Use of robots and AI in agriculture

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Executive Summary

This document presents a comprehensive overview on the use of robots and artificial intelligence (AI) in agriculture in the European context. It showcases the current state of the art of innovations categorising them by their Technology Readiness Levels (TRLs), ranging from fully deployed systems to early-stage research, and explores their potential to enhance productivity, sustainability, and resilience in farming.

The paper finds that AI is already benefitting a wide spectrum of agricultural applications. Besides the well-known tools like precision irrigation, variable-rate application (VRA) of fertilisers and pesticides, crop health checks, yield forecasts, and local weather updates, AI is also supporting livestock and fish farming. These include smart sensors for animal health monitoring, AI-driven milking systems, and real-time fishery analytics. Many AI models are now increasingly integrated into farm dashboards, enabling holistic real-time monitoring and decision-making. Advanced applications under development include AI agents capable of performing multiple agronomic tasks through modular, interoperable systems. Digital twins are also being tested for scenario planning, climate impact forecasting, and risk simulation. In this way, they offer predictive insights into complex environmental and economic variables. Federated learning models are also gaining momentum, given their capacity to allow collaborative AI development across farms while preserving data privacy and sovereignty—an especially important consideration in the EU context.

Robotics is also offering a diverse ecosystem of technologies with promising applications currently at different maturity levels. At the high end, large-scale autonomous machinery is already operational, bringing positive effects, such as efficiency improvement and labour dependency reduction. These systems are also integrable with precision input application and real-time monitoring AI tools. At the medium TRL level, small-scale Unmanned Vehicles (UxVs) are being deployed for their low soil compaction, energy efficiency, and adaptability to diverse cropping systems, particularly suitable to smallholder farms and fragmented plots. Precision robotics is also under development to cover for tasks requiring delicate handling of high value crops. These include selective harvesting, pruning, grafting, and seeding. Lastly, cooperative robotics constitutes and emerging frontier, with fleets of autonomous agents can coordinate with each other to perform large-scale monitoring. Examples include both human-robot collaboration (e.g., cobots assisting in complex tasks) and swarm robotics.

The synergic integration of AI and robotics can enable more efficiency in tasks such as real-time monitoring, decision-making, and execution, enhancing productivity, accelerating learning cycles, and supporting adaptive responses to climate change and market volatility. However, significant challenges also exist: from technical issues such as AI reliability and cybersecurity to regulatory hurdles related to the EU AI Act and data privacy laws. Just as important are economic barriers to adoption, and societal concerns about digital inequality and the changing role of farmers.

To illustrate these developments, a series of EU-funded use cases are presented, including drone-based monitoring platforms, federated data systems for livestock management, AI-powered farm assistants, and smart viticulture tools. These examples demonstrate the real-world impact of AI and robotics in improving efficiency, sustainability, and decision-making in agriculture.

The paper concludes with a set of policy recommendations aimed at fostering responsible and inclusive adoption of these technologies.

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Introduction

Artificial Intelligence (AI) and robotics can potentially bring improvement to the agricultural sector which is currently experiencing a major push for digitalisation and automation of its processes and services. Their combination can reshape traditional farming practices, making them more efficient, sustainable, and responsive to current socioenvironmental and economic challenges. Among its uses, the integration of AI-based smart solutions, can help optimise crop yields, reduce waste, and manage resources more effectively.

The integration of AI and robotics tech applications represent an opportunity to boost the competitiveness of the EU agricultural sector, while at the same time, align with some of the main policy objectives of the Common Agricultural Policy (CAP).[1] The uptake of such intelligent systems can help the European agricultural sector to stay competitive while also filling the workforce gap and improving the sector's overall resilience. Moreover, integrating smart applications in the agricultural value-chain contributes to an efficient natural resource management system, to climate targets and to the EU Green Deal's main goals.

Concurrently, the introduction of AI particularly but also robotics, raises issues for the agricultural sector concerning external dependencies (for data management), power imbalances (especially the concentration of economic power in the hands of few companies), ethics and environmental impact of the technological infrastructure. These issues, while of major importance, are briefly mentioned in Section 3 but will not be addressed in depth in the current document as they will deserve a dedicated publication space.

This paper explores the current and future impact of AI and Robotics on agriculture, exploring into various AI-powered technologies and robotics applications and their benefit for the sector and their current application level. Such a wider set of applications is observed according to four-tier criteria looking at different adoption and development level of the technologies under scrutiny to negotiate concision and complexity. Both robotics and AI innovations are divided into 4 main categories:

- **Already there (High TRL levels)**: technologies already operational and on the market with possibility to improve patents and interoperability
- **Prototypes, first developments (High-Medium TRL levels)**: technologies presenting a high to medium development level (e.g. prototypes, trials and pilots)
- **Prototypes, coming soon (Low TRL level)**: technologies not in the initial stage but presenting a low development level (e.g. proof of concepts, demonstrations)
- **Research in progress:** technologies at the earliest development level, needing significant development stages to be adopted (e.g. simulations)

The document also analyses the intersection of the two domains and current policy challenges, overviewing key topics and the main related policy challenges. These include regulatory sandboxes, standardisation, interoperability, and business models and the importance of stakeholder involvement.

[1] See Key policy objectives of the CAP 2023-27 - European Commission

This document is structured as follows:

- **Sections 1 and 2** provide a bird's eye view of AI and robotics applications in agriculture according to their maturity and adoption level (with linkages on use cases described in section 4).

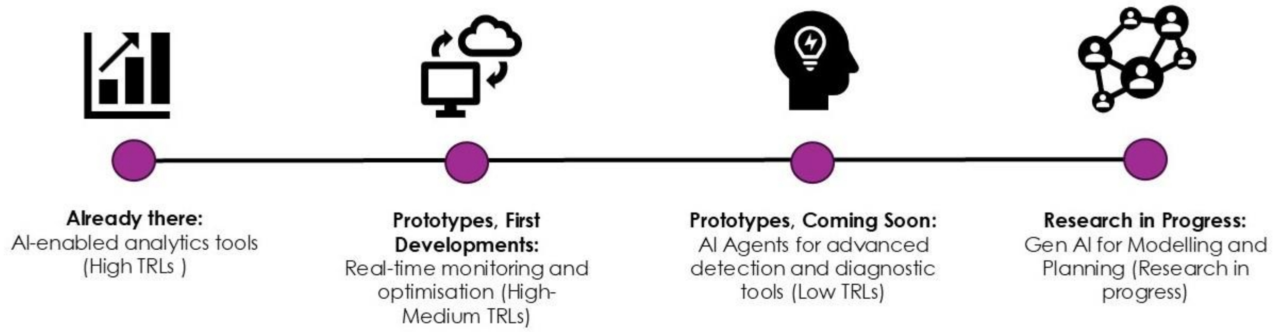
- **Section 3** presents concise overview of intersection of AI and robotics with main policy challenges associated to both areas against the current EU policy framework and the importance of regulatory sandboxes.

- **Section 4** outlines the latest use cases in the agriculture sector developed in the EU with links to different applications and tools described in sections 1 and 2.

- **Section 5** lists a concise set of policy recommendations based on the insights provided by the paper to seize the momentum and allocate resources to bridge key technological and industrial gaps.

1. Artificial Intelligence

The classification of AI tools in this section is structured around their Technology Readiness Levels (TRLs), classifying them according to their maturity, deployment status, and potential impact. This framework helps distinguish between tools that are already integrated into operational environments and those still in the conceptual or experimental phase. AI applications are therefore organised along a market-readiness criterion: from fully deployed analytics platforms to early-stage generative AI for planning.



1.1 Already there: AI-enabled analytics tools

In the face of increasingly adverse and prolonged weather conditions, AI applications are helping farmers to maintain the viability of their production offering enhanced instruments for climate resilience technology applications against erratic climatic patterns (e.g. droughts, unpredictable rainfall, and heat waves) which are putting agricultural operations at risk.

AI-enabled analytics tools support the utilisation of drought-resistant crops, smart irrigation systems, and advanced forecasting tools. These allow farmers monitoring variables such as soil humidity, temperature and crop status through IoT sensors and data analysis platforms to make data-driven decision-making, automate tasks, and optimise input use (Subesh and Metha 2021). Moreover, these tools allow them to reduce excess water, fertiliser, and agrochemical use, lowering environmental impact and improving soil health.

1.1.1 Precision Irrigation Control

AI-powered irrigation tools can help farmers optimise irrigation schedules and improve water management by analysing weather patterns, soil conditions (e.g. moisture data), and crop types/growth. These systems try to determine the required water levels and automate irrigation schedules accordingly. They can also incorporate localised weather forecasts to anticipate rainfall and adjust plans. Just as importantly, AI tools can help harmonise datasets and formats, including unit conversions and handling missing values. Based on the available pool of data, they can be trained on standard hardware (office laptop) with lightweight explainable algorithms and able to periodically improve their accuracy (Rauch et al. 2025).

1.1.2 VRA for Fertilisers and Pesticides

Variable Rate Application (VRA) technologies apply AI to remote sensing applications to intelligently apply fertilisers, pesticides, and seeds adjusting to soil and crop data and field variability. Datasets are taken from satellite and camera imagery, drone data, and sensor inputs, helping farmers determine input levels and locations, create prescription maps and zonal management systems in relation to soil composition, crop type, growth stage, and weather conditions. Other relevant parameters are the total utilised agricultural area, crop rotation, historical yields, and regional climate conditions. In Greenhouses, similar technologies determine the optimum irrigation flows and fertilizer content. In addition, paired with precision agriculture technologies (e.g. variable rate applicators linked to AI-generated prescription maps) these optimisation systems can also reduce nutrient runoff and chemical use. Studies have estimated 60% fertilisers use reduction and 80% pesticide use decrease (Papadopulous et al. 2024; Masi et al. 2023).

Overall, the use of such AI models in agriculture provides farmers and policymakers with data-driven recommendations to reduce input costs, boost yields, and meet environmental targets (Martinho 2023). This reduces costs, minimises environmental impact, maximise yields and supports sustainable practices by avoiding over-application and thereby preserve soil health.

1.1.3 Crop Health and Quality Detection (Image-Based)

AI-driven image analysis tools relying on remote sensing and deep learning techniques can support early detection of diseases, pests, and nutrient deficiencies in plants. Using high-resolution images from drones, smartphones, or field cameras fine-tuned on plant imagery (transfer-learning-based computer-vision classifiers), machine learning models can identify symptoms not visible to the human eye (Rauch et al. 2025). These systems distinguish between different types of stress and provide treatment recommendations, enabling, in principle, timely interventions and reducing crop losses. This should allow data-driven interventions that improve yields forecasts and support sustainable agriculture. Post-harvest, quality detection systems help to grade and sort produce.

1.1.4 Yield Prediction Models

AI models trained on data such as soil composition, crop variety, weather, and historical yields are already trained at scale to deliver predictive insights on production outcomes. Such forecast systems can support decisions on planting, harvesting, and marketing, and contribute to supply chain and food security planning. Deep learning algorithms like Convolutional Neural Networks (CNNs), Decision Trees, Random Forests, and LSTM models process satellite and drone imagery, weather data, and real-time sensor inputs for yield prediction (Goel & Padney 2024). Several agricultural platforms like IBM Watson Decision Platform for Agriculture and Microsoft FarmBeats already integrate these AI models for operational use by farmers and agribusinesses.

Recent studies report exceptional predictive performance (0.92) and low mean squared errors, reflecting high precision in real-world applications. In addition, explainable AI (XAI) techniques are increasingly used to make predictions transparent and actionable for users, revealing the most influential factors in yield outcomes (Mohan et al. 2025). As more data becomes available, these models are expected to become more detailed and adaptive.

1.1.5 Localised Weather Forecasting

AI models for localised weather forecasting can provide improvements in accuracy, speed, and resolution, processing massive volumes of meteorological data (e.g. satellite imagery, weather station readings, sensor inputs data, and historical records) through advanced machine learning algorithms to create hyper-local weather predictions. These inform decisions on irrigation, fertilisation, and harvesting. They can also simulate future weather scenarios, helping farmers prepare for extreme events and reduce climate-related risks. For instance, they can forecast wildfire risks and spread.

Studies throughout Europe, covering 35 crop-country combinations, show that machine learning significantly enhances regional crop yield forecasting, making predictions timelier and more reliable (Paudel et al. 2022). In protected horticulture, such as greenhouses, AI combined with sensor networks can help control local climate, irrigation, and crop quality, and to predict yield outcomes with high precision (EPRS 2023). These tailored forecasts enable farmers to make proactive, data-driven decisions about irrigation, spraying, and harvesting, increasing productivity and resilience against weather variability.

1.1.6 Livestock and fishery related AI applications

In cattle husbandry, smart ear-sensors track cows' temperature, rumination and activity; barn and overhead cameras help monitor movement anomality and inflammations in cows, pigs and chicken. AI is also used to analyse the data and provide real-time alerts to farmers regarding illnesses, stress or air quality issues (Pichlbauer et al. 2024). In fishery, real-time catch analysis and quantification allocate fish to the right commercial categories (Kim, S.-G. et al. 2024), potentially directly connected to the companies' ERP systems. Scale debris or bone splinters in meat are automatically detected using AI X-Ray image analysis, reducing recalls.

1.2 Prototypes, First Deployments (High-Medium TRLs): Real-Time Monitoring and Optimisation

Real-time monitoring systems are starting to be deployed in smart agriculture. Embedded AI-enabled models offer predictive insights that enable farmers to make timely and informed decisions. The result can be a more efficient use of resources, reduced operational costs, and improved crop performance.

1.2.1 Pest and Disease Early Warnings

AI-driven early warning systems can improve pest and disease management. Machine learning models trained on large datasets can detect patterns that precede outbreaks, such as changes in temperature, humidity, or crop physiology. As a result, they help farmers act and prevent damage, issuing alerts before symptoms become visible. Combined with image-based diagnostics and remote sensing, these tools enhance surveillance and may reduce the need for blanket pesticide applications. Multimodal models can analyse different types of data simultaneously.

In addition to their predictive capabilities, AI-powered pest and disease early warning systems can leverage on advanced techniques (e.g. convolutional neural networks) to classify crop stress and distinguishing between disease symptoms and nutritional deficiencies based on spectral data (e.g., Colorado Potato Beetle), allowing for focused interventions rather than blanket treatments. Integrating data from multiple sources—including microclimatic sensors, hyperspectral imaging, and UAVs (Unmaned Aerial Vehicles)— can help further refine these predictions and support real-time monitoring (Aziz et al. 2025; Dong et al. 2024).

1.2.2 Harvest Timing Prediction

AI systems can help determine optimal harvesting windows by analysing crop maturity, weather forecasts, and environmental conditions. These systems consider factors such as sugar content, moisture levels, and predicted rainfall to minimise post-harvest losses and ensure product quality. This helps farmers to better coordinate labour, logistics, and storage.

Recent advancements have applied deep learning models, such as long short-term memory (LSTM) neural networks, to predict harvest dates for crops like wheat, maize, and soybeans using multi-source data—including radar satellite imagery, weather records, and high-frequency field monitoring. These AI models are valuable for improving harvest accuracy under varying climatic conditions, with proven performance even across different European agricultural landscapes (Mimic et al. 2025). Time-series image analysis, such as the work on cauliflower harvest-readiness, demonstrates that combining phenotypic data from multiple key developmental stages leads to more accurate and efficient harvest scheduling, reducing the need and cost of manual crop inspections (Kierdorf et al. 2024)

1.2.3 Real-Time Farm Dashboards

Farm dashboards powered by AI and IoT integration offer a centralised view of farm operations, consolidating data from sensors, drones, weather stations, and machinery. These tools allow farmers to monitor field conditions, track input usage, and receive alerts or recommendations. Some systems include voice-enabled assistants or chatbot interfaces to improve accessibility, or edge AI smartphone apps for in-field diagnosis.

The adoption of AI-enabled, real-time dashboards is growing across European farms. One example is provided by the AgriDataValue project, which uses federated deep machine learning and human-explainable AI. These platforms have enabled data collection of over 160 variables—ranging from soil moisture and leaf health to air quality—across thousands of hectares and multiple countries. The dashboards not only centralise sensor, satellite, and operational data, but also provide actionable recommendations by integrating big data analytics, blockchain for traceability, and edge computing for on-site intelligence. Voice-enabled interfaces and semantic interoperability (ensuring systems "speak the same language") are being piloted to improve usability and accessibility for a diverse farming workforce, with ongoing efforts to evaluate their effectiveness in large-scale, heterogeneous European agricultural environments.[2]

1.3 Prototypes, Coming Soon (Low TRLs): LLMs for Advanced Detection and Diagnostic Tools

Large language models (LLMs) are increasingly being experimented in agriculture to support agronomic advisory and extension services. Models like GPT-4 can perform well on agronomy certification exams, suggesting their usefulness in education and decision-making. LLMs are also used to provide accurate responses to farmers' questions, improving access to technical knowledge (Kuska et al., 2024).

[2] Learn more at https://agridatavalue.eu/

1.3.1 AI Agents for multiple use

A new generation of AI agents can help support distinct agricultural tasks, contributing to education, assessment, and crop management practice by providing farmers with valuable insights (Silva et al. 2023). This form of AI differs from the previous generation in taking on "agentic" capabilities i.e. to directly intervene in the digital environment. These modular agents communicate via standard protocols to ensure interoperability and are adaptable to local conditions. Unlike broader AI systems currently in use, they are still in the prototype or early deployment stages. As outlined in recent studies focusing on AI-driven crop monitoring and soil analysis, intelligent agents can collaborate dynamically in farming environments by sharing real-time data and using reinforcement learning for decision-making, thereby improving efficiency and sustainability in precision agriculture (Judith, 2025).

1.3.3 Soil Health and Carbon Mapping

AI models trained on data from in-field sensors, laboratory soil analyses, and remote sensing can contribute to mapping soil health parameters (e.g. organic matter, pH, and carbon sequestration potential) with high spatial and temporal resolution. Using machine learning and data fusion techniques integrating Sentinel satellite data and local soil measurements, digital soil health maps enable farmers to track changes in carbon stocks and assess soil fertility variations. This information is essential for participation in carbon credit markets and for scientific monitoring of soil degradation risks. Overall, these tools are critical for monitoring soil sustainability and supporting regenerative agriculture practices in line with the European Green Deal.

1.3.4 Nutrient Deficiency Detection

AI-powered spectral imaging combined with advanced classifiers, including convolutional neural networks (CNNs) and modern object detection models is increasingly effective at detecting nutrient deficiencies such as nitrogen, phosphorus, and potassium in crops by identifying distinct spectral and morphological signs of nutrient stress. These AI-based tools contribute to precision nutrient management by enabling early intervention, thus improving fertiliser use efficiency, decreasing runoff, and supporting sustainable farming practices. Recent studies demonstrate applications in soybean and other key crops, using UAV or handheld sensors for rapid, site-specific diagnosis to optimise fertiliser application and reduce environmental impacts (Yin et al. 2024; Abioye et al. 2025).

1.4. Research in Progress, Initial Stages: Digital Twins for Modelling and Planning

Digital Twins are also currently being explored for agricultural modelling and strategic planning to simulate different agricultural scenarios involving planting schedules, irrigation strategies, and crop rotations. This allows farmers and planners to test options and optimise decisions before implementation. As development progresses, Digital Twins are expected to support more adaptive planning based on real-time environmental and market data (Purcell et al. 2023, Pylianidis et al. 2021, Tagarakis et al. 2024).

1.4.1. Climate Impact Forecasting

To tackle the challenge to adapt agriculture to the uncertainties imposed by climate change, digital twins are being developed to simulate real-world farms by integrating heterogeneous data streams from IoT sensors, satellite imagery, and regional climate models. These intelligent systems can dynamically model the effects of extreme weather events—such as droughts, floods, and heat waves—on crops, soil health, and agricultural inputs, facilitating simulation of "what-if" scenarios for risk assessment and management.

Recent research highlights a gain of over 90% in yield prediction accuracy using digital twin–based climate risk simulations, underscoring their potential for guiding agricultural decision-making and policy under climate variability and change (Rajeswari et al. 2024).

An example is the European Destination Earth (DestinE) initiative, which is leveraging exascale computing and AI to deliver operational multi-decadal climate projections at fine spatial resolutions (kilometer scale), a highly accurate digital replicas of Earth systems. This enables stakeholders to plan adaptive strategies aligned with the European Green Deal objectives (Wedi et al. 2025). Similarly, the EOAgriTwin project integrates satellite data, weather forecasts, and farm management information to develop an earth observation–based digital twin specifically designed for resilient agriculture under multiple stressors.[3]

1.4.2 Federated Farm Data Learning

Federated learning approaches are also emerging as promising solutions for agriculture to address critical concerns around data privacy, sovereignty, and the federated nature of agricultural data sources. This technique is particularly relevant for smallholders and cooperatives, as it allows AI models to be trained collaboratively across multiple farm datasets without requiring centralised data storage, preserving data ownership and guaranteeing confidentiality (Kondaveeti et al. 2024).

Recent research showcases how federated learning can harness distributed sensor data and heterogeneous datasets from diverse agroecosystems to build inclusive, robust AI models working across spatial and temporal scales (Gavai et al. 2025). Federated approaches leverage on decentralised model training to support digital inclusion, foster trust among stakeholders, and promote equitable benefits from AI-driven innovations. These characteristics are critical for the European agri-food sector's digital transformation, facilitating cooperative data sharing while complying with data protection regulations such as GDPR.

1.4.3 Risk Simulation Tools

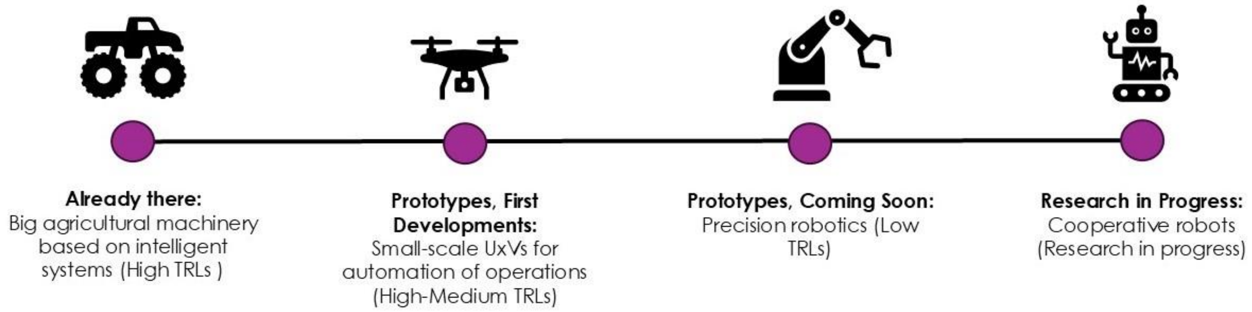
AI-powered risk simulation tools can model a wide array of agricultural risks thanks to their capacity to analyse extensive historical and real-time data encompassing climatic, biotic, and economic indicators. This data-driven risk management approach is crucial for sustainable farming practices, given the growing exposure of European agriculture to climate variability and economic uncertainty.

Examples include pest and disease outbreaks, market price fluctuations, and supply chain disruptions. These models use probabilistic and explainable AI approaches to estimate the likelihood and severity of potential adverse events on crop yields and farm profitability. For instance, novel AI systems can enable pre-emptive risk management in agriculture through multi-hazard early warning systems on climate extremes (e.g. droughts and frosts) that integrate expert knowledge with advanced explainable AI (Hrast Essenfelder 2025). Such probabilistic models provide farmers with uncertainty detection and quantification tools to efficiently allocate resources and implement targeted mitigation strategies. Additionally, sophisticated risk simulation frameworks enhance the resilience of agricultural supply chains, combining multiple data layers and dynamic modelling to support scenario-based planning in volatile market conditions (EFSA 2024).

[3] Learn more at https://www.eoagritwin.eu/

2. Robotics

Just like in the case of AI tool, the classification of robotics technologies below is based on their development stage and real-world applicability in the agricultural sector as measured by Technology Readiness Levels (TRLs). Following this framework, distinctions can be made between mature, widely adopted systems and those still in early research or prototyping phases. Such classification, ranging from large-scale intelligent agricultural machinery already in use, to emerging cooperative robotics in exploratory research, helps stakeholders better frame current capabilities, anticipate future innovations, and strategically plan for integration and investment.



2.1 Already there: Big Agricultural Machinery based on intelligent systems

Big Agricultural Machinery are already widely permeating the landscape of modern farming. From autonomous operations and precision interventions to advanced harvesting, these applications are helping the convergence toward data-driven, sustainable, and highly efficient agricultural ecosystems (Ren et al., 2020).

2.1.1 Automation of agricultural operations

Agricultural robotics has progressively automated operations previously carried out by traditional agricultural machinery. These advancements have paved the way for intelligent automation in agricultural operations, including precision crop harvesting and livestock farming. Most research has concentrated on perception and reasoning, involving object identification, product quality evaluation, monitoring plant and animal growth, yield prediction, forestry inventories and machine guidance.

Modern robotics is also enabling agricultural interventions with a level of precision that was previously impossible. Autonomous vehicles equipped with input application systems allow localised treatments of water, fertilizers, biopesticides, or phytosanitary products, reducing consumption and environmental impact (Rao Mogili & Deepak, 2018). Autonomous machinery, such as self-driving tractors and robotic harvesters, improves efficiency by performing tasks with precision and minimal human intervention. Furthermore, in modern livestock operations—especially dairy farms—robotic systems for milking, feed delivery, and barn cleaning have become widespread.

2.1.2 Harvesters

Advanced robotic manipulators can perform delicate agricultural tasks such as selective harvesting, pruning, or weed removal. These systems adjust grip strength and movement to avoid damage (minimising bruises and post-harvest losses) or even use lasers, maintaining product quality and reducing the reliance on specialised labour. Automated harvesting systems have become the fastest-growing segment in Europe's agricultural robotics market by 2024–2025, also as a result labour shortages, stricter environmental laws, and the demand for premium, undamaged produce.

Adopting these technologies helps boost productivity, reduce resource waste, and align with the EU Green Deal's sustainability goals. Overall, these systems offer practical solutions to balancing profitability, product quality, and regulatory compliance amid continued pressure on agricultural labour resources (IMARC 2024).

2.1.3 Monitors

Most research efforts in agricultural robotics have concentrated on perception and reasoning systems. Robots equipped with advanced sensing technologies play a critical role in several related tasks:

- Object identification (distinguishing between crops, weeds, or livestock)
- Product quality evaluation (assessing ripeness, damage, or disease)
- Monitoring plant and animal growth patterns
- Predicting yields based on environmental and biological data
- Providing navigation and guidance for autonomous machines (Spagnuolo et al. 2024)

Recent research emphasises the utility of monitoring systems as proactive management tools beyond routine data collection. Examples include the detection of irrigation leaks, mechanical blockages, component wear, or electrical faults, much before escalations impacting productivity. Instances include real-time data collection on soil conditions, crop health, and livestock behaviour, enabling precision agriculture and informed decision-making throughout the production cycle (Sander et al. 2021).

2.2 Prototypes, first deployments (high-medium TRLs): Small-scale UxVs for automation of operations

Small-scale Unmanned Vehicles (UxVs) offer a low-impact, cost-effective, and energy-efficient solution for agricultural monitoring. Their lightweight structure reduces soil compaction and can adapt to various crop types. Compact design allows them to operate in narrow or irregular plots, making them ideal for smallholder farms and diversified cropping systems. This flexibility enhances their usability across different agricultural contexts, from vineyards to vegetable farms. The main features of small-scale UxVs for agriculture are discussed more in detail below.

2.2.1 Low impact (e.g. soil compaction)

Soil compaction is a major issue in conventional agriculture, as it restricts root growth, reduces water infiltration, and ultimately lowers crop yields. With their lightweight, UxVs help maintain optimal soil conditions, better adapting to different plots. Conventional large tractors and equipment exert pressures often exceeding 1.0 kg/cm^2 on soils, leading to irreversible compaction that harms root development, water infiltration, and ultimately crop yields. In contrast, innovative platforms such as those developed in the EU-supported Autonomous Lightweight Agricultural Vehicle (ALAV) project maintain ground pressures around 0.3 kg/cm^2, well below the critical threshold of 0.5 kg/cm^2 where irreversible soil damage occurs. These vehicles feature patented suspension and electric drivetrains that adapt dynamically to field conditions, preserving soil structure even with repeated passes required for monitoring or intervention. This ensures that even repeated monitoring or intervention does not degrade the soil, making them suitable for long-term, sustainable deployment, especially important in conservation agriculture and organic farming (Calleja-Huerta 2023a and 2023b).

2.2.2 Cost effectiveness

UxVs can also potentially democratise sustainable data-driven farming, providing a cost-effective alternative to traditional manual or large-scale mechanised methods for data-driven monitoring and managing of agricultural terrains. First, automation and minimised labour requirements reduce operational costs (Merz et al. 2022). Similarly, smaller autonomous machines, often adapted from existing equipment, offer significant savings in fuel, labour, and maintenance compared to conventional heavy machinery (Lowenberg-DeBoer et al. 2021).

These cost efficiencies make precision agriculture technologies accessible to small- and medium-sized farms often facing persistent rural labour shortages, including those in developing regions or operating on tight margins.

2.2.3 Energy efficiency

UxVs also offer a low-impact, cost-effective, and energy-efficient solution for agricultural monitoring. Their small size and optimised flight or navigation paths significantly reduce energy consumption compared to traditional machinery. Energy efficiency is further enhanced when UxVs are deployed in coordinated swarms (although this is still in a low TRL, see Section 2.4), which minimise redundant coverage and maximise data collection per unit of energy used. This makes them ideal for sustainable farming practices and aligns with global efforts to reduce agriculture's carbon footprint.

Other advantages include real-time data collection reducing manual labour while improving monitoring efficiency and supporting optimised resource use. UAV-based remote sensing lowers operational costs compared to conventional approaches by enabling precise crop growth and stress monitoring (Aierken et al. 2024). Additionally, studies on UAV applications in forage and specialty crops show that advanced sensor technologies such as multispectral and thermal imaging facilitate early detection of plant stress, helping reduce input wastage and energy consumption (Santos et al. 2024).

2.2.4 High granularity/precision

Unmanned vehicles (UxVs) equipped with high-resolution cameras and advanced deep learning algorithms—especially Convolutional Neural Networks (CNNs)—can enhance the granularity and precision of crop monitoring. Recent research confirms the robustness of CNN architectures with integrated residual connections and attention mechanisms that can achieve up to 98% accuracy in automated plant disease identification (Timileyin 2025).

Moreover, continental-scale crop type mapping research using modular deep learning models on satellite and UAV data can enable site-specific management decisions, further improving spatial and temporal resolution (El Sakka et al. 2025). These advances allow for timely and precise targeting of treatments, reducing input use while supporting a resilient, data-driven approach to crop management that optimises yield and resource efficiency across European farming systems. Autonomous underwater vehicles, combined with AI interpreting complex sensor data, allow fishery habitat mapping and stock surveys, leading to reduced cost, pollution and overfishing.

2.2.5 Sensor-equipped monitoring

UxVs equipped with a diverse array of sensors, including high-resolution RGB cameras, multispectral, thermal, and soil moisture sensors can improve agricultural monitoring, allowing farmers to detect plagues prematurely, monitor crop growth dynamically, and adapt management practices precisely to localise field variability.

Advanced sensor suites capable to capture detailed, multidimensional data provide a comprehensive, real-time view of crop health, soil conditions, and microclimatic variations across fields. For more complex off-site analyses, UGVs (Unmanned Ground Vehicles) can collect soil and nutrient sampling. Conversely, UAV-mounted multispectral and thermal sensors can accurately detect early stress symptoms in vineyards—such as water deficits and fungal disease—well before visual indicators. This enables timely and site-specific interventions that reduce input use and improve yield quality (de Castro et al. 2021). Thermal imaging combined with moisture sensing can also help identify zones prone to pest outbreaks through canopy temperature anomalies detection linked to insect activity. This facilitates early pest management strategies and reduces pesticide application (Santesteban et al. 2017).

2.2.6 Actuators embedded platforms

Autonomous platforms integrated with precision spraying systems and micro-irrigation technologies enable precise, site-specific application of agricultural inputs based on real-time sensor data or pre-mapped field conditions. This transforms autonomous platforms from passive remote sensing devices into active, site-responsive operators of agronomic management (Abdulsalam, 2023).

For example, UAVs can conduct rapid aerial surveys using multispectral imaging to detect crop stress and then apply foliar nutrients or water exactly where needed during heat stress or drought events, enhancing crop resilience and input efficiency (Padhiary et al., 2024). Meanwhile, UGVs navigate precisely between crop rows to deliver irrigation directly to the root zone or deploy slow-release fertilizers, improving nutrient uptake and minimising losses by runoff or volatilisation (Abdulsalam, 2023). Fruit thinning and blossom counting are other capabilities used in fruit cultivation. In cage-based aquaculture, robots start to inspect and maintain underwater structures.

2.3 Prototypes coming soon (low TRLs): Precision robotics

High-precision and delicate robotic handling is a promising area of research for enabling new farming modalities such as vertical farming, where space is limited and crop handling must be exceptionally accurate. Examples of tasks enabled by these systems are selective harvesting, pruning, grafting, and seeding with minimal damage and high consistency—capabilities that are essential in controlled environments where traditional machinery is impractical.

2.3.1 High-precision, delicate handling

Precision robotic systems are being developed to perform delicate agricultural tasks with a level of accuracy and care that exceeds traditional machinery. These systems integrate advanced manipulators, for instance soft robotics grippers, computer vision, and AI to dynamically adjust grip strength and movement, enabling them to handle sensitive crops such as berries, tomatoes, and grapes without causing damage, or harvest shellfish with care. This capability is essential for maintaining product quality and minimising post-harvest losses, especially in high-value crop sectors (Padhiary et al. 2025). An example is emerging robotic pollination systems employing special manipulators and mechanisms like spray or vibration in controlled environments like greenhouses and vertical farms. Despite their significant progress, challenges remain in adapting robotic systems to the variability of plant morphology and environmental conditions.

2.3.2 Selective harvesting

Selective harvesting robotics promises to automate one of the most labour-intensive and costly tasks in agriculture. Robots are being trained to identify ripe produce using visual and sometimes tactile cues, harvesting only what is ready while leaving the rest of the crop to mature. This technique is especially beneficial for crops with uneven ripening patterns, such as tomatoes, apples, and strawberries.

Selective harvesting remains a technically challenging task due to high variability in crop appearance, occlusion by foliage, and the need for gentle handling to avoid damage. Despite these challenges, recent advances in deep learning and 3D vision have improved fruit detection and localisation, with an estimated 61% success rate in optimal conditions (Koostra et al. 2021).

2.3.3 Pruning, Grafting, Seeding

Precision robotics is increasingly being applied to tasks requiring a high degree of dexterity and adaptability, such as pruning, grafting, and seeding. In pruning, robotic systems are being developed to address the labour-intensive nature of the task, particularly in orchards and vineyards where manual pruning can account for up to 25% of annual labour costs. Recent advances in machine vision, plant skeletonisation, and AI-driven control strategies have enabled robots to identify and execute precise cuts, even in complex canopy structures (Navone et al. 2025).

In grafting, robotic platforms are being designed to automate delicate operations such as seedling alignment, cutting, and union, which are critical for successful grafting. While semi-automated systems are already in use in some countries, full automation remains a challenge due to variability in plant morphology and the need for integration with seedling biotechnology (Yan et al. 2022).

Seeding is another area where precision robotics shows promise. Technologies such as GPS-guided navigation, variable rate seeding, and AI-based decision support systems enable site-specific seed placement, adjusting depth and spacing based on real-time soil and environmental data. This improves germination rates and reduces input waste—key goals for sustainable and high-efficiency farming (Yadav & Singh 2025).

2.4 Research in progress, initial stages: Cooperative robots

Human-robot cooperation remains an emerging research frontier in agricultural automation, offering potential solutions for tasks where full autonomy is still out of reach. Collaborative robots are being explored as tools to support human workers in complex, physically demanding operations, aiming to enhance productivity without replacing human judgment. Swarm robotics is also being investigated as a decentralised approach to machine collaboration, showing promise in large-scale monitoring and resource management.

2.4.1 Cooperation with humans

Collaborative robots, or cobots, are designed to assist human operators in labour-intensive tasks demanding both dexterity and complex decision-making. Unlike fully autonomous systems, cobots incorporate advanced safety features and adaptability, sharing workspaces with humans and responding dynamically to inputs in real time. This allows to augment human productivity while improving ergonomics, reducing physical strain and fatigue without compromising the precision and care required in delicate operations.

Effective human-robot collaboration in agriculture capitalises on combining robotic precision and endurance with human cognitive skills, enabling systems that are both efficient and socially acceptable (Yerebakan & Hu, 2024). Ongoing studies focus on developing intuitive communication interfaces, improving robot adaptability to diverse agricultural conditions, and embedding safety protocols such as wearable sensors to monitor human activity. This ensures safe and seamless integration into existing workflows. Moreover, Human-Robot Cooperation (HRC) systems can also be seen as transitional frameworks integrating social and technical dimensions (e.g. actively involving human feedback) to enhance acceptance and functionality in real-world settings. (Adamides & Edan, 2023).

2.4.2 Cooperation with other robots (swarm robotics)

Swarm robotics involves large groups of autonomous robots (e.g. drones and ground vehicles) capable to collaboratively perform tasks through decentralised coordination, distributed communication, and dynamic task allocation. This approach provides advantages in operational flexibility, resilience, and cost-effectiveness compared to traditional heavy machinery. Robotic swarms leverage inter-agent communication protocols and algorithms for scaling automation, combining distributed intelligence with real-time adaptability. This allows them to meet the diverse and evolving challenges of modern large-scale farming systems: efficiently cover extensive farm areas, optimise task division, and respond robustly to unexpected events such as weather changes or equipment malfunctions (Adamides & Edan, 2023). The multi-agent systems' ability to dynamically reallocate resources and share high-resolution sensory data, including multispectral and hyperspectral imaging, supports detailed, multimodal crop health mapping and precision resource management (Abdullah Al-Amin et al. 2025).

3. Benefits and Challenges of combining AI and robotics

The synergy between the AI-driven sensing and decision-support tools described in Chapter 1 and the robotic platforms outlined in Chapter 2 can form a closed “sense-think-act” loop directly in the field or may occur in a staged workflow in which data are gathered, processed by AI, and the results then fed back to robotic executors. In either case, combining these two technology streams produces outcomes greater than the sum of their parts. Autonomous machines translate AI-generated prescription maps into site-specific actions—for example variable-rate spraying or seeding—while simultaneously streaming real-time sensor readings that continuously refine the underlying models. Data captured by robots across many sensors and successive seasons enhances traceability, accelerates AI learning cycles and can help farms respond rapidly to weather or market shocks. AI performance improves further as robots automatically collect large volumes of high-resolution data that humans could not feasibly gather. Consequently, investments in robotic equipment are utilised more efficiently and reach pay-back sooner, strengthening the economic case for adoption. By tightly coupling AI analytics with physical execution, these integrated systems lift farm productivity and profitability, support environmental goals through precise input use, and reinforce overall sector resilience.

The integration of AI and robotics into precision agriculture poses an opportunity to create a holistic approach to boost agricultural productivity and mitigate different risk factors (e.g. climate imbalances, labour shortages), supporting future sustainable agriculture. However, integration of AI-enabled technologies in agricultural activity presents some risks and challenges that must be carefully addressed.

3.1 AI-powered machinery decision-making

3.1.1 AI Reliability & Decision Transparency

Ensuring robust AI models is essential to prevent biased decision-making or adversarial attacks that could disrupt agricultural processes. Robustness in AI models involves rigorous testing and validation to ensure they perform reliably under various conditions. This includes addressing potential biases in data and algorithms to avoid skewed outcomes that could negatively impact agricultural operations. Transparent frameworks and explainable AI approaches are crucial in this context. Explainable AI provides insights into how decisions are made, allowing stakeholders to understand and trust the automation processes and gain confidence in the technology, understanding how it can operate fairly and effectively.

Moreover, adopting AI in agriculture requires substantial technological infrastructure, which can be prohibitively expensive for many farmers, particularly those in low-income areas. Costs are associated with infrastructure expenses, including sensors, advanced robotics, and data analysis tools. The complexity of AI systems demands significant data processing power and reliable internet access, which are often lacking in rural or remote areas. Additionally, maintaining and ensuring the reliability of these technological systems can be challenging, as AI frameworks frequently require updates and repairs, which can be difficult in harsh electronic environments. Moreover, the costs associated with accessing and maintaining AI systems are high, not to mention the training required for farmers to effectively use these technologies. This situation is especially challenging for smallholder farmers and those in developing regions, who may not benefit from these advancements unless substantial investments are made by governments or private organisations to bridge the digital divide (Aijaz et al. 2025).

3.1.2 Regulatory & Ethical Compliance

Another obstacle to AI and robotics adoption in agriculture is the regulation surrounding AI technologies. Agriculture often involves sensitive information that farmers may be reluctant to share with others, including corporations or governments. Additionally, ethical concerns related to AI's role in genetic engineering and breeding could lead to new regulations. Governments are typically reluctant in adopting breeds emerging as the result of AI assistance without extensive testing and long-term impact assessments, which can delay the implementation of potentially beneficial technologies.

Data privacy legislation and agricultural data ownership are also growing concerns, as most AI systems require substantial data from farms to operate efficiently. Farmers may be worried about who owns this data and how it is used, prompting calls for stricter data protection measures. A clear regulatory framework that addresses ethical concerns and data privacy issues without stifling innovation is therefore very important. Engaging in direct discussions with farmers, policymakers, and other experts in the agricultural sector constitutes a first step toward establishing guiding principles that balance the benefits of AI with social and ethical responsibilities (Aijaz et al. 2025).

Just as importantly, the deployment of autonomous machinery in agriculture must adhere to stringent safety standards and regulatory frameworks to ensure the technology is safe and ethically sound. This involves complying with regulations that govern the use of autonomous systems, including those related to environmental impact, worker safety, and data privacy. Human-in-the-loop systems play a vital role in this compliance framework, as they involve human oversight in the decision-making process, ensuring that autonomous systems act within acceptable ethical and regulatory boundaries. Controlled environment validation is another critical aspect, where autonomous machinery is tested in a controlled setting to verify its reliability and safety and identify potential risks before large-scale implementation.

3.1.3 Cybersecurity & Operational Safety

As agricultural operations become more interconnected and increasingly rely on digital platforms for data storage and processing via cloud-based services, new challenges such as cybersecurity and data privacy emerge. To successfully integrate AI in agriculture, it is crucial to implement robust cybersecurity measures, including encryption to protect data during transmission and storage. Fail-safe protocols are necessary to ensure that systems can recover from disruptions or attacks without compromising safety or functionality. Strict access control measures must be in place to limit access to authorised personnel only, reducing the risk of malicious activities. By prioritising cybersecurity and operational safety, agricultural AI systems can maintain their integrity and reliability, ensuring that they continue to function effectively and securely in an increasingly digital landscape. Achieving this objective requires collaboration among technology providers, governments, and other stakeholders in agriculture.

3.2 Policy Challenges at EU level

Deploying intelligent systems to benefit different productive sectors is also a building block of the EU'2024 AI Act, provided that their long-term impact on the individual, society and democracy is duly monitored and assessed through continuous assessment, best practices and standards.4 For this purpose, the AI Act regulatory framework is designed to ensure the safe and ethical development of AI within the European Union, with a strong emphasis on risk management for high-risk AI systems to build trust in AI technologies while promoting their responsible use across various vertical sectors and safeguarding public interest. Understanding how, and to wat extent, the AI Act needs to be applied is crucial to align with the goals of the Union harmonisation legislation, which seeks to facilitate the free movement of products within the internal market and ensure the exclusive availability of compliant products.

Following the AI Act, providers must establish and maintain a continuous, iterative risk management system throughout the AI system's lifecycle, identifying and analysing foreseeable risks to health, safety, and fundamental rights. They must adopt measures to manage these risks, ensuring any remaining risks are minimised and acceptable. Post-market monitoring is required to gather data on the AI system's performance and incidents, helping to identify new risks and improve risk management measures. Special consideration is given to AI systems, particularly when integrated as safety components in products, could pose significant health and safety risks. Providers must also document all aspects of the risk management process and make this documentation available to regulatory authorities to ensure compliance and transparency. Such set of rules is needed to prevent the side effects of so-called "high-risk AI systems", that is products or safety components of a product requiring third-party assessment according to Annex I of the AI Act. Such definition also concerns agricultural and forestry vehicles as well as motor vehicles and trailers in general as items listed under the Eu harmonisation legislation.

While the AI Act's main purpose is to promote the cross-border uptake and free circulation of AI solutions while ensuring a high-level of protection to health, safety and fundamental civil rights according to the European Union's Fundamental Rights Charter, it also poses a significant challenge for the prompt evolution of AI and robotics applications in agriculture. As agriculture evolves towards AI-enabled machineries with self-evolving behaviours based on neuromorphic learning techniques, the AI Act's current classification of high-risk AI systems could significantly hamper the adoption of disruptive tech innovations in the agricultural sector. High-risk applications often mean a large administrative burden for farmers and increased equipment costs. This is particularly significant in the European continent, according to CEMA the largest global manufacturers of agricultural machinery, with an industrial worth of approximately €40 billion per year and over 300,000 direct and indirect jobs underpinning the economy of rural communities.[5]

Just as importantly, according to the AI Act, AI-powered robots can be classified as "high-risk AI applications" because of their potential impact in safety and society. For example, increasingly autonomous robots, whether used in manufacturing or for personal assistance and care, must be capable of operating safely and effectively in complex environments. Such regulation does not only apply to the health sector, with advanced diagnostic systems, but also for robotics-based applications in agricultural and forestry vehicles (Regulation No 167/2013), and also to broader regulations such as 2014/68 on pressure equipment, 2026/424 on cableway installations and 2019/2144 on motor vehicles, trailers, systems and components.

Aside from potentially hampering competitiveness, such administrative burdens also challenge the timely development of cutting-edge machinery that can enable farmers to reduce the use

[4] EUR-Lex - 52021PC0206 - EN - EUR-Lex
[5] CEMA_Industry_Report_2022-.pdf

of inputs like chemical fertilisers, plant protection products, fuel and labour costs, increasing yields and profitability while at the same time reducing the environmental footprint.

3.2.1 The role of regulatory Sandboxes

To accelerate the adoption of AI and robotics solutions in the agricultural sector, harmonising regulatory needs and rising AI-enabled applications, real-world testing and experimentation facilities and sandboxes are an essential asset to ensure the swift and responsible adoption of AI within the scientific community, providing testbeds for still unregulated high-risk applications.

A regulatory sandbox is a controlled testing environment where companies, startups, and innovators can develop, test, and validate new technologies or solutions under real-world conditions with temporarily relaxed or modified regulations. This allows for experimentation and validation with compliance coaching, reduced legal restrictions, and limited liability. Technical experts, known as Test and Experimentation Facilities (TEFs), establish these sandboxes and collaborate with national or regional authorities and other stakeholders to ensure both innovation and regulatory compliance.

Regulatory sandboxes are particularly useful when regulations are still being developed or do not fully cover the innovative product or service, and when there are no established technical methods for ensuring or verifying conformity. They allow companies to test and improve their products or services in a controlled and monitored environment, in cooperation with public authorities. In the European continent, this a timely effort considering the multiple issues of technological competitiveness and environmental challenges currently at stake. Overall, sandboxes help reduce the time and cost required to introduce new products, ensure regulatory compliance, and validate technologies in real-world conditions. In the agrifood sector, potential examples include sandboxes for novel foods, autonomous tractors, spraying and seeding drones, livestock monitoring, food traceability, smart greenhouses, and water and nutrient management.

Other potential advantages are the mutual adaptation of field and farm systems to new technologies, implementing integrated testing in real-life environments and ensuring a safe setting for humans, crops, and animals to interact with AI protocols and interoperable solutions. Just as importantly, regulatory sandboxes can potentially contribute to the enhancement of the European cloud to improve EU-based services, bridging the technology adoption gap, and building trust in technologies, particularly human-robot collaboration.

4. Use cases/Examples

This section aims to illustrate some of the practical developments and applications of the concepts outlined in the paper through concrete examples and real-world projects. Analysing use cases developed by several projects in the European context, it showcases some examples of innovation projects addressing pressing challenges in agriculture, forestry, and livestock management in the EU-context. The case studies collected in this paper provide a demonstration of the potential impact of AI and robotics applications for sustainability, collaboration, and innovation.

4.1 SPADE

The SPADE project developed a multi-purpoSe Physical-cyber Agri-forest Drones Ecosystem for governance and environmental observation.[6] SPADE develops an Intelligent Ecosystem to address the multiple purposes concept in the light of deploying UAVs to promote sustainable digital services for the benefit of a large scope of various end users in the sectors of agriculture, forestry, and livestock. This includes individual **UAV usability, UAV type applicability (e.g., swarm, collaborative, autonomous, tethered), UAV governance models availability and trustworthiness**. Multi-purposes will be further determined in the sensing dataspace reusability based on **trained AI/Machine Learning (ML) models**. These will enable sustainability and resilience of the overall life cycle of developing, setting up, offering, providing, testing, validating, refining as well as enhancing digital transformations and 'innovation building' services in Forestry, Cropping and Livestock Farming. Pilot prototypes contribute towards challenges such as deforestation, precision cropping and animal welfare. SPADE creates a digital platform to realise the benefits to be reaped from the use of drones. SPADE platform **makes drone operations better accessible and controllable and** provides a service channel for value added services enabled by drones. SPADE demonstrates three innovative use cases of drones making use of the digital platform. While demonstrating the use cases, the benefits coming from the use of drones are analysed and quantified, on a detailed stakeholder level basis. It demonstrates the new business opportunities. The demonstrations/pilots also serve as an analysis platform to investigate the regulatory framework at international and national level. Open calls provide 12 further use cases.

4.2 GC4SHEEP

The GC4SHEEP[7] project developed a secure federated platform based on datalake with artificial intelligence, divided into 4 sections:

- **Federated platform**: this computer system allows different livestock associations to access and analyse information about their sheep flocks in a unified way, even if the data is distributed in different locations and systems. This type of platform establishes a coordination layer that allows participating associations to consult and share information about their sheep (such as genealogical, productive or reproductive data) as if all the information were in a single place, while each association maintains independent control of its own data. Through shared protocols and standards, the platform facilitates the exchange of information between the different livestock associations, ensuring that each maintains sovereignty over its data while allowing controlled and secure access to shared sheep information.
- **Security through a digital signature process**: the platform incorporates a digital signature process where each association, when entering data about its sheep, certifies it by means of a unique cryptographic signature permanently linked to that information. When other associations subsequently access this shared data through the federated platform, they can automatically verify these digital signatures to confirm that the information has not been altered from its original record and comes from the association that claims to have created

[6] Learn more at Home - Spade Project
[7] https://gc4sheep.com/

it. This signature and verification mechanism adds an additional layer of trust to the system, allowing each livestock association rely on the authenticity and accuracy of the shared data.

- **Versatile and modern datalake storage**: The federated platform of livestock associations uses a data lake as a central storage system for all the sheep data that the different associations share. When an association contributes information through the federated system, this data goes through a standardisation process to ensure compatibility. Once standardised and verified by digital signatures, the data is stored in the data lake, a large digital repository containing any type of information in its original format – from structured animal records (e.g. genealogy, health or production data) to unstructured data (e.g. veterinary documents, images or sensor readings from farms). This architecture allows the storage of massive volumes of historical data that can be analysed later to discover trends or patterns in sheep production. It also facilitates the incorporation of new types of data without the need to modify the structure of the system. Further, it reduces costs by not requiring complex data transformations for its storage. Finally, it allows for the storage of data in the original format.
- **Data explainability through Artificial Intelligence**: The federated platform allows livestock associations to perform advanced analysis on shared sheep insemination data. When an association wants to better understand what factors influence the insemination success of its flocks, it can select what information it wants to analyse (e.g. age of ewes, time of year, techniques used, environmental conditions, or genetic characteristics). The system then accesses all this standardised data in the data lake and uses machine learning techniques to identify patterns and relationships between the different variables and insemination success. The techniques used allow for a precise understanding of how much each factor contributes to the outcome. For example, the system could generate a report showing that for a specific group of ewes, age has a 40% influence on insemination success, the time of year 30%, and the farm it belongs to 20%, while other factors have a lesser influence. This detailed analysis helps livestock associations to make more informed decisions, allowing them to adjust their insemination practices based on concrete evidence drawn from the data shared by all participating associations.

The platform described represents a significant innovation for the sheep sector due to several fundamental aspects:

- **Secure Collaboration**: It allows different livestock associations to share valuable information while maintaining control of their data, thanks to the federated system and digital signatures that guarantee the authenticity of the information shared.
- **Standardisation and Accessibility**: Transforms data dispersed in different formats and systems into standardised and easily accessible information, allowing a more complete view of the sheep sector.
- **Versatile Storage**: The data lake allows all types of sheep information (from basic records to images and sensor data) to be stored efficiently and economically, maintaining a complete history with traceability.
- **Advanced Analytics**: The ability to perform machine learning analysis on federated data allows for the discovery of patterns and relationships that would be impossible to detect by analysing data from a single association, especially in critical processes such as insemination.
- **Data Driven Decision Making**: Shapley's values provide an accurate understanding of what factors influence the success of different processes, enabling more informed decisions and improvements in livestock practices.
- **Scalability**: The architecture allows for easy incorporation of new data types, associations and analytics, allowing the platform to grow and evolve with the needs of the industry.
- **Sectoral Improvement Potential**: By facilitating collaboration and joint data analysis, the platform can drive significant improvements in efficiency and productivity across the sheep sector.

4.3 EU FarmBook Farm Assistant

The EU FarmBook project has developed a repository for outputs of DG Agri funded Horizon 2020 and Horizon Europe projects as well as the outputs of EIP-AGRI funded Operational Groups.[8] The platform provides a systematic infrastructure for these outputs (documents, presentations, videos, etc.) to be catalogued and uploaded, searched, retrieved and translated. Interface and search are currently available in all EC languages. AI (specifically LLMs) have been used in two ways. First, to semi-automate the extraction of metadata from documents uploaded to the platform. Second, to create a Farm Assistant, a chatbot, enabling easy access to the collection of knowledge objects in the platform.

The chatbot/assistant handles five languages currently and is built using a European LLM (Mistral) on a Retrieval Augmented Generation architecture to eliminate the possibility of hallucinations. Users are greeted by a prompt with which they can have a natural language conversation, and results are presented to the suer with links to the supporting knowledge objects, thereby ensuring transparency and maximum utility.[9]

4.4 DISAVIT

The DISAVIT project develops an intelligent decision support system for smart viticulture, powered by advanced AI and an integrated IoT system.[10] Drawing on data from a diverse sensor ecosystem—including weather stations, UAV and satellite imagery, and in-field soil probes—the platform applies cutting-edge artificial intelligence techniques and machine learning algorithms to transform raw environmental and phenological data into actionable insights for vineyard management. AI-driven modules have been implemented and validated in pilot vineyards to detect and predict key vine diseases such as downy mildew, powdery mildew, and gray rot, helping viticulturists respond proactively rather than reactively. One module process continuous stream of sensor readings to forecast disease occurrence based on microclimatic and plant health data, while another module uses ML-based image analysis on drone-acquired leaf imagery to assess vine health. These intelligent applications are integrated into a scalable, cloud-based IoT framework with secure blockchain-enabled traceability, ensuring transparency across the production chain. The system delivers fast, data-driven, and site-specific recommendations to viticulturists through intuitive web and mobile interfaces, enabling informed decision-making on irrigation, pest management, and harvesting strategies. The result is a low-cost, highly responsive tool that enhances resource efficiency, crop quality, and environmental resilience, from disease prediction and to traceability.

4.5 U-GARDEN

The U-GARDEN initiative, featuring BEIA Consult International, promotes AI- and IoT-powered urban gardens and agroforestry systems across European cities to enhance sustainable urban development.[11] The platform integrates high-precision air and soil telemetry, automatic irrigation actuators, and plant health sensors in Urban Living Labs (ULLs) across Bucharest, Brașov, Valencia, Warsaw, and Gothenburg. Data from these sensors are transmitted in real-time to a cloud backend, analysed with machine learning and GIS-driven multicriteria decision-making (MCDM) to generate interactive maps for optimal garden placement and resource allocation. The AI engine identifies environmental conditions, forecasts irrigation needs, and triggers alerts for anomalies or pest risks. Users access intuitive dashboards to monitor metrics like soil moisture, air quality, and plant health, with alerts and recommendations tailored to five garden typologies: social, educational, recreational, productive, and environmental.

Pilots have demonstrated the framework's effectiveness in enhancing community engagement, learning outcomes, and green governance. By enabling stakeholders to co-create sustainable urban food systems and foster innovative business models, U-GARDEN bridges urban planning, environmental education, and agri-technology. U-GARDEN empowers cities to deploy data-

[8] https://www.eufarmbook.eu/en
[9] The Farm Assistant can be found here: https://www.eufarmbook.eu/en/farm-assistant.
[10] Learn more at https://beiaro.eu/disavit/
[11] Learn more at https://beiaro.eu/u-garden/

driven, AI-enhanced urban gardens, improving ecological resilience, social cohesion, and local food production, with validated business strategies and policy recommendations ahead of its May 2025 conclusion.

4.6 Portable MCE-on-robot system

The objective is to autonomously sample, analyze, and quantify contaminants in remote or hazardous environments (e.g., wastewater sites, agricultural fields, or disaster zones). Integrating microchip capillary electrophoresis (MCE) with robotic systems enables autonomous, in-situ analysis of environmental contaminants (e.g., heavy metals, pesticides) with lab-grade accuracy. A robotic platform equipped with a miniaturised MCE chip can perform sampling, preprocessing, and separation in real time, ideal for hazardous or remote sites. For example, a robotic arm could collect water samples, filter particulates, and inject analytes into an MCE module buffered with MES/His + CTAB for heavy metal detection via contactless conductivity (C4D). The system's portability (<50W power) and rapid throughput (10–20 samples/hour) outperform traditional lab methods, while wireless data transmission allows immediate contamination alerts. This approach is validated for sub-ppb detection limits (e.g., Pb^{2+}, Cd^{2+}) and aligns with EPA/WHO monitoring standards, offering a scalable solution for industrial, agricultural, or disaster-response applications.

Key Components:

- **Microchip CE Module**: the system uses a miniaturised microchip capillary electrophoresis (MCE) chip with integrated electrodes for both separation and detection. Detection methods include contactless conductivity detection (C4D) for ionic species and laser-induced fluorescence (LIF) for organic compounds. Buffers are tailored to specific contaminants, such as MES/His with CTAB for metal ions and micellar electrokinetic chromatography (MEKC) for pesticide analysis.
- **Robotic Integration**: a robotic arm equipped with a microfluidic syringe enables automated sampling from sources like soil leachates or water bodies. On-board preprocessing is handled through microfluidic cartridges that perform filtration and pH adjustment. Data is transmitted in real time via a wireless connection to the cloud, allowing immediate mapping of contaminant levels.
- **Target Applications**: the system targets heavy metals such as lead (Pb^{2+}) and cadmium (Cd^{2+}) using MCE-C4D with a lactic acid buffer. For pesticide detection, MEKC is employed with SDS micelles and UV detection to identify organic residues.
- **Advantages Over Lab-Based Methods**: the robot-mounted MCE system is portable and operates directly in the field, eliminating delays associated with transporting samples to a lab. It functions autonomously with pre-programmed sampling and analysis cycles, such as hourly water quality checks. The robotic platform also enhances safety by accessing hazardous environments like chemical spill sites.
- **Workflow**: the robot collects a water sample and filters out particulates. The MCE module then injects and extracts analytes, completing separation in under two minutes. Detection is performed using C4D or LIF, and results are transmitted to a dashboard. An AI system monitors the data and flags any exceedances of regulatory limits, such as EPA thresholds for lead.
- **Measurement Metrics**: the system achieves sub-part-per-billion detection limits for metals, with validation against standard methods like ICP-MS. It can process 10 to 20 samples per hour, significantly faster than traditional lab workflows. Power consumption remains below 50 watts, making the system suitable for battery-powered field deployment.

4.7 AGRIDATAVALUE

Core Goals

AgriDataValue aims to address critical challenges in agriculture and environmental sustainability by developing an open, decentralised Agri-Environment Data Space (ADS).[12] The project focuses on:

- **Optimising Agricultural Efficiency**: real-time monitoring helps reduce water waste by preventing overirrigation. The system also minimises the use of synthetic fertilizers and pesticides, reducing contamination risks to soil and aquifers. Precision farming techniques are employed to enhance crop yields while maintaining resource efficiency.
- **Mitigating Environmental Impact**: the platform contributes to lowering greenhouse gas emissions from livestock and farming operations. It supports biodiversity by encouraging sustainable land and resource management practices. Data-informed decision-making tools help stakeholders adapt to climate change more effectively.
- **Empowering Stakeholders with Data**: farmers, researchers, and policymakers gain access to secure, interoperable tools for data sharing. AI-driven insights support improved crop management, disease forecasting, and efficient resource allocation. The system ensures compliance with EU agricultural regulations, such as the Common Agricultural Policy (CAP), while upholding GDPR standards for data privacy.
- **How It Works**: AgriDataValue integrates distributed AI, IoT sensors, and big data analytics into a unified platform. It collects and processes real-time data from various sources, including soil sensors, satellites, and weather stations. Federated learning is used to analyse data locally, preserving privacy while enhancing farm-level decisions. The platform also promotes collaboration through standardised, open-source data exchange among stakeholders.
- **Expected Outcomes**: the system enables more sustainable farming by reducing water, chemical, and energy waste. It contributes to improved food security through higher and more climate-resilient crop yields. Transparent data sharing supports stronger policy alignment and facilitates regulatory compliance and subsidy distribution.

By merging agricultural expertise with advanced data technologies, AgriDataValue seeks to transform farming into a more efficient, eco-friendly, and equitable system for future generations.

[12] See https://agridatavalue.eu/

5. Conclusions and recommendations

Digitalisation is shifting agriculture towards smarter, data-driven frameworks. In particular, AI and robotics are already helping the agriculture sector in different ways: automating tasks, improving decision making, or optimising the use of resources. We will likely witness in years to come a deeper transformation of agriculture thanks to the fast evolution of these technologies.

Among the main **opportunities** detected, we can mention:

- AI and robotics can help to overcome the increasing problem of lack of manpower in the agriculture sector.
- In particular, small-scale robotics opens the door to automation of tasks while keeping cost effectiveness and low environmental impact.
- Even in tasks where high precision is required, where human intervention was seen until now as unreplaceable, new-generation robots could become viable solutions.
- In cases where full automation is not viable, collaboration between specialise robots and human workers can still improve productivity.
- Highly specialised robots will be essential for emerging industries like vertical farming.
- AI, and in particular GenAI, can make technological solutions more usable through more friendly interfaces, isolating the user from the underlying complexity of the technology.
- GenAI enables the democratisation of highly specialised agronomic advisory services, thus playing a relevant role in future AKIS.
- GenAI, in combination with digital twins, opens the door to more advanced adaptive strategies for risk mitigation and planning, which is particularly important under the rise of climate change and increasing unpredictability of weather events.
- AI can reduce administrative/management burden of daily farm activity, automating paperwork and management tasks.

To ensure a robust, resilient, and sustainable agrifood value chain in Europe, it is essential to harness the transformative potential of AI and robotics. This strategic approach also presents a unique opportunity to grow a **European-based, innovation-driven technological sector — one capable of reinforcing the EU's food system and positioning Europe as a global leader in agritech. European food sovereignty will not be possible without agritech sovereignty**.

All farms, regardless of their size, should be able to benefit from the adoption of AI and robotics. A responsible and inclusive implementation, fully aligned with European values, is needed to ensure food security and sustainability without leaving anyone behind.

As demonstrated in this document, unlocking the full potential of AI and robotics in agriculture requires addressing technical, regulatory and socio-economic challenges. To this end, the following recommendations are proposed:

1. Ensure a Safe, Trustworthy AI and Robotics Deployment	▪ Promote explainable and transparent AI to mitigate bias and build trust, preventing biased decision making and unexpected behaviours that could impact negatively agriculture operations. ▪ Support open-source and interoperable AI models tailored to agriculture. ▪ Establish EU-wide certification schemes for agricultural AI and robotics. ▪ Mandate cybersecurity-by-design in all AI and robotic systems. ▪ Provide training and resources for farmers and SMEs on digital security.
2. Foster the development of full-European agritech solutions with global scope	▪ Promote the development of agritech solutions minimising dependence with non-EU technology providers. ▪ Promote an open European stack for AI-powered robotics which can support a sovereign EU agrifood ecosystem. ▪ Enhance interoperability among Standards Development Organisations (SDOs) for drones/robotics.[13] ▪ Develop proper semantic interoperability frameworks applied to drones/robots, minimising costs for local farmers and optimised data management strategies to ensure reliability at system-level ▪ Reuse of ontologies for robotics and drones. Encourage best practices.[14]
3. Unlock the Value of Farm Data	▪ Develop interoperable, farmer-centric data spaces enabling AI systems to be properly trained and adapted to the needs of real operations. ▪ Incentivise data sharing through CAP-linked mechanisms. ▪ Ensure compliance with GDPR and the Data Act while preserving farmer data ownership.
4. Clarify and Adapt Regulatory Frameworks	▪ Define sector-specific guidance for AI-powered robotics under the AI Act. ▪ Reflect on the definition and implementation of a European framework for sandboxes for high-risk innovative applications of AI and robotics in real-world agriculture settings. ▪ Align data governance models with EU privacy and ownership principles.
5. Promote Inclusive Access and Affordability	▪ Expand rural digital infrastructure through targeted EU investment. ▪ Prioritise funding for small-scale farms and low-income regions. ▪ Promote testing and validation facilities for robotics and AI, accessible to technology developers.
6. Foster Innovation and New Business Models	▪ Encourage public-private partnerships and agritech incubators for supporting the scale-up of small, innovative companies. ▪ Support the development of new scalable, sustainable business models for robotics, such as Robotics-as-a-Service (RaaS) and cooperative ownership models. ▪ Promote EU-based manufacturing and maintenance to reduce external dependencies and promote EU technological sovereignty in agrifood.
7. Empower Farmers in the Digital Transition	▪ Integrate digital skills into agricultural education and training programs. ▪ Establish advisory networks to support strategic farm management in face of the incoming digitalisation of the sector. ▪ Recognise the evolving role of farmers as data-driven decision-makers, demanding proficiency in a new set of management skills.

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[14] Learn more at https://lov4iot.appspot.com/?p=lov4iot-robotics.

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AIOTI is the multi-stakeholder platform for stimulating AI, IoT and Edge Continuum Innovation in Europe, bringing together small and large companies, academia, researchers, policy makers, end-users and representatives of society in an end-to-end approach. We strive to leverage, share and promote best practices in the AI, IoT and Edge Continuum ecosystems, be a one-stop point of information to our members while proactively addressing key issues and roadblocks for economic growth, acceptance and adoption of the AI, IoT and Edge Continuum Innovation in society. AIOTI contributions goes beyond technology and addresses horizontal elements across application domains, such as matchmaking and stimulating cooperation by creating joint research roadmaps, defining policies and driving convergence of standards and interoperability.