, one field study is also associated to a review.

### 2.3.2. Defining robotic operations

Robots can execute tasks, which are intended as the unit of work compared with practices tasks and operations. Practices are a set of repeated tasks executed consistently to achieve an agricultural goal, while operations are a coordinated sequence of tasks that often encompass an entire agricultural process involving multiple practices (Landais and Deffontaine, 1988). Operations result from the local combinations of farmer's capabilities, material, and goals, and are addressed by agronomic research to reduce negative outcomes, increase sustainability, or account for innovations in the material means and available technologies (Huttunen, 2019). In this study, information on the task capabilities of the robots was coded into three types of operations based on common goal and similar involved materials: crop and soil management, data collection, and navigation and communication (Table 1 and Fig. 6). Crop and soil management operations regroup the main task executed by

robots contributing to agricultural production, while the other two types of operations regroup supporting tasks, partially overlapping with precision farming technologies (Bechar, 2021).

Practices falling within the first type of operations include seeding, weeding, spraying, harvesting and soil preparation (Fountas et al., 2020). Data collection encompasses the various tasks required for robot autonomy and it is critical to prepare subsequent tasks. Sensors, cameras, and other data collection tools allow robots to monitor fields or plants and gather information on soil conditions, crop health, and environmental factors (Bhagat et al., 2024; Madhavi et al., 2023; Roggiolani et al., 2023; Vasavi et al., 2022). In addition, UAVs equipped with multispectral or hyperspectral sensors can enhance crop and environmental monitoring, adding a complementary perspective. At a later stage imagery is then treated to enhance quality, followed by segmentation to distinguish between different elements such as crops, weeds, and soil (Nikolić et al., 2021; Vasavi et al., 2022). Technologies such as deep and machine learning algorithms enable data analysis at different speeds, depending on the employed technique (Mahesh, 2018).

Navigation and communication tasks of agricultural robots need to account for complex unstructured environments, avoidance of moving obstacles, and reliable connectivity to ensure the safety of operators. Global Navigation Satellite Systems (GNSS) and Real Time Kinematic (RTK) capabilities provide accurate location and path planning (Bazargani and Deemyad, 2024; Santos et al., 2020). Dedicated algorithms are then employed for path planning (Santos et al., 2020). Recent developments integrate vision sensors and adaptive multi-ROI (region of interest) techniques for precise navigation in challenging agricultural environments (Quaglia et al., 2020). Furthermore, communication technologies can also enable the coordination between multiple robotic units (e.g. as a swarm), and/or a central control system, for data sharing and task allocation. This connectivity increases operational efficiency and responsiveness by enabling timely adjustments based on real-time data inputs from the field (Santos et al., 2020). Finally, robots can leverage connectivity with on-field sensors and stationary devices to synchronize different operations (Said Mohamed et al., 2021).

### 2.3.3. Agroecological principles at the field level

Each document was analysed for implicit or explicit references to the four agroecological principles at the field level defined by the High Level Panel of Experts (HLPE, 2019) (Table 2). Notably, we excluded the principle related to animal health and welfare because outside the scope of this review, consistently with the exclusion of livestock robots. The coding framework considers both direct and indirect contributions of robots to these principles. Direct contribution occurs when robots' characteristics or the tasks that it can execute explicitly operationalize

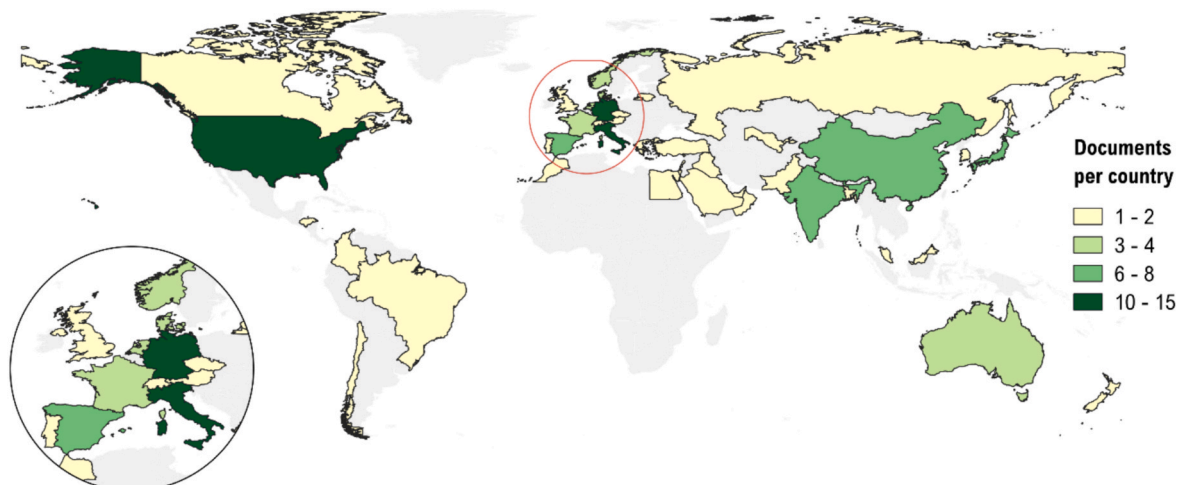


Fig. 3. World map of the affiliation countries of documents' authors (Source: elaboration from Scopus metadata).

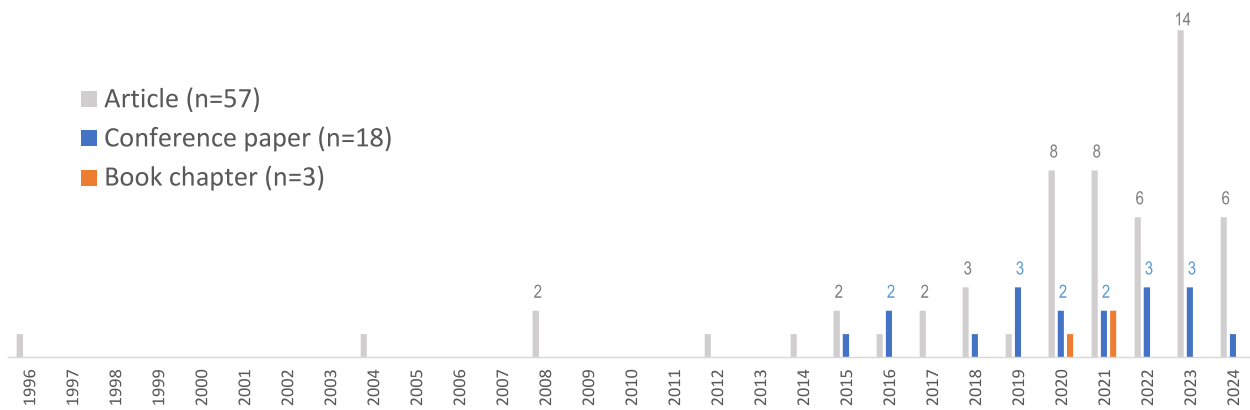


Fig. 4. Temporal distribution of documents by publication type. Labels are shown only for occurrences greater than one.

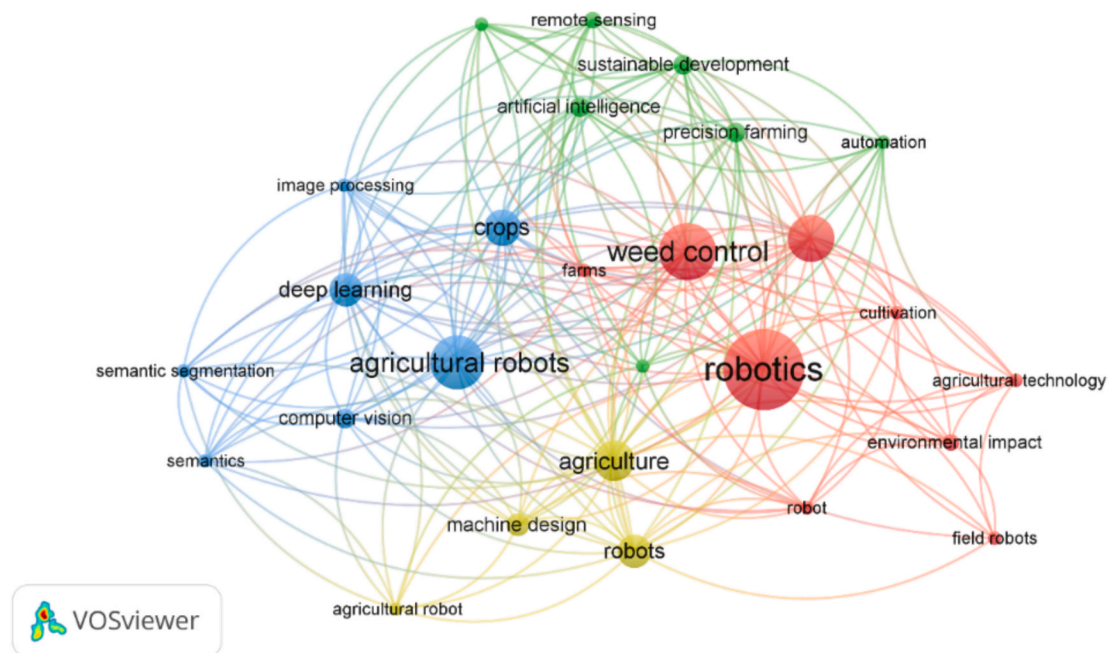


Fig. 5. VOSviewer network illustrating keywords co-occurrence in the analysed documents. Only keywords with a minimum occurrence of four are included. Label and dot sizes are proportional to keyword frequency, while colours distinguish four clusters based on association strength.

**Table 1**  
Description of robot field operations retrieved in the analysed literature.

| Operation                    | Description   | Associated practices         | Examples  |
|------------------------------|---|------------------------------|---|
| Crop and soil management     | Physical manipulation of crops and soil to ensure optimal growth conditions and maximize productivity | Soil preparation             | (Bazargani and Deemyad, 2024; Sara et al., 2024; Jude et al., 2022a)  |
|                              |   | Seeding                      | (Bazargani and Deemyad, 2024; Cruz et al., 2021; Nagchaudhuri et al., 2023; Vahdanjoo et al., 2023)   |
|                              |   | Harvesting                   | (Jawad et al., 2020; Jude et al., 2022a; Torero, 2021)  |
|                              |   | Weeding                      | (Ball et al., 2015; Dash et al., 2021; Du et al., 2022; Fadlallah and Goher, 2016; Gerhards et al., 2022; Li et al., 2019; Mitsui et al., 2008; Sarri et al., 2020; Slaughter et al., 2008; Vahdanjoo et al., 2023) |
| Data collection              | Set of practices specific to data-driven and precision agriculture technologies                       | Spraying                     | (Ball et al., 2015; Du et al., 2022; Filho et al., 2020; Jiang et al., 2023; Martinez-Guanter et al., 2020; Ozgul and Celik, 2018; Umeda et al., 2022; Vahdanjoo et al., 2023; Vijayakumar et al., 2023)            |
|                              |   | Vegetation and field mapping | (Bhagat et al., 2024; Botta and Cavallone, 2022; Hung et al., 2016; Jensen et al., 2014; Lottes et al., 2018; Madhavi et al., 2023; Umeda et al., 2022; Weyler et al., 2023; Winterhalter et al., 2018)             |
| Navigation and communication | Positioning and coordination of autonomous machines with no direct effects on crop production         | Crop monitoring              | (Gil et al., 2023; Hama et al., 2021; Jensen et al., 2014; Ryo et al., 2023; Sa et al., 2018)   |
|                              |   | Path recognition             | (Bak and Jakobsen, 2004; Ball et al., 2016; Ponnambalam et al., 2020; Quaglia et al., 2020; Santos et al., 2020; Shah et al., 2021; Ünal and Topakci, 2015; H. Wang et al., 2021)                                   |
|                              |   | Communication                | (Bak and Jakobsen, 2004; Jensen et al., 2014; Rai et al., 2023)   |

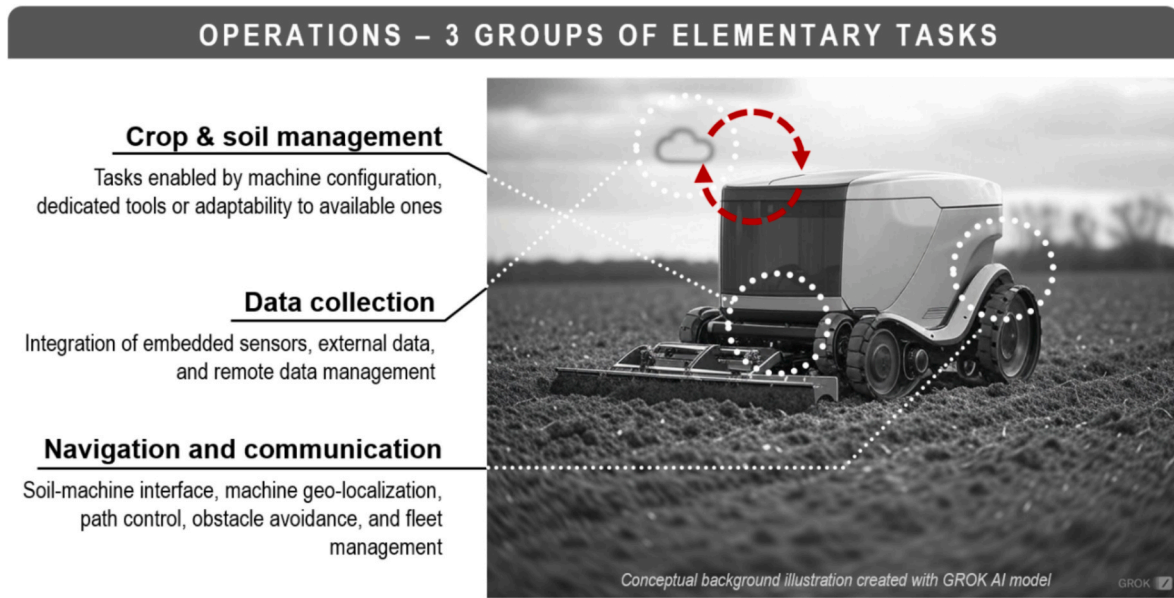


Fig. 6. Conceptual representation of three main operations that describe an agricultural robot, as a group of elementary tasks.

**Table 2**  
Field level agroecology principles considered for the document analysis.

| Principle    | Description used as reference for the coding   |
|--------------|--|
| Recycling    | Preferentially use local renewable resources and close as far as possible resource cycles of nutrients and biomass. It includes contributions to the improvement of resource efficiency.               |
| Soil health  | Secure and enhance soil health and functioning for improved plant growth, particularly by managing organic matter and enhancing soil biological activity.  |
| Biodiversity | Maintain and enhance diversity of species, functional diversity, and genetic resources and thereby maintain overall agroecosystem biodiversity in time and space at field, farm, and landscape levels. |
| Synergy      | Enhance positive ecological interaction, synergy, integration, and complementarity amongst the elements of agroecosystems (animals, crops, trees, soil, and water).                                    |

Adapted from HLPE (2019).

one of the principles. For example, a solar-powered robot, which is a renewable source, contributes to the recycling principle. Indirect contribution includes secondary outcomes of primary operations, such as data collecting robots or UAVs whose treatment can enable better soil health management.

### 3. Results

#### 3.1. How robots operationalize field level agroecological principles

The literature reviewed indicates an uneven operationalization of

the four-field level agroecological principles by agricultural robots. Nearly half of the reviewed documents address a single principle, in particular synergy and soil health. Fewer studies mention a combination of three or all four principles. Recycling is the least represented, while biodiversity is most often addressed in conjunction with synergy and soil health (Fig. 7). The studies that explore the four key agroecological principles simultaneously (biodiversity, synergy, soil health, and recycling) at the field level share a broader common goal: the pursuit of sustainable farming practices. While these studies may not always address the principles in the exact terms of agroecology, their underlying goal aligns closely with the core values of the discipline. In the case of robots themselves, even if they do not explicitly define their work within the context of these agroecological principles, the design and functionality of the robots often consider them in practice. Ultimately, these studies, and the robots themselves, share the broader goal of improving agricultural practices, whether directly or indirectly, through the integration of these principles. The real advantage of robots lies in their ability to refine and enhance these principles through innovative technologies that can be applied with precision, paving the way for more sustainable agroecological farming practices. The specific contributions of agricultural robots to each principle are detailed below.

##### 3.1.1. Recycling

Recycling in agroecology involves enhancing biological processes and reusing biomass, nutrients, and water to increase profitability while reducing costs and environmental impacts (Barrios et al., 2020). Increasing recycling means prioritizing the use of local renewable resources and closing resource cycles of nutrients and biomass as much as

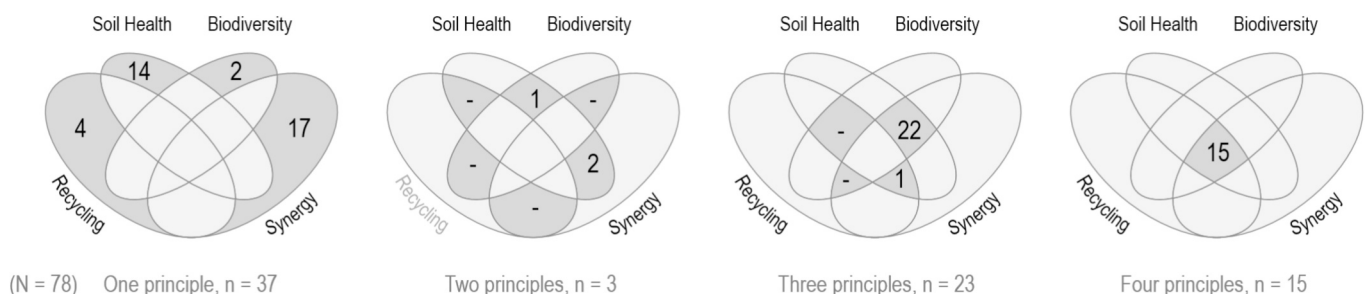


Fig. 7. Distribution of the 78 reviewed documents in terms of field level agroecological principles (as defined by HLPE, 2019) operationalized by robots.

possible (Wezel et al., 2020). Recycling is operationalized in 20 of the reviewed documents, mostly in combination with other field level principles.

**3.1.1.1. Crop and soil management.** Robots contribute to recycling within the system by reducing dependence on external chemical inputs through precise application techniques. For example, Jiang et al. (2023) reported herbicide savings of over 80 % using robots compared to conventional chemical weeding. In another study, Vahdanjoo et al. (2023) demonstrated that hourly operating costs of robots are 57 % lower than tractors, and quantified further improvements in input use efficiency, such as precise microdosing of herbicides by targeting weeds at optimal growth stages, which also reduces fuel consumption (Vahdanjoo et al., 2023).

**3.1.1.2. Data collection.** Robots minimize waste and maximize the recycling of nutrients and energy within the system through data collection and historical field data for integrated management strategies. For example, Young et al. (2017) explored weed management based on ecological interactions and responses to the environment, pre-germination identification of weed seeds in the soil, and historical field data for preventive integrated weed management strategies. Jawad et al. (2020) introduced a prototype that can execute fertilization, irrigation, and harvesting tasks with environmental monitoring capabilities.

**3.1.1.3. Navigation and communication.** The main contribution to recycling comes from enabling the use of renewable energies. The use of solar energy with onboard panels is widely documented in the reviewed documents (Bručienė et al., 2021, 2022; Cavallone et al., 2021; Ditzler and Driessen, 2022; Jawad et al., 2020; Mitsui et al., 2008; Ozgul and Celik, 2018; Jude et al., 2022a; Shah et al., 2021). For instance, Nagchaudhuri et al. (2023) described a solar-powered robotic weeding companion to an outdoor FarmBot set up in a high tunnel with solar and wind turbines, developed for a student project. Ozgul and Celik (2018) described the use of buzzers attached to solar panels to generate signals to repel insects without using toxic materials, demonstrating an eco-friendly approach to pest management. Finally, Harik (2021) worked on a robotic arm to automate the recharging of electric robots.

### 3.1.2. Soil health

Soil health underpins agroecosystem resilience by mitigating disturbances while maintaining the core functions, structure, identity, and feedback mechanisms of agroecosystems (Barríos et al., 2020). Agricultural robots contribute significantly to this principle, either independently (14 studies), or in combination with others.

**3.1.2.1. Crop and soil management.** A key benefit of using agricultural robots is the reduction of soil compaction, which in turn improves soil health and crop management (Bazargani and Deemyad, 2024; Ditzler and Driessen, 2022; Sara et al., 2024). Robots that execute weed control with non-chemical methods – such as mechanical weeding, laser or thermal treatments – help preserve soil microorganisms from phytochemicals side effects, thus maintaining the overall soil health and resilience (Ozgul and Celik, 2018; Sharipov et al., 2023). Even in the case of chemical weed treatment, agricultural robots provide a more sustainable alternative to conventional methods, which indiscriminately spray herbicides over the entire field, affecting soil, crops, and weeds alike (Du et al., 2022). Instead, these robots can adjust herbicide mixtures to the actual distribution of weed species in the field. This precision in herbicide application can double the potential for herbicide savings compared to conventional patch spraying systems using single tank boom sprayers (Gerhards et al., 2022) helping to protect the soil from overexposure to phytochemicals. In this regard, Bručienė et al. (2022) showed that robotic weeding in sugar beet production is significantly more effective and less harmful to soil health than conventional weed

control. UAVs also contribute to soil health as a radical alternative to ground equipment. Finally, concerning pest control, Martínez-Guanter et al. (2020) developed a UAV-mounted spraying system for precise agrochemical applications in olive and citrus orchards, emphasizing cost savings and operator safety compared to conventional sprayers.

**3.1.2.2. Data collection.** Advanced sensing technologies and artificial intelligence are enabling non-invasive soil and crop monitoring by integrating high-resolution imagery from satellites, UAVs, and onboard sensors at multiple scales through techniques such as convolutional neural networks, transfer learning, and few-shot learning, which are transforming data analysis for applications like land mapping, crop classification, stress monitoring, and yield prediction (D. Wang et al., 2022). Du et al. (2022) introduced AIWeeds, a dataset of 10,000 images of flax and 14 common weeds from North Dakota, California, and Central China, enabling precise weed treatment, and by deploying the MobileNetV2 model on the SAMBot robot, it achieved 90 % accuracy in real flax fields, effectively identifying and spraying weeds despite disturbances such as crop presence, distortion, and shadows. Mitsui et al. (2008) demonstrated the effectiveness of a robot in rice paddy fields to significantly reduce weed density, with adaptations to operate in submerged soils. In another study, Ball et al. (2015) detailed the development of a robot, based on a modified John Deere TE Gator, enhanced for precision farming tasks such as weed management, explicitly targeting the reduction of soil compaction. Finally, Umeda et al. (2022) used data collection to evaluate the effectiveness of smart agricultural technologies in addressing labour shortages in Japanese agriculture. Specifically, they compared pest control costs and workloads between boom sprayers, power sprayers, and UAVs for rice cultivation. The study found that UAVs cut labour costs in half and reduced physical activity levels compared to conventional machines; in addition, 63.86 % of tasks using UAVs had a low risk of musculoskeletal injury (Umeda et al., 2022).

**3.1.2.3. Navigation and communication.** Robots equipped with advanced navigation systems, such as LiDAR and RTK-GNSS, thus with improved ability to operate in diverse field conditions, contribute to sustainable soil management by optimizing the path (Sara et al., 2024). In addition, robots reduce soil compaction compared to conventional machines also because of their lighter weight (Bazargani and Deemyad, 2024; Cavallone et al., 2021; Ditzler and Driessen, 2022; Harik, 2021; Mitsui et al., 2008; Sara et al., 2024; Sarri et al., 2020).

### 3.1.3. Biodiversity

Biodiversity acts as a buffer by stabilizing the provision of ecosystem services through the contribution of different species that respond differently to environmental change (Barríos et al., 2020). In the literature reviewed, biodiversity is operationalized in 40 reports but rarely alone (2 studies), and often along with soil health (38 studies) and synergy (37 studies), and, occasionally, recycling (15 studies). Advances in data collection technologies, particularly sensing and precision tools, are improving the capacity of agricultural robots to balance crop productivity and biodiversity conservation. Notably, no specific contribution appears to come from robot navigation itself.

**3.1.3.1. Crop and soil management.** Selective weed removal emerges as a prominent example of robot contribution to biodiversity, as it helps preserve non-target plant species, reduce chemical herbicide use, and minimize soil disturbance. Overall, these robots contribute to this principle by preserving soil microbiota and habitats for beneficial organisms (Zingsheim and Döring, 2024). Robots are increasing weeding accuracy under different abiotic and biotic conditions by combining cultural, mechanical, biological, and chemical tactics, thus minimizing environmental and health risks, eventually enabling true integrated weed management (Young et al., 2017). Some of the robots contribute by reducing the reliance on high-dose herbicides that can harm non-

target organisms and disrupt ecological balance (Dash et al., 2021). For example, Ozgul and Celik (2018) presented a robot prototype for accurate pesticide spraying showing that they considered should be the baseline for building a weed-spraying robot, with the goal of improving sustainability without phytochemical effects to human labour and the environment. Another example is the use of agricultural robots for autonomous strip cropping to support biodiversity and ecosystem services in the field (Al-Amin et al., 2024).

**3.1.3.2. Data collection.** Robotic data collection contributes to biodiversity through algorithmic advances such as convolutional neural networks for semantic segmentation of soil types, crops, and weeds (Du et al., 2022; Fatima et al., 2023; Madhavi et al., 2023; Roggiolani et al., 2023; Shah et al., 2021; Vasavi et al., 2022; Vijayakumar et al., 2023; Weyler et al., 2023; Yonbawi et al., 2023). Early detection and treatment of diseases, as demonstrated by Bhagat et al. (2024), also contribute to biodiversity facing specific challenges. They showed how to address real-time detection taking into account disease spread and limited datasets to support biodiversity conservation while mitigating the impact of pathogens. Other data collection tasks, particularly mapping and imaging, were also deployed using UAVs (Esposito et al., 2021; Inoue, 2020; Sa et al., 2018). For example, Sa et al. (2018) developed a novel crop/weed segmentation and mapping framework using multi-spectral imagery from UAVs with RedEdge-M cameras and processed with a neural network through a sliding window approach to improve precision farming by addressing mapping challenges. They achieved high segmentation performance and used data from sugar beet fields with high weed pressure to enable targeted interventions. Similar applications include camera-driven agricultural robots (Esposito et al., 2021; Lottes et al., 2018). Finally, Wunder et al. (2012) described a robot that can generate maps with individual plant metrics such as location, plant height, and number of leaves; this capability facilitates the management of different plant species, enables tailored interventions based on specific plant needs, ultimately supporting plant field diversity.

#### 3.1.4. Synergy

Synergy in agroecosystems refers to the interaction or cooperation of elements – plants, animals, soil, and water – resulting in a combined effect greater than the sum of their individual contributions (HLPE, 2019; Wezel et al., 2020). This principle is addressed in 57 studies reviewed, often in combination with biodiversity (37 studies) or soil health (40 studies).

**3.1.4.1. Crop and soil management.** Robots contribute to synergy in terms of multi-task combinations within a single pass, minimizing resource consumption, soil compaction, or phytochemical overuse. For example, Bručienė et al. (2022) highlighted the benefits of a multi-tasking robot for sowing and weed control of sugar beet, while Nagchaudhuri et al. (2023) reported improved water management and efficient crop growth in peanut cultivation using an agricultural robot, compared to conventional farming. Similarly, Jude et al. (2022b) and Jawad et al. (2020) developed multitasking robots to improve the sustainability of labour-intensive tasks such as seeding or harvesting, with precise irrigation and fertilization strategies that improve synergy between water and nutrient management.

**3.1.4.2. Data collection.** Machine vision systems and the integration with other sensors potentially enhance synergy by enabling robots to operate multiple tasks in unstructured environments (Al-Amin et al., 2024; Ball et al., 2015; Bechar and Vigneault, 2017; Botta and Cavallone, 2022; Jensen et al., 2014; Shah et al., 2021). This includes UAVs, as examined by Umeda et al. (2022), for pest control to reduce workloads and associated risks of injury, thus freeing farmers to focus on more strategic aspects of farming and increase the overall synergy of

tasks. In their review of automation in agriculture, Bazargani and Deemyad (2024) focused on the Cäsar and Greenbot robots designed for soil fertilization, pest control, and planting tasks, utilizing RTK-GNSS for precise navigation.

**3.1.4.3. Navigation and communication.** The contribution of data collection to synergy relies on robust navigation systems, to support the manipulation of different plant sizes, the misalignment of the row structure, and weed identification (Winterhalter et al., 2018). Robots employing RTK-GNSS for precision navigation improve the synergy between fertilization, pest control, and planting (Bazargani and Deemyad, 2024). By ensuring precise and localized input applications, robots enable the integration of technological advances with crop and soil needs, improving productivity with minimal adverse environmental impacts. To provide reliable navigation Ünal and Topakci (2015) proposed a robot control via 3G internet, in combination with embedded GPS and image processing capabilities, with also a remote joystick control for manual navigation and real-time video transmission for monitoring. Visual guidance solution has been developed also in Norwegian strawberry fields (Ponnambalam et al., 2020), through semantic segmentation based on convolutional neural network overlapping with data collection, finally highlighting how synergy between navigation technology and crop-specific requirements can improve field operations.

## 4. Discussion

Beyond the immediate impact at the field level, agricultural robots should also be questioned for their capabilities to offer broader social and environmental benefits, such as healthier ecosystems, reduced environmental degradation, and enhanced food security. They also inevitably influence labour dynamics and rural livelihoods. Understanding these interactions is crucial for evaluating the alignment of robotics with agroecological transitions, framing their responsible integration with both environmental sustainability and social equity. In the following paragraphs, we discuss the study limitations before addressing some emerging perspectives within the scope of our research (Fig. 8).

### 4.1. Limitations of the study

The geographical distribution of authors' affiliations of the reviewed documents may reflect the uneven regulatory frameworks (Lowenberg-DeBoer et al., 2021). For example, the use of UAVs for crop protection is prohibited in Europe but permitted in China. These regional differences shape research priorities and the development of specific applications and can also influence how agroecological principles are considered and addressed.

This review highlights the complexity of integrating agroecology principles into agricultural robots. Despite the reference to elements and principles, agroecology appears to be still a highly polysemic term with different interpretations, especially in the context of ecological and technological intensification (Tittonell, 2014), which may even reflect power imbalance and misuse of the terms (Sumberg et al., 2023). On the one hand, these differences led to different implementations across studies, which were difficult to consider. On the other hand, the literature sample may have been biased by an overhyped reference to agroecology and sustainability, similar to the mention of climate change even in research that does not directly address the topic (Brown, 2023).

Although paywall restrictions reduced the available literature body, the overall limited number of documents addressing agricultural robotics and agroecology also reflects the nascent nature of this field. The selected database and screening criteria may have excluded some relevant studies. For example, the choice of a single database (i.e. Scopus) can have inherently biased the results, as some relevant studies may not be indexed in it. However, other databases are either more restricted (e.

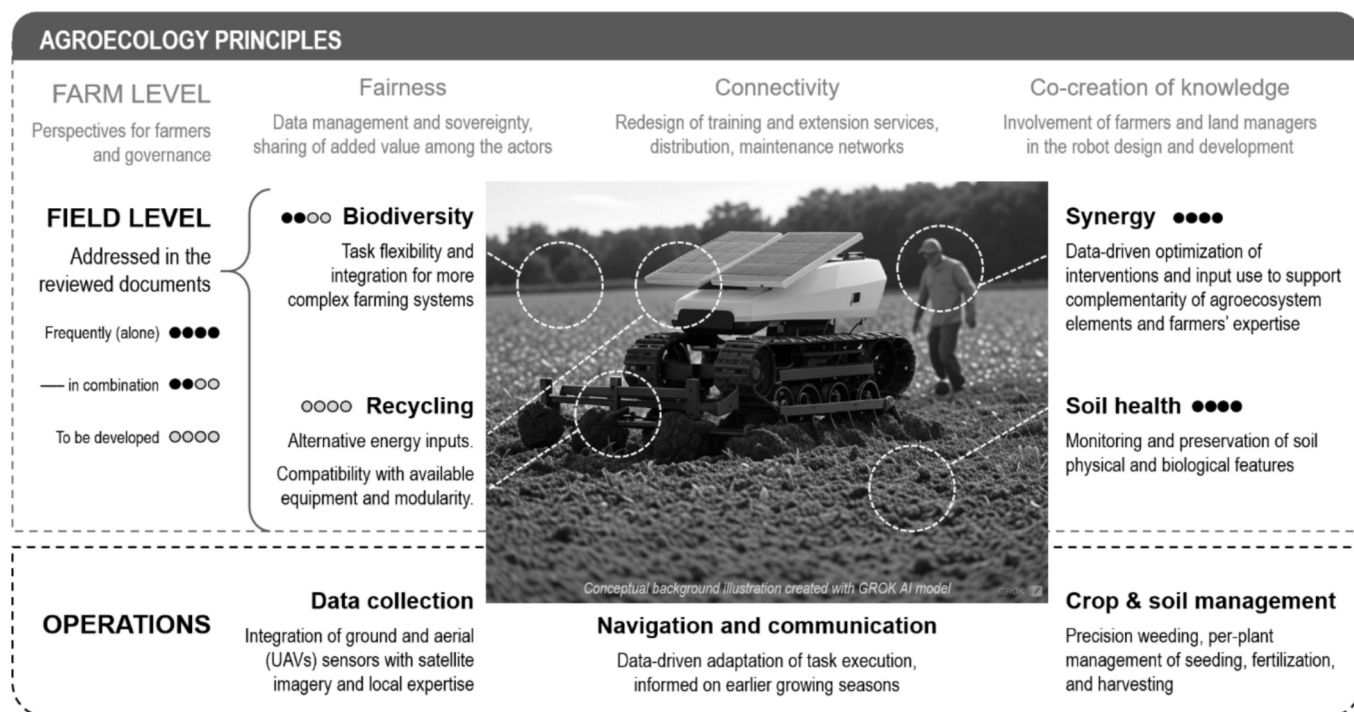


Fig. 8. Schematic summary of the operationalization by agricultural robotics of field level agroecology principles, based on the reviewed documents, and emerging perspectives.

g. Web of Science), unstructured (e.g. Google Scholar), or non-relevant for the subject (e.g. PubMed). Concerning the screening, the first phase based on keywords and abstracts may have overlooked pertinent research due to misclassification or lack of detail in the text. Moreover, the focus on field level principles excluded other critical agroecological elements, such as economic viability, farm resilience, and connectivity. Finally, the rapid pace of technological advances in robotics and related technologies creates a risk of obsolescence of the studies reviewed, although the review criteria remain valid.

#### 4.2. Perspectives on agricultural robotics for agroecological transitions

Despite the listed limitations, this study highlights some perspectives for research about agricultural robotic operationalization of agroecology concerning three topics: technology, farming systems, and the implications for farmers and governance.

##### 4.2.1. Technologies for sustainable farming practices

The reviewed documents have demonstrated the potential of agricultural robotics to support some operational needs of agroecology. For example, robotic integration of mechanical or chemical weeding with real-time weed detection can be improved by early data collection to increase precision, maximize effectiveness and reduce intervention costs (Bručienė et al., 2022; Mitsui et al., 2008). The integration of these detection models with robotic platforms enables targeted weed management methods, such as mechanical weeding, laser or thermal treatments (Cutulle and Maja, 2021), to optimize crop yield while considering ecological and socio-economic constraints (Bajwa et al., 2015; Bručienė et al., 2021; Fatima et al., 2023; Zingsheim and Döring, 2024). Similarly, autonomous spraying systems leverage data-driven decisions to apply pesticides or fertilizers with accuracy tailored to specific crop needs and field conditions (Umeda et al., 2022; Vijayakumar et al., 2023). In this regard, the analysis could be extended beyond agroecology to encompass other sustainable farming practices such as agroforestry, conservation agriculture, organic farming (Giagnocavo et al., 2025). In conservation agriculture, robots lighter than

conventional machinery can improve the preservation of soil structure and reduce compaction (Calleja-Huerta et al., 2024), in line with the principle of minimum soil disturbance. In agroforestry systems, robots with high mobility can navigate and manage the complexity of inter-cropped trees and shrubs to execute tasks such as pruning or precision nutrient application (Chowdhary et al., 2019; Van Cauwenberghe, 2023). In summary, agricultural robotics can meet and integrate the needs of all these systems for precision, adaptability, and resource efficiency to minimize environmental impacts and enhance productivity through the development of data-driven, site-specific multi-task integration, although their implementation must consider the unique characteristics of each system (Javaid et al., 2022).

##### 4.2.2. Integrating robotization in farming system design

Robots are tools that need to be integrated in the wider farming system design. Their contribution to diverse and complex farming systems poses technical and agronomic challenges. Some of the robots are primarily designed to optimize uniformity and efficiency in conventional monocropping or simplified cropping systems (Ditzler and Driessen, 2022). First, robots can support farmers to redesign farming systems for tasks such as seeding, harvesting, and soil preparation, in a comparable way to other precision agriculture technologies. The use of precise geolocation systems ensures uniform seed placement and spacing, optimizing germination rates and crop density (Nagchaudhuri et al., 2023). This precision can be then mobilized by robots, using advanced sensors and imaging technologies to streamline the collection process, to ensure efficient crop retrieval while minimizing damage and loss at the harvest (Madhavi et al., 2023). In addition, robots are demonstrating advanced capabilities to identify and selectively harvest ripe fruits or vegetables based on colour, size, and maturity indicators, further optimizing yield and quality (Ball et al., 2015). On the background, constant data collection tasks across the entire farming cycle can help creating feedback loops to continuously refine and improve agricultural practices. Overall, robots also have a greater potential than conventional machines to adapt to ecological and operational diversity thanks to their smaller size and greater modularity (Griepentrog and

Stein, 2024). This could operationalize the deployment of complex agroforestry, intercropping, and other diversified systems (Donat et al., 2022). However, this requires further advances in navigation and communication tasks to allow robots to navigate irregular terrains while monitoring soil health and crops or fruits (Bechar and Vigneault, 2016). Advanced algorithms enable these systems to adjust spraying patterns in real-time based on environmental variables, ensuring optimal application and minimizing drift.

#### 4.2.3. Next steps in the transition towards sustainable and agroecological farming

The transition to agroecology and sustainable farming practices supported by robotics primarily has been driven by precision agriculture and conventional automation goals, such as maximizing efficiency in monocultures or simplified cropping systems (Ditzler and Driessen, 2022). Nonetheless, current technological advances promote ecological integrity and resilience across diverse systems. For example, the development of agricultural robotics is addressing the redefinition of the life cycle assessment for machinery design (Pradel et al., 2022), with a potential contribution to the recycling principle at the system level. Beyond practices, agroecological transition concerns also livelihood and governance, which raises challenges for farmers and for governance.

First, research on agricultural robotics should include farmers' mastery of automation, and their capacity building to lead the related digitalization. Compared to conventional machinery, agricultural robots allow for the development of collaborative human-robot interactions, or "co-bot" approaches. This would help integrate robots into sustainable farming without displacing labour or marginalizing traditional farming knowledge (Ditzler and Driessen, 2022). By combining human expertise with robotic precision, these technologies can optimize tasks while maintaining the flexibility required in complex, diversified farming environments. On another front, the role of low-tech solutions in agroecology and other sustainable farming practices should be considered to avoid perpetuating the digital divide and support the inclusion of low-income regions (Gkissakis and Damianakis, 2020). Low-tech options are often more accessible and can help bridge the gap for farmers transitioning to sustainable practices (Comi, 2023; Vandôme, 2023). The integration of low-tech and high-tech approaches can create a hybrid model that leverages the strengths of both, offering scalability and inclusiveness (Bellon-Maurel et al., 2022).

Second, governance is expected to link agricultural robotics advances and the transition to agroecology (Bellon Maurel and Huyghe, 2017; Lowenberg-DeBoer et al., 2021). On the one hand, interdisciplinary collaboration will play a critical role in bridging the technical, social, and economic dimensions of robotics and low-tech solutions, to ensure their effective and equitable deployment (Ayris et al., 2024). By prioritizing adaptability, inclusivity, and accessibility, agricultural technologies — including both advanced robotics and simpler tools — can become integral to advancing sustainable farming practices across diverse contexts and levels. On the other hand, participatory and inclusive design processes remain essential for developing technologies that are consistent with the principles of sustainability and equity (Eastwood et al., 2022; Grahmann et al., 2024). Finally, agricultural robotics is challenging the machinery manufacturing sector through the emergence of new actors (Rizzo et al., 2019), thus opening new opportunities to engage with farmers, researchers, and other stakeholders by design to integrate specific requirements of different sustainable farming systems.

#### 4.2.4. Future research

The results highlight three operational contributions of agricultural robots to agroecological transitions: (1) increased precision in resource management, (2) reduced environmental impact through targeted interventions, and (3) improved data collection for adaptive management. However, challenges remain in achieving full integration with all agroecological principles, at the field level and beyond, particularly in

integrating complex decision making and ecological understanding. The review identified three areas to consider for this integration.

First, technologies. The design of robots and their equipment should meet the evolving needs of farmers to cope with greater weather uncertainty and the societal demand for greater sustainability in food production. For example, the use of robots that are lighter than conventional machines can extend field accessibility and enable timely and repeated mechanical weeding even in difficult soil conditions, with benefits for biodiversity and soil health. In addition, the automation of weed control with non-chemical methods (Fennimore and Cutulle, 2019), further supported by data collection and processing (Ghatrehsamani et al., 2023), and accurate navigation, can contribute to manage herbicide resistant species (Bloomer et al., 2024; Yu et al., 2024).

Second, data collection. The widespread use and development of a growing range of sensors, together with the integration with other data collection devices, and historical data, is improving the understanding of agro-environmental processes. This new added value needs to be mastered by farmers to leverage their expertise. Dedicated training and advisory support should enable farmers to understand data management and automation (Mattetti et al., 2022; Ritz et al., 2019) and make them aware of privacy and cybersecurity issues (Arreaga et al., 2023; FBI, 2016; Jararweh et al., 2023). Regarding data itself, the lack of accessible, structured, and curated datasets to train algorithms hinder advances. Individual investments by robot manufacturers and developers are a relevant challenge and limit the comparability of performance, although some research projects are addressing this issue (Regnier et al., 2021; Vayssade et al., 2023). This applies to the execution of crop and soil management tasks, robot navigation, and the definition of safety standards. Finally, for navigation and communication, the increasing accuracy of geolocation is improving path planning. In addition, reliance on satellite data is being reduced by using onboard image analysis and physical data collection to improve the reliability of navigation both for farming tasks and operator safety. A key emerging challenge is to enable the communication between robots to operate as a fleet. This might enable the coordination of lightweight units to perform multiple tasks, thus facilitating the replacement of conventional heavy machines with swarms of modular lighter units better adapted to complex farming systems.

## 5. Conclusion

This scoping review identified both the potential and limitations of agricultural robots in operationalizing agroecological principles at the field level. While robots operationalize promise in areas such as precision farming and automation, their integration with agroecological practices is currently limited to technical factors. Among the field level principles, research in agricultural robotics for agroecology is addressing synergy (e.g. integrating data sources to improve task planning), and soil health (e.g. lightweight machinery to reduce soil compaction). Biodiversity is mostly addressed in combination with synergy and soil health (e.g. selective weeding to preserve non-target species and soil health based on data integration). Recycling, however, remains a principle that needs to be further developed, to go beyond the already positive implementation of solar-powered robots, and enable wider system efficiency.

In summary, future developments should focus on designing robots that can adapt to diverse farming systems while supporting, rather than replacing, traditional agricultural knowledge. Integration between practices is critical to advance agroecological transition at the farm level and beyond, and this can be supported by better connectivity between flexible pieces of equipment. Challenges for research and development include: (1) integrating multiple agroecological principles into robot development "by design", especially with respect to the recycling principle; (2) supporting the design of farming systems based on a redefinition of operational units within the field, to take into account and

promote biodiversity, soil health synergy; (3) ensuring farmers' mastery of agricultural robot technologies including low-tech alternatives.

### Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used different online free generative AI services in order to improve the fluidity and clarity of the text. The Grok 2.0 AI algorithm was used to generate the background conceptual illustration for Figs. 6 and 8. ChatGPT 3.5 was used to check for English Language consistency. After using these services, the authors carefully reviewed and edited the content as needed and take full responsibility for the content of the publication.

### CRedit authorship contribution statement

**M. Naim:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **D. Rizzo:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization. **L. Sauvée:** Writing – review & editing. **M. Medici:** Writing – review & editing, Writing – original draft, Validation, Supervision, Project administration, Methodology, Conceptualization.

### 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.

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### Data availability

The data supporting this study has been deposited in a publicly accessible Zenodo repository and is available via a DOI provided in the Methodology section of the manuscript.

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