Progress in Agricultural Engineering Sciences
DOI: 10.1556/446.2026.00313

Evolution of smart farming for the European Green Deal: A review of IoT, artificial intelligence and robotics in sustainable precision agriculture

ANIKÓ NYÉKI*

Department of Biosystems Engineering and Precision Technology, Albert Kázmér Mosonmagyaróvár Faculty of Agricultural and Food Sciences, Széchenyi István University, Mosonmagyaróvár, Hungary

ORIGINAL RESEARCH PAPER

Received: February 28, 2026 • Accepted: March 26, 2026

ABSTRACT

Smart farming is constitutes a means of facilitating the European Green Deal and the Farm to Fork strategy. However, credible sustainability results require measurable and validatable indicators, verifiable data and automation that is reliable even under field conditions. This overview study presents developments in IoT-based sensing, artificial intelligence-based analysis and autonomous robotics, and links them to EU target areas. The peer-reviewed studies (2000–2025) were retrieved from the Scopus, Web of Science, and Google Scholar databases and supplemented with key EU legal and strategic documents. The article proposes a policy-driven digital agroecological management (PDAM) framework that establishes adaptable indicators based on past trends in EU targets (pesticides, nutrients, soil, biodiversity and climate) and then develops a system of perception-analysis-implementation based on these indicators. The most effective tools support GNSS-based machine control, variable rate application, and remote sensing, while AI-based decision support tools, autonomous weed control, and digital twin field validation are still weaker.

Interoperability, data governance, cybersecurity and safety regulation emerge as critical scaling constraints for auditable smart farming systems.

KEYWORDS

precision agriculture, internet of things, artificial intelligence, agricultural robotics, European Green Deal

* Corresponding author. E-mail: nyeki.aniko@sze.hu

1. INTRODUCTION

Agriculture must deliver reliable food and feed supplies while reducing its contribution to climate change, biodiversity loss and water and air pollution. Despite decades of agronomic innovation, a substantial share of reactive nitrogen, phosphorus and pesticide inputs still leaves the intended production pathway, contributing to eutrophication, soil degradation, non-target effects and greenhouse-gas emissions (Tilman, 1998; Tilman et al., 2002; Neményi et al., 2022). Climate variability and the increasing frequency of extreme weather events further increase the need for management approaches that are both resource-efficient and resilient.

In the European Union (EU), these challenges are translated into explicit sustainability objectives through the European Green Deal (EGD) and the Farm to Fork (F2F) strategy. The F2F strategy sets quantitative 2030 ambitions, including reductions in the use and risk of chemical pesticides and nutrient losses, lower antimicrobial sales, and an expansion of organic farming. The reformed Common Agricultural Policy (CAP) 2023–2027 strengthens the implementation of environmentally friendly practices through eco-schemes and results-oriented conditionalities that may reward practices supported by precision farming. Today, scientific analyses also emphasise that digital technologies and precision farming play a central role, while legal interventions and market development still represent critical challenges for farmers (Reinhardt, 2023; Popp et al., 2024).

The regulatory path for some objectives is politically dynamic. For example, on March 27, 2024, the European Commission revoked its proposal for a regulation on the sustainable use of pesticides because no agreement was foreseen; therefore, the Directive on the sustainable use of pesticides (2009/128/EC) remains in place (European Commission, 2024a). This reinforces the importance of accurate monitoring, reporting, and verification (MRV) approaches that can work across different national regulations and agricultural limitations.

From an engineering point of view, this political environment translates into three closely related requirements. First, policy objectives need to be translated into measurable indicators at field, farm and (in some cases) landscape scales (e.g., pesticide risk indicators, nitrogen surplus, soil organic carbon stocks, biodiversity-relevant landscape metrics). Second, digital systems must support traceability and auditable documentation of operations and inputs. Third, the generated information must enable adaptive management through timely, site-specific interventions based on result indicators rather than purely ex post compliance checks. Because biodiversity-based ecosystem services depend strongly on landscape structure and heterogeneity, result based indicator design and digital monitoring should also consider non-crop habitat configuration and connectivity beyond field boundaries (Landis, 2017).

Over the last three decades, precision agriculture has evolved from GPS/GIS-based mapping and variable-rate application towards connected, data-intensive cyber-physical systems integrating in-field sensing, remote sensing, machine telemetry and advanced analytics. Internet of Things (IoT) architectures and wireless sensor networks (WSNs) allow dense spatio-temporal monitoring of soil, crop, animal and microclimate states; edge/fog/cloud computing supports scalable data handling; and artificial intelligence (AI) methods increasingly convert multi-source data streams into predictions, classifications and recommendations (Wolfert et al., 2017; Kamilaris and Prenafeta-Boldú, 2018; Liakos et al., 2018; Alahmad et al., 2023). In parallel, agricultural robotics and autonomous machinery expand the actuation layer by enabling high-resolution interventions (e.g. targeted or non-chemical weed control) and by serving as mobile sensing platforms (Shamshiri et al., 2018). Recent economic and policy analyses underline that digital innovations can support sustainability and resilience, but the benefits are contingent on governance conditions, incentives and institutional arrangements that avoid lock-in and uneven distribution of value (Finger, 2023).

In addition to environmental goals, the EU is also developing rules on access to data, data sharing and reliable automation. The Data Governance Act (Regulation 2022/868/EU) and the Data Protection Act (Regulation 2023/2854/EU, applicable from September 12, 2025) have an impact on how data generated by networked products and related services can be accessed and reused. In addition, the Artificial Intelligence Act (Regulation 2024/1689/EU) and the Machinery Regulation (Regulation 2023/1230/EU, applicable from January 20, 2027) are relevant for AI-based and autonomous agricultural machinery. These regulations highlight that technological performance alone is not enough: interoperability, governance, cybersecurity, and safety considerations in design are becoming the primary limitations for scalable smart agriculture.

The literature has analysed and presented IoT sensor technologies, big data analytics, AI applications and agricultural robotics from a technological and application perspective (e.g., Wolfert et al., 2017; Kamilaris and Prenafeta-Boldú, 2018; Liakos et al., 2018; Klerkx et al., 2019; Rejeb et al., 2025). Further studies show that digital agriculture only contributes to sustainability if environmental, socio-economic, and ethical aspects are integrated into innovation processes, advisory systems and public administration (Rose and Chilvers, 2018; Eastwood et al., 2019). However, two gaps remain particularly relevant for agricultural and environmental engineering. First, reviews rarely translate policy targets into result-based measurable indicators and then into concrete specifications for sensing architectures, data management, analytics and automation at appropriate spatial and temporal scales. Second, deployment constraints (interoperability, safety, responsibility, data governance and the robustness of measurement under real farm conditions) are often treated as secondary, even though they determine whether solutions can be scaled and audited.

This review addresses these gaps by combining (i) an ecocentric agriculture-landscape-natural ecosystem (ALNE) perspective, which frames agricultural production as a coupled system of energy, matter and information flows that must be optimised under ecological boundaries (Neményi and Milics, 2010; Neményi et al., 2022), with (ii) an indicator- and policy-driven engineering view of digital systems.

Accordingly, the objectives of this review are: (1) to synthesise the state of the art in IoT-enabled sensing, AI analytics and agricultural robotics for sustainability-oriented precision agriculture, with emphasis on engineering building blocks and deployment constraints; and (2) to introduce PDAM and a summary matrix that links major EU Green Deal and Farm to Fork target domains to result-based indicators and to corresponding digital and robotic solution components, thereby highlighting maturity levels and research gaps for policy-relevant smart farming.

Unlike existing reviews that predominantly discuss IoT, AI or robotics in isolation, or that treat sustainability at a high level, this review provides a policy-to-engineering backcasting approach. The paper proposes the Policy-Aligned Digital Agroecosystem Management (PDAM) framework that links EU Green Deal and Farm-to-Fork objectives to measurable indicators and further to the digital and robotic system capabilities required across sensing, analytics and actuation. In addition, the evidence is organised by validation maturity and synthesises cross-cutting deployment constraints (interoperability, data governance, safety and auditability) as first-order engineering requirements. This integrated mapping enables an evidence-based identification of what is field-ready today and what remains a research and standardisation gap for policy-relevant smart farming.

To address these gaps, this review makes three contributions:

(i) It introduces the Policy-Aligned Digital Agroecosystem Management (PDAM) framework that maps EU sustainability targets to operational indicators and to sensing-analytics-actuation design requirements;
(ii) It provides an evidence map that distinguishes laboratory prototypes from field-validated and scalable solutions using validation/maturity tiers; and
(iii) It synthesises interoperability, data governance, safety and auditability constraints as primary determinants of real-world deployability and compliance.

2. MATERIALS AND METHODS

This study uses bibliometric analysis to systematically organise academic data on precision agriculture, digital agriculture, IoT, AI and field robotics, with a focus on their alignment with EU sustainability targets in a quantitative and objective manner. This method allows for the evaluation of publication volume, citation impact, and shifts in the conceptual structure of the research field over time. To ensure the transparency and reproducibility of the study, the document selection process was strictly carried out according to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines and the PRISMA extension for scoping reviews, including the stages of identification, screening, and determination of data suitability (Tricco et al., 2018; Page et al., 2021).

In the first step, an article database was created from publications on precision agriculture and IoT, as well as fundamental ALNE and sustainability analyses (Neményi and Milics, 2010; Neményi et al., 2022, 2023; Alahmad et al., 2023). After that, a structured keyword search was performed in the Scopus, Web of Science Core Collection, and Google Scholar databases for the period 2000–2025, with a particular focus on publications after 2010, when IoT, AI, and robotics became widely used in precision farming. The search terms combined three keyword blocks: (i) digitisation and management (e.g., "precision agriculture," "smart farming," "digital agriculture," "FMIS"); (ii) enabling technologies (e.g., "Internet of Things," "wireless sensor network," "edge computing," "machine learning," "computer vision," "agricultural robot*," "agricultural robotics"); and (iii) sustainability and policy context (e.g., "sustainable agriculture," "ecosystem services," "European Green Deal," "farm-to-fork," "CAP eco-schemes," "soil health," "biodiversity"). Finally, a manual search was conducted to find EU legal documents, strategies, and regulations related to measurement, data management, and autonomous machines (including Regulation (EU) 2018/848 on organic production, the Data Governance Act, the Data Act, the Artificial Intelligence Act, etc.).

The criteria for eligibility were purposely formulated broadly to reflect the heterogeneity of evidence on digital agriculture. Sources were included if they (i) reported original research on IoT sensing, remote sensing, AI analytics, decision support or agricultural robotics applied in smart farm systems; (ii) provided review/survey syntheses on technological and/or sustainability aspects of digital agriculture; or (iii) contributed conceptual, methodological or socio-economic analyses relevant to policy-aligned sustainability assessment and management. Sources were excluded if they focused on non-agricultural domains without a clear link to agroecosystems, were purely technical without connection to agronomic or environmental performance, or represented non-reviewed marketing material (except official EU documents).

Screening was performed at title/abstract level followed by full-text assessment for relevance to at least one PDAM layer: (i) policy targets and indicators; (ii) sensing and data acquisition; (iii) data management and analytics; or (iv) automation and actuation.

Data charting and synthesis followed a PDAM-informed coding scheme. Each included source was mapped to (a) the primary technology domain (Table 1); (b) the main sustainability target domain(s) addressed (Table 3); and (c) a qualitative validation tier (Table 2) that distinguishes conceptual work from lab, experimental farm and on-farm evidence. Because of heterogeneity in outcomes, indicators and experimental designs, a quantitative meta-analysis was not pursued; instead, results are presented as a thematic synthesis with evidence mapping and a policy-to-technology alignment matrix.

Table 1. Major technology domains and their roles in PDAM

Technology domain	Precision technology	Main PDAM contribution
In-field sensing	Soil/crop/animal sensors; proximal spectroscopy; microclimate monitoring	Field-level state estimation; indicator input variables; early detection
Remote sensing (RS)	Satellite/UAV imagery; multispectral/hyperspectral; LiDAR	Spatial monitoring of crop status, soil cover, biodiversity; upscaling
Connectivity and computing	WSN/LPWAN; edge/fog/cloud computing; stream processing	Real-time data pipelines; cost/energy optimisation; latency control
Data platforms and interoperability	FMIS; machine data; APIs; semantics; ISO 11783/ISOBUS; data spaces	Cross-vendor integration; traceability; reusable, auditable datasets
AI analytics and modelling	Machine learning; computer vision; data fusion; uncertainty quantification; digital twins	Prediction, classification and optimisation linked to indicators; scenario analysis
Decision support	DSS; human-in-the-loop interfaces; explainability; advisory services	Translation of analytics into actionable recommendations; adoption support
Actuation and robotics	Variable-rate application; autonomous machines; field robots; UAV actuation	High-resolution, low-input interventions; closing the sense-act loop
MRV and reporting	Operation logs; geotagged records; certification workflows	Evidence generation for eco-schemes, compliance and policy evaluation

Abbreviations: LiDAR, light detection and ranging; LPWAN, low-power wide-area network; API(s), application programming interface(s).

Table 2. Qualitative validation tiers used for evidence mapping in this review

Tier	Definition	Typical evidence
V0 - Conceptual	Conceptual frameworks, simulations or architecture proposals without empirical agronomic validation	Simulation studies; conceptual reference architectures
V1 - Lab/controlled	Bench, greenhouse or controlled-environment validation of components	Sensor calibration; algorithm tests on curated datasets
V2 - Experimental field	Small-plot or experimental-farm trials in field conditions	Single-season trials; limited operational integration
V3 - On-farm pilot	Pilot deployment on commercial farms with operational constraints	Multi-field or multi-season pilots; integration into workflows
V4 - Scaled deployment	Multi-farm, multi-region deployment with demonstrated operational stability and documented performance	Services/platforms adopted across farms; evidence of repeatability

Records were identified through a structured search of the Scopus, Web of Science Core Collection and Google Scholar databases and were exported to a bibliographic dataset. Duplicates were manually removed before filtering. A total of 700 results were selected (Scopus, $n = 351$; Web of Science Core Collection, $n = 147$; Google Scholar, $n = 202$). After removing 209 duplicate records, 491 records were left for title and abstract screening. After this, 399 hits were excluded, leaving 92 scientific articles for review. Eleven reports were unavailable, so 81 full-text reports remained, which were evaluated for suitability. After the full-text evaluation, 46 reports were excluded because they were not directly relevant to the topic ($n = 23$), did not have a sufficient connection to sustainability and policy contexts ($n = 14$), or were excluded for other reasons, including overlaps and insufficient evidence ($n = 9$). The final set of literature, which had been reviewed contained 35 documents. The process of selecting the studies is summarised in Fig. 1. In addition, EU legal, strategic, and policy documents were identified using targeted manual searches and were used as supplementary contextual sources for the policy analysis.

3. RESULTS

3.1. EU policy and regulatory context

The EGD frames agriculture as both a driver and a potential solution to climate change, biodiversity loss and pollution. The F2F strategy recognises the need for a fair, healthy and environmentally friendly food system and defines quantitative ambitions for pesticides, fertilisers/nutrients, antimicrobials, organic area and food waste by 2030 (European Commission, 2020a). Related strategies, such as the EU Biodiversity Strategy for 2030 and the EU Soil Strategy for 2030, emphasise protection and restoration of ecosystems, soil health and biodiversity-related landscape elements (European Commission, 2020b, 2021).

Implementation increasingly depends on indicator definitions and MRV capacity. For pesticides, the EU has introduced Harmonised Risk Indicators (HRIs) and regularly reports on progress; recent Commission reporting shows a long-term decrease in the use and risk of

Table 3. PDAM mapping of EU sustainability target domains to candidate indicators and digital, robotic requirements

Target domain (examples)	Candidate indicators (examples)	Digital requirements (sensing/analytics/ actuation)	Typical maturity (qualitative)
Pesticides and crop protection risk (F2F; SUD 2009/128/EC; SUR proposal withdrawn)	HRI1/HRI2; treated area; application rate and timing; drift risk proxies	Geo-referenced spray logs; canopy/weed/ disease detection (CV/ AI); decision support; targeted spraying; robotic/mechanical weeding	High for logging & VRA (V3–V4); Medium for AI-assisted scouting (V2–V3); Low-Medium for autonomous weeding at scale (V2–V3)
Nutrients and fertiliser use (F2F nutrient loss target; CAP conditionalities)	*N* surplus/balance; NUE; soil *N* status; leaching risk proxies; yield-scaled nutrient intensity	Soil/crop sensing; yield maps; variable-rate fertilisation; models for *N* dynamics; edge/cloud analytics; auditable prescriptions and records	High for VRA and yield mapping (V3–V4); Medium for model-based optimisation and real-time sensing (V2–V3)
Soil health and carbon (EU Soil Strategy; Soil Monitoring Law)	Soil organic carbon; soil cover; compaction; erosion risk; biological activity proxies	Proximal spectroscopy; remote sensing for soil cover and vegetation, controlled traffic and compaction monitoring; long-term data management for baselines	Medium for monitoring proxies (V2–V3); Low for integrated SOC MRV at scale without sampling (V1–V2)
Biodiversity and landscape elements (Biodiversity Strategy; eco-schemes)	Landscape heterogeneity; non-productive area; field margin length; crop diversity; habitat proxies	remote-sensing-based land cover mapping; computer vision for habitat features; geospatial planning tools; documentation of management actions	Medium for RS mapping (V2–V4 depending on indicator); Low for causal attribution to practices (V0–V2)
Climate mitigation and energy efficiency (EGD; climate reporting)	Fuel and energy use; GHG footprint per ha or per product; carbon intensity of operations	Machine telemetry; operation-level logs; optimisation of routes and timeliness; integration with LCA/ carbon calculators	Medium (V2–V3); limited harmonisation across tools
Water quantity and quality (Water Framework context; drought resilience)	Irrigation water use efficiency; soil moisture deficit; nitrate concentration proxies; runoff risk	Soil moisture networks; irrigation control; RS evapotranspiration estimates; predictive scheduling; runoff risk models	Medium (V2–V3); high local variability

Abbreviations: CV, computer vision; VRA, variable-rate application; NUE, nitrogen use efficiency; SOC, soil organic carbon; GHG, greenhouse gas; LCA, life cycle assessment.

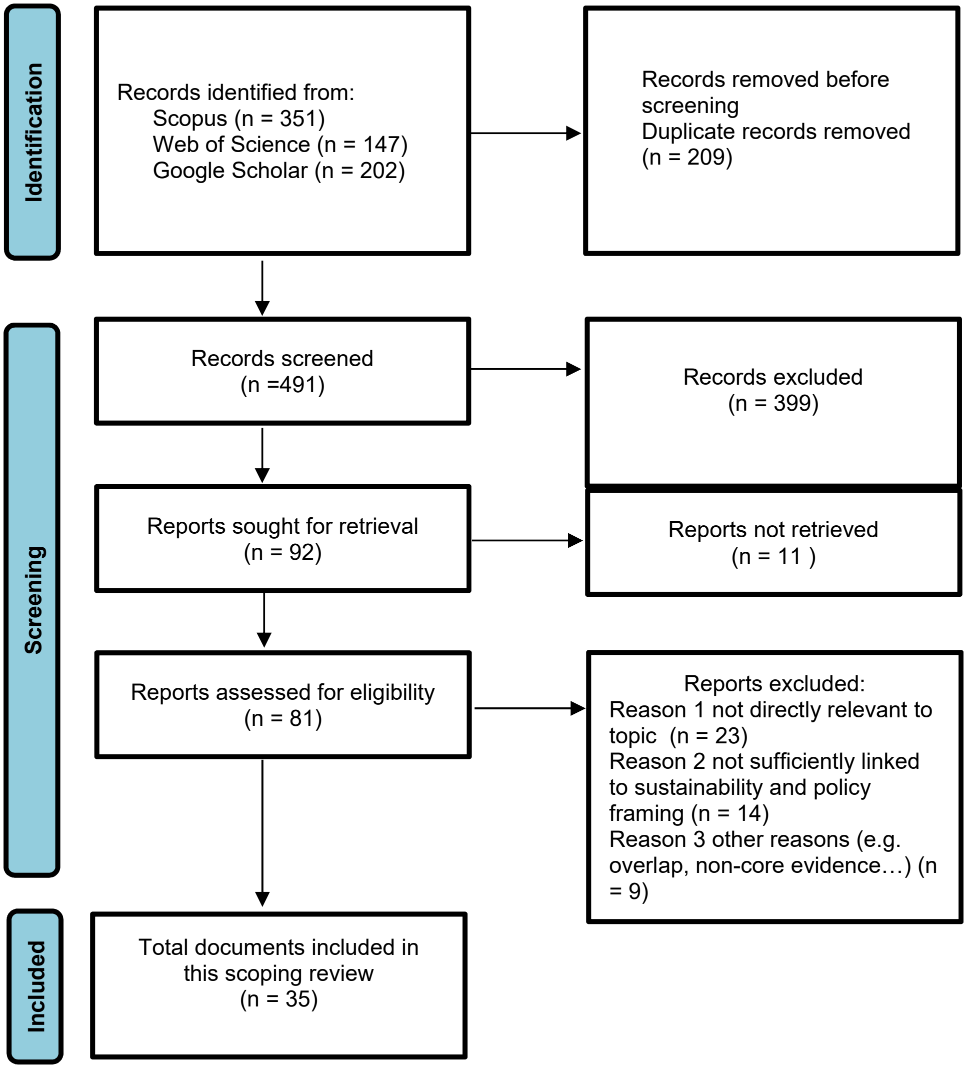

Fig. 1. Method of study selection (adapted from the PRISMA 2020 flow diagram, Page et al., 2021; under the terms of the Creative Commons CC BY 4.0 license)

chemical pesticides across 2011–2023, although trends vary by Member State and indicator type (European Commission, 2025). Such reporting highlights the need for consistent data pipelines and transparent assumptions behind indicators (e.g., baseline periods, risk weights).

CAP eco-schemes and result-based payments may further strengthen the demand for robust, low-burden evidence on the adoption and outcomes of sustainability practices, including those supported by precision agriculture (European Commission, 2023). At the same time, policy pathways remain dynamic. The withdrawal of the SUR proposal on 27 March 2024 underscores that environmental ambition, food security concerns and political acceptability may change over time; therefore, engineering solutions should remain adaptable to evolving indicator definitions and compliance rules (European Commission, 2024a). Recent discussion of Green Deal and F2F implementation also emphasises the tension between environmental ambition, food and energy security under geopolitical shocks (Popp et al., 2024).

In parallel to environmental policy, the EU is building an integrated regulatory environment for data and automation. The Data Governance Act (Regulation (EU) 2022/868) aims to increase trust in data sharing and to support re-use of certain categories of data, while the Data Act (Regulation (EU) 2023/2854, applicable from 12 September 2025) introduces harmonised rules on fair access to and use of data generated by connected products and related services. For smart farming, these acts are relevant because agricultural machinery, sensors and farm platforms increasingly behave as connected products generating operational and environmental data.

Recent initiatives also move towards EU-wide data sharing infrastructures in agriculture. The European Strategy for Data has supported the preparation and roll-out of a Common European Agricultural Data Space (CEADS), including blueprint recommendations (European Commission, 2024b) and a deployment action launched in 2025 (Fraunhofer IESE, 2025). In addition, a Horizon Europe co-funded European Partnership Agriculture of Data was launched in October 2025 to accelerate data-driven solutions for sustainable agriculture and to strengthen policy monitoring capacities (European Commission, 2025b).

Finally, the EU AI Act (Regulation (EU) 2024/1689) and the Machinery Regulation (Regulation (EU) 2023/1230, applicable from 20 January 2027) highlight safety, transparency and accountability requirements for AI-enabled and autonomous products. Together with domain standards (e.g., ISO 18497 for highly automated agricultural machinery), these frameworks motivate a shift from prototype-focused innovation towards trustworthy, certifiable cyber-physical systems capable of generating auditable evidence of sustainability outcomes.

These policy and regulatory developments motivate PDAM, which treats targets and legal requirements as design specifications for what digital agroecosystem management systems must measure, record and control.

3.2. Theoretical model: from ALNE to Policy-Aligned Digital Agroecosystem Management

The ALNE (agriculture-landscape-natural ecosystem) approach views agricultural production as part of an interconnected ecosystem in which the flow of energy, materials, and information links farming to the functioning of the landscape-level ecosystem. Thus, sustainability is not only a question of efficiency at the farm level, but also a question of the sustainability of ecological constraints and systems, including water regulation, soil functions, biodiversity, and climate change (Neményi and Milics, 2010; Neményi et al., 2022; Landis, 2017).

PDAM (Policy-Aligned Digital Agroecosystem Management) extends the logic of ALNE by directly linking policy objectives to the digital system architecture. Rather than viewing environmental policy as an external, formal limitation, PDAM treats goals as design specifications that determine (i) what to measure, (ii) at what spatial and temporal resolution, (iii) with what uncertainty, and (iv) how activities and results should be documented for monitoring and learning purposes.

PDAM can be viewed as a closed-loop process of sensory perception-model-decision-action-control. The process begins with policy goals and constraints (e.g., reducing pesticide risks, reducing nutrient losses, improving soil health, protecting biodiversity). These are implemented in indicator models that define the desired variables, baseline values, and aggregation standards. Based on the indicators, the requirements for sensing and data collection (IoT sensors, machine telemetry, remote sensing), data management and analysis (including artificial intelligence models and digital twins), and decision support and control are defined. Finally, implementation is achieved through machine and robotic solutions (e.g., variable rate application, targeted spraying, mechanical and laser weeding), and results are monitored to provide information for both farm management and policy review.

Figure 2 summarises this approach in a policy-technology backcasting map. The framework is technologically neutral: different sensor architectures, models, or robotic solutions can meet the same criteria, provided that their inaccuracies, compatibility with each other, and controllability are addressed.

3.3. Internet of Things, smart sensing and data infrastructures for policy-coherent precision agriculture

PDAM means that digital agriculture should be assessed not only on the basis of technological innovations, but also on its ability to provide reliable, policy-coherent information and enable effective action. Table 1 summarises major technology domains and how they contribute to PDAM layers. Across domains, two principles recur: (i) measurement quality (calibration, uncertainty, spatial/temporal resolution) and (ii) trustworthy data handling (interoperability, governance, cybersecurity and auditability).

To determine the level of progress of the technologies under review, the data were classified into qualitative validation stages, as summarised in Table 2.

3.4. Sensing, telemetry and communication architectures

IoT-enabled sensing in agriculture spans fixed in-field sensor nodes, mobile sensing on machinery, and remote sensing platforms. Fixed sensors provide high-frequency measurements of microclimate, soil moisture, soil electrical conductivity and (in some cases) nutrients, enabling early warning and improved scheduling of irrigation and fertilisation (Adamchuk et al., 2004; Alahmad et al., 2023). However, sensor drift, calibration needs, power constraints and spatial representativeness remain major engineering challenges, particularly when indicators must be auditable and comparable across farms.

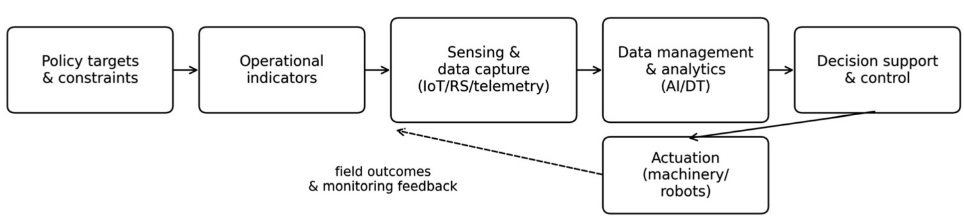

Fig. 2. The PDAM process of sensing-modeling-decision-action-control and feedback loops

Remote sensing complements in situ sensors by providing spatially continuous information at field-to-landscape scales. Satellite programs (e.g. Sentinel) and UAV platforms enable the monitoring of vegetation indices, canopy temperature and vigor, soil cover, and other indicators related to crop yield prediction, nitrogen availability, and drought stress (Hunt and Daughtry, 2018; Alahmad et al., 2023). For PDAM, remote sensing is often the primary method for scaling field measurements to regional indicators, but its effectiveness depends on ground-based validation databases and reliable modeling procedures.

The telemetry of tractors and work machines and operational files with geographic positioning (logging) provide an additional layer of sensing that is often underutilised in the modeling of environmental indicators. Modern tractors and work machines generate large amounts of data on GPS position, speed, engine load (which is related to soil conditions), machine settings and application parameters. Linking this data to agronomic operations is essential for traceability and input process reconstruction, but this requires compatibility and standardised definitions. Connection and computing architectures (WSN, LPWAN, 4G/5G, edge/fog/cloud) determine whether data collection enables narrowed real-time decision-making or only occasional reporting. Edge computing is increasingly coming to the front in order to reduce latency, bandwidth, and data security risks, as it processes data close to the source, while cloud infrastructures are still suitable for farm-to-farm comparisons and large-scale analytics. Decisions should be made based on the use of the data (e.g., temporal resolution of pesticide drift risk or irrigation scheduling) and the energy consumption of digital technologies.

3.5. Big data, AI analytics and digital twins

AI is increasingly being used to transform different agricultural data flows into useful knowledge. Some of the most common uses include identifying plants, weeds, and diseases through computer vision (Ambrus et al., 2024), predicting crop yields, optimising irrigation and fertilisation, and monitoring livestock (Liakos et al., 2018; Alahmad et al., 2023). The most important question for PDAM is not whether AI alone increases predictive accuracy, but whether it improves the effectiveness of decision-making in farm conditions while providing verifiable and interpretable proof for the reporting of indicators. According to recent studies, machine learning-based crop yield prediction and nitrogen status estimation are among the most intensively researched applications of precision agriculture, but applicability among years, locations, and devices continues to be a major limitation (Chlingaryan et al., 2018).

Several technical trends are particularly relevant for sustainable, policy-aligned precision agriculture. First, multimodal data fusion (combining proximal sensors, remote sensing and telemetry) can improve robustness to missing or noisy data. Second, uncertainty quantification and out-of-distribution detection help to avoid overconfident recommendations under domain shift (e.g., new cultivars, unusual weather). Third, privacy-preserving approaches such as federated learning can enable cross-farm model training without centralising sensitive farm data (Rizman Žalik and Žalik, 2023).

Digital twins are emerging as a bridging concept between measurement, modelling and decision support. In smart farming, digital twins can represent crops, fields or farm operations as dynamic models continuously updated by sensor data, enabling scenario analysis and optimisation (Verdouw et al., 2021; Wang, 2024). However, most agricultural digital twin work remains at conceptual or experimental stages (Table 2), and further research is needed on data quality requirements, interoperability, computational efficiency and the integration of human decision-making. Systematic literature reviews describe agricultural digital twins as an emerging field with limited large-scale, on-farm validation and substantial challenges around data availability, model coupling and interoperability (Purcell and Neubauer, 2023).

Generative AI approaches are beginning to appear in advisory services and knowledge management. While these tools may reduce the cognitive burden on farmers and advisors, their use in decision support raises additional requirements for transparency, provenance of recommendations and risk management, especially when recommendations affect regulated inputs such as pesticides.

3.6. Decision support, adoption and human-in-the-loop design

Precision agriculture technologies deliver sustainability benefits only if they are adopted, correctly configured and embedded into farm management routines. Empirical studies highlight that adoption depends on farm type, skills, advisory ecosystems and perceived value, not only on technical performance (Reichardt et al., 2009; Paustian and Theuvsen, 2017; Klerkx et al., 2019). In PDAM, this implies that decision support should be designed as a socio-technical system with clear responsibilities, user-centred interfaces and feedback on outcomes. At the macro level, cross-country differences in digital competence and infrastructure are substantial across Europe (Yarovenko et al., 2025), which may translate into uneven readiness for smart-farming adoption. Farm management information systems (FMIS) play a key role in transforming multiple data sources into implementable management practices, but their application and usability remain uneven across commercial and academic solutions (Fountas et al., 2015).

AI-based recommendations and automation also raise socio-ethical issues, including data rights, regulatory imbalances, dependence on platforms developed by others and the scale of risks and benefits (Rose and Chilvers, 2018; Eastwood et al., 2019). Sustainable innovation approaches recommend a combination of transparency, cooperative development and institutional monitoring. From a technological perspective, this includes user-friendly interfaces and monitoring that allows for human supervision to play a significant role.

3.7. Compatibility and data management

Compatibility is the main aim to the introduction of smart farming solutions. Farms typically purchase machines and sensors from multiple manufacturers, so they need standardised data transfer, interpretation, and interfaces. For agricultural machinery, ISO 11783 (ISOBUS) is the main international standard for serial control and communication between tractors and implements, providing common data transfer capabilities between machines. Standardisation initiatives (e.g., the Agricultural Industry Electronics Foundation, AEF) aim to improve compatibility between brands.

Compatibility extends beyond machines to agricultural data formats, as manufacturers' different interfaces (APIs), proprietary dashboards and data formats prevent data re-use and sharing. Data management adds further complexity: data management and data protection laws aim to enable clear and reliable data sharing in Europe, which may affect how farmers access and share data generated by agrotechnological processes. Data management programs such as CEADS specifically aim at interoperable data sharing that preserves autonomy across the entire agriculture and food value chain (European Commission, 2024b; Fraunhofer IESE, 2025).

From a PDAM perspective, compatibility and interoperability are not optional infrastructure features. They determine whether indicator reporting can be automated, documentation can be verified and performance measurement and learning across farms can be achieved. Future engineering work should prioritise reporting compatibility, machine-readable metadata and transparency that supports farmer activities and regulatory compliance.

3.8. Cybersecurity, safety and automation

Smart farming systems are increasingly dependent on networked devices and software-controlled machines, which increases the attack surface and mitigates the effects of failures. Cybersecurity attacks can not only compromise data security, but also impact environmental productivity and outcomes (e.g., manipulated variable speed settings or operator instructions and data manipulation). Engineering solutions include secure device identification, authentication, security update methods, file sharing and management and event management protocols tailored to the agricultural environment.

Autonomy is increasing, making security and authenticity of key importance. Standards such as ISO 18497 address safety principles for highly automated agricultural machinery, including requirements related to risk assessment and safe behaviour in the presence of humans. At the regulatory level, the Machinery Regulation and the AI Act highlight requirements for safe design, documentation and accountability for AI-enabled products. PDAM therefore motivates research on verifiable autonomy, fault-tolerant sensing, safe human-machine interaction and the integration of safety evidence with sustainability evidence in MRV (monitoring, reporting, verification) systems.

3.9. Agricultural robotics and autonomous systems for sustainable interventions

Agricultural robots and autonomous machines can be interpreted as the actuation and mobile sensing layer of PDAM. By enabling high-resolution interventions, robotics has the potential to reduce input use (e.g. pesticides, fuel) and to support non-chemical practices such as mechanical or thermal weeding. At the same time, field robotics must operate in unstructured outdoor environments under strict safety requirements, which explains why many solutions remain at V1–V3 validation tiers (Table 2).

Robotic functions in arable and horticultural systems typically require robust localisation, perception and decision-making. GNSS-based navigation and machine vision are widely used; however, occlusion, variable illumination, plant growth stages and soil conditions complicate perception. Sensor fusion (GNSS, inertial measurement, LiDAR, RGB and multispectral cameras) and learning-based perception are common solution pathways (Shamshiri et al., 2018; Duckett et al., 2018).

Site-specific pesticide application is an important area of use in view of sustainability. Precision spraying and spot application, combined with accurate weed and disease detection and precise operation, can reduce pesticide use. Robotic mechanical weed control and relatively new laser and thermal methods aim to reduce herbicide application (Lytridis and Pachidis, 2024; Andreasen et al., 2022). These applications highlight one of the challenges of PDAM, as sustainability indicators (e.g., pesticide risk) require the location of input application and the exact reason for application to be documented, which is also recorded by the on-board system of the power and work machine.

Unmanned aerial vehicles (UAVs) play an important role in both monitoring and work operations. Remote sensing by UAVs supports rapid detection and mapping of variability; and in some regulatory environments, UAV-based applications are also used for precision farming, although safety and drift issues may limit their widespread adoption in Europe. The operation of UAVs therefore demonstrates the need for integrated risk management and regulatory requirements to be considered in the planning of autonomous systems.

Robotics can also contribute indirectly to climate change mitigation and soil health by regulating traffic, reducing soil compaction with light vehicles, and improving the timing of operations. However, potential risks must be taken into account, including the energy requirements of robotics and digital tools, harmful effects (more operations because it becomes easier) and the risk that smaller farms will be disadvantaged due to investment requirements.

Agricultural robotics is fundamentally a future-oriented field, but it is also diverse and includes a wide range of different solutions. Robust evidence of sustained environmental benefits at farm and landscape scales remains limited, which motivates stronger integration between robotics experiments and indicator-based MRV designs.

3.10. PDAM matrix: linking EU target domains, indicators with digital and robotic solution pathways

Table 3 summarises the PDAM mapping logic by linking major EU sustainability target domains to representative indicators and to corresponding digital and robotic solution pathways. The mapping is not intended as a definitive indicator list; instead, it illustrates how policy targets can be translated into measurable variables, and how these variables drive requirements for sensing, analytics, actuation and documentation.

Because EU targets are implemented through a combination of strategies, directives/regulations and CAP instruments, indicator definitions and reporting rules may differ across Member States and over time. Therefore, PDAM should be interpreted as a flexible design map that can be updated when policy definitions or scientific understanding changes.

4. DISCUSSION: DATABASE GAPS, POSSIBLE SOLUTIONS AND RESEARCH PLAN FOR SMART FARMING

Overall, the results in the literature indicate that precision farming and smart agricultural technologies offer significant opportunities to reduce input use, optimise the timing of interventions and improve monitoring efficiency. However, a policy-relevant improvement in sustainability performance can only be expected if these technologies provide reliable, comparable and controllable indicator data and if their application results in demonstrable changes in farming outcomes. Although the latest analyses summarising empirical economic and environmental impacts indicate significant benefits, their extent depends largely on the specific production and environmental context. This makes it particularly important to take a transparent approach to indicator selection and to apply more consistent reporting standards across studies (Papadopoulos et al., 2024).

GNSS navigation, yield mapping and variable rate application are relatively proven technologies that are already widely used in practice (often V3–V4), while many AI-based decision-making tools are not yet sufficient and their effectiveness is uncertain, so they are often only validated in controlled databases or under experimental conditions (V1–V2). Agricultural robotics is innovating rapidly, but with limited control, partly due to safety requirements, regulations, high investment costs and the complexity of environments.

Compatibility and governance are emerging as key barriers to the widespread adoption of smart farming systems. The lack of harmonised data models, machine-readable metadata and interfaces subject to conformance testing results in high transaction costs and growing dependence on particular suppliers, which can make it harder to combine and use multiple technologies together. The evolution of the EU regulatory environment, including data governance frameworks (Data Governance Act, Data Act), emerging data spaces and regulations for machines and artificial intelligence, is driving standardisation, while increasing documentation and compliance requirements. Consequently, ensuring interoperability, data sovereignty and conformance by design should be a priority in technical research.

Safe and secure smart farming also requires a clearer understanding of uncertainty and risk. Since policy indicators often combine data from multiple sources and even small measurement mistakes can result in considerable errors when scaled up to the regional level. Therefore, future research should pay more attention to validated methods for tracing uncertainty from sensors through to indicators. These developing approaches offer reliable information for farmers, advisors, who can readily interpret and use it.

Digital infrastructures and robotics come with their own energy and material costs, greater sensing intensity can add to electronic waste and automation may change human relations and farmers autonomy. Whether these technologies are adopted in practice depends not only on economic aspect, but also on skills and advisory networks. In PDAM terms, this means that sustainability assessment needs to cover environmental, economic and technological aspects. It is consistent with ALNE and ecocentric perspectives.

This study points to several key aims and directions for future research in precision crop production technology development: (i) first priority is the design of indicator-driven experiments in which field studies are planned around indicators and MRV requirements. (ii) Secondly, the compatibility is equally important in free and preserving databases that can operate with the living standards and emerging data infrastructures. (iii) Future directions should also strengthen the robustness of AI-based technologies under domain shift, particularly through improved uncertainty quantification and privacy-preserving forms of collaboration. (iv) Development of agricultural robot systems including safety-certified autonomy in accordance with ISO 18497 and the practical challenges of human–robot interaction. (v) Uniform frameworks are needed to assess agronomic efficiency and environmental outcomes across growing seasons and farms.

5. CONCLUSIONS

This paper brings together research on IoT sensing, artificial intelligence analysis and agricultural robotics from the aspect of EU sustainability goals and related policy requirements. The PDAM model provides a structured way of working backwards from policy aims to indicators and from the sensing, analytics and actuation capacities requirements in practice.

Based on the available documentation, the strongest technologies are related to elements of precision agriculture that are already widely used, such as GNSS-based guidance, remote sensing monitoring and site-specific applications. Autonomous weeding, field robotics, digital twins and AI solutions have significant potential, but their development and practical validation are still more limited. There are limited results of multi-farm and multi-seasonal testing, validation and safety-compliant adaption are still only partially set on.

EU policy and regulation increasingly extend beyond environmental targets to include data access and sharing, trustworthy AI and machinery safety. Consequently, future smart farming research and development should integrate interoperability (ISO 11783/ISOBUS and data standards), data governance (Data Governance Act and Data Act), cybersecurity and safety-by-design as prerequisites for scalable sustainability impact. Indicator-driven evaluation and MRV-ready digital systems are essential for translating technological innovation into measurable contributions to the European Green Deal.

EU policies and regulations are increasingly moving beyond environmental goals. These are growing emphasis on data access and sharing, AI and the safety of agricultural machinery. Future smart farming research and technology development should not treat compatibility, data governance, cybersecurity, but as fundamental requirements for delivering sustainability benefits. This involves compatibility with standards (e.g. ISO 11783/ISOBUS), and the future EU regulatory framework including the Data Governance Act and the Data Act. Besides, indicator-driven evaluation and MRV-ready digital systems will be crucial for ensuring that technological innovation can be adapted into measurable progress towards the objectives of the European Green Deal.

Conflict of interest: The author declares no conflict of interest.

Data availability: No new datasets were generated or analysed during this study.

ACKNOWLEDGEMENTS

Supported by the János Bolyai Research Scholarship of the Hungarian Academy of Sciences (BO/00193/21/4) and the author thanks the Precision Bioengineering Research Group for research support.

ABBREVIATIONS

- AI artificial intelligence
- ALNE agriculture-landscape-natural ecosystem perspective
- CAP Common Agricultural Policy
- CEADS Common European Agricultural Data Space
- DSS decision support system
- DT digital twin
- EGD European Green Deal
- F2F Farm to Fork Strategy

- FMIS - farm management information system
- GNSS global navigation satellite system
- HRI Harmonised Risk Indicator (for pesticides)
- IoT Internet of Things
- ISOBUS ISO 11783 tractor-implement communication standard
- LCA life cycle assessment
- MRV monitoring, reporting and verification
- PDAM Policy-Aligned Digital Agroecosystem Management
- RS remote sensing
- SUR Sustainable Use of Pesticides Regulation proposal
- TRL technology readiness level
- UAV unmanned aerial vehicle
- WSN wireless sensor network

REFERENCES

Adamchuk, V.I., Hummel, J.W., Morgan, M.T., and Upadhyaya, S.K. (2004). On-the-go soil sensors for precision agriculture. *Computers and Electronics in Agriculture*, 44(1): 71–91, https://doi.org/10.1016/j.compag.2004.03.002

Alahmad, T., Neményi, M., and Nyéki, A. (2023). Applying IoT sensors and big data to improve precision crop production: a review. *Agronomy*, 13(10): 2603.

Ambrus, B., Teschner, G., Kovács, A.J., Neményi, M., Helyes, L., Pék, Z., Takács, S., Alahmad, T., and Nyéki, A. (2024). Field-grown tomato yield estimation using point cloud segmentation with 3D shaping and RGB pictures from a field robot and digital single lens reflex cameras. *Heliyon*, 10: e37997, https://doi.org/10.1016/j.heliyon.2024.e37997

Andreasen, C., Scholle, K., and Saberi, M. (2022). Laser weeding with small autonomous vehicles: friends or foes? *Frontiers in Agronomy*, 4: 841086, https://doi.org/10.3389/fagro.2022.841086

Chlingaryan, A., Sukkarieh, S., and Whelan, B. (2018). Machine learning approaches for crop yield prediction and nitrogen status estimation in precision agriculture: a review. *Computers and Electronics in Agriculture*, 151: 61–69, https://doi.org/10.1016/j.compag.2018.05.012

Duckett, T., Pearson, S., Blackmore, S., and Grieve, B. (2018). *Agricultural robotics: the future of robotic agriculture*. UK-RAS White Papers, pp. 27.

Eastwood, C., Klerkx, L., Ayre, M., and Dela Rue, B. (2019). Managing socio-ethical challenges in the development of smart farming: from a fragmented to a comprehensive approach for responsible research and innovation. *Journal of Agricultural and Environmental Ethics*, 32: 741–768, https://doi.org/10.1007/s10806-017-9704-5

European Commission. (2020a). *A Farm to Fork Strategy for a fair, healthy and environmentally-friendly food system*. COM(2020), pp. 381, final.

European Commission. (2020b). *EU biodiversity strategy for 2030: bringing nature back into our lives*. COM(2020), pp. 380, final.

European Commission. (2021). *The new common agricultural policy 2023-27: factsheets and eco-schemes*. Publications Office of the EU, Luxembourg.

European Commission. (2023). CAP eco-schemes, Available at: https://agriculture.ec.europa.eu/common-agricultural-policy/income-support/eco-schemes_en (accessed 14 February 2026).

European Commission. (2024a). Sustainable use of pesticides - proposal for a regulation on the sustainable use of plant protection products (SUR) (proposal withdrawn 27 March 2024), Available at: https://food.ec.europa.eu/plants/pesticides/sustainable-use-pesticides_en (accessed 14 February 2026).

European Commission. (2024b). Blueprint proposal for the common European agricultural data space. Shaping Europe's digital future (publication 02 May 2024), Available at: https://digital-strategy.ec.europa.eu/en/library/blueprint-proposal-common-european-agricultural-data-space (accessed 14 February 2026).

European Commission. (2025). EU trends in the use and risk of chemical pesticides and more hazardous pesticides (progress 2011-2023), Available at: https://food.ec.europa.eu/plants/pesticides/pesticide-reduction-targets-progress/eu-trends_en (accessed 14 February 2026).

European Commission. (2025b). Launching of the European partnership agriculture of data (event, 09 October 2025), Available at: https://agriculture.ec.europa.eu/media/events/launching-european-partnership-agriculture-data-2025-10-09_en (accessed 14 February 2026).

Finger, R. (2023). Digital innovations for sustainable and resilient agricultural systems. *European Review of Agricultural Economics*, 50(4): 1277–1309, https://doi.org/10.1093/erae/jbad021

Fountas, S., Carli, G., Sørensen, C.A.G., Tsiropoulos, Z., Cavalaris, C., Vatsanidou, A., Liakos, B., Canavari, M., Wiebensohn, J., and Tisserye, B. (2015). Farm management information systems: current situation and future perspectives. *Computers and Electronics in Agriculture*, 115: 40–50, https://doi.org/10.1016/j.compag.2015.05.011

Fraunhofer IESE. (2025). CEADS paves the way for secure agricultural data exchange in Europe (press release, 09 July 2025), Available at: https://www.iese.fraunhofer.de/en/media/press/pm_2025_07_09_ceads.html (accessed 14 February 2026).

Hunt, E.R. and Daughtry, C.S.T. (2018). What good are unmanned aircraft systems for agricultural remote sensing and precision agriculture? *International Journal of Remote Sensing*, 39(15–16): 5345–5376, https://doi.org/10.1080/01431161.2017.1410300

Kamilaris, A. and Prenafeta-Boldú, F.X. (2018). Deep learning in agriculture: a survey. *Computers and Electronics in Agriculture*, 147: 70–90.

Klerkx, L., Jakku, E., and Labarthe, P. (2019). A review of social science on digital agriculture, smart farming and agriculture 4.0: new contributions and a future research agenda. *NJAS - Wageningen Journal of Life Sciences*, 90–91: 100315, https://doi.org/10.1016/j.njas.2019.100315

Landis, D.A. (2017). Designing agricultural landscapes for biodiversity-based ecosystem services. *Basic and Applied Ecology*, 18: 1–12, https://doi.org/10.1016/j.baae.2016.07.005

Liakos, K.G., Busato, P., Moshou, D., Pearson, S., and Bochtis, D. (2018). Machine learning in agriculture: a review. *Sensors*, 18(8): 2674.

Lytridis, C. and Pachidis, T. (2024). Recent advances in weeding robots: a review. *AgriEngineering*, 6(3): 3279–3296, https://doi.org/10.3390/agriengineering6030187

Neményi, M., Ambrus, B., Teschner, G., Alahmad, T., Nyéki, A., and Kovács, A.J. (2023). Challenges of ecocentric sustainable development in agriculture with special regard to the internet of things (IoT), an ICT perspective. *Progress in Agricultural Engineering Sciences*, 19(1): 113–122, https://doi.org/10.1556/446.2023.00099

Neményi, M. and Milics, G. (2010). Energy in agriculture: balances and sustainability. *Hungarian Agricultural Engineering*, 23: 5–12.

Neményi, M., Teschner, G., Ambrus, B., Nyéki, A., and Kovács, A.J. (2022). Challenges of sustainable agricultural development with special regard to internet of things (IoT): a survey. *Progress in Agricultural Engineering Sciences*, 18(1): 95–114.

Page, M.J., McKenzie, J.E., Bossuyt, P.M., Boutron, I., Hoffmann, T.C., and Mulrow, C.D., et al. (2021). The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. *BMJ*, 372: n71, https://doi.org/10.1136/bmj.n71

Papadopoulos, G., Arduini, S., Uyar, H., Psiroukis, V., Kasimati, A., and Fountas, S. (2024). Economic and environmental benefits of digital agricultural technologies in crop production: a review. *Smart Agricultural Technology*, 8: 100441, https://doi.org/10.1016/j.atech.2024.100441

Paustian, M. and Theuvsen, L. (2017). Adoption of precision agriculture technologies by German crop farmers. *Precision Agriculture*, 18: 701–716, https://doi.org/10.1007/s11119-016-9482-5

Popp, J., Oláh, J., Neményi, M., and Nyéki, A. (2024). Global challenges and the 'farm to fork' strategies of the European green deal: blessing or curse. *Progress in Agricultural Engineering Sciences*, 20(1): 101–111, https://doi.org/10.1556/446.2024.00113

Purcell, W. and Neubauer, T. (2023). Digital twins in agriculture: a state-of-the-art review. *Smart Agricultural Technology*, 3: 100094, https://doi.org/10.1016/j.atech.2022.100094

Regulation (EU) 2018/848 of the European Parliament and of the Council of 30 May 2018 on organic production and labelling of organic products and repealing council regulation (EC) No 834/2007. *Official Journal of the European Union*. Available at: https://eur-lex.europa.eu/eli/reg/2018/848/oj/eng (accessed: 14 February 2026).

Regulation (EU) 2022/868 of the European Parliament and of the Council of 30 May 2022 on European data governance and amending Regulation (EU) 2018/1724 (data governance act). *Official Journal of the European Union, L*, 152, 3.6.2022.

Regulation (EU) 2023/1230 of the European Parliament and of the Council of 14 June 2023 on machinery and repealing Directive 2006/42/EC and Council Directive 73/361/EEC (Machinery Regulation). *Official Journal of the European Union, L*, 165, 29.6.2023.

Regulation (EU) 2023/2854 of the European Parliament and of the Council of 13 December 2023 on harmonised rules on fair access to and use of data (data act). *Official Journal of the European Union*.

Regulation (EU) 2024/1689 of the European Parliament and of the Council of 13 June 2024 laying down harmonised rules on artificial intelligence (Artificial intelligence act). *Official Journal of the European Union, L*, 2024/1689.

Reichardt, M., Jürgens, C., Klüble, U., Hüter, J., and Moser, K. (2009). Dissemination of precision farming in Germany: acceptance, adoption, obstacles, knowledge transfer and training activities. *Precision Agriculture*, 10: 525–545, https://doi.org/10.1007/s11119-009-9112-6

Reinhardt, T. (2023). The farm to fork strategy and the digital transformation of the agrifood sector-An assessment from the perspective of innovation systems. *Applied Economic Perspectives and Policy*, 45: 819–838, https://doi.org/10.1002/aepp.13246

Rejeb, A., Rejeb, K., and Hassoun, A. (2025). The impact of machine-learning applications in agricultural supply chains: a topic-modelling-based review. *Discover Food*, 5: 141.

Rizman Žalik, K. and Žalik, M. (2023). Federated learning in agriculture: a review. *Sensors*, 23(23): 9566, https://doi.org/10.3390/s23239566

Rose, D.C. and Chilvers, J. (2018). Agriculture 4.0: broadening responsible innovation in food and farming. *Frontiers in Sustainable Food Systems*, 2: 87.

Shamshiri, R.R., Weltzien, C., Hameed, I.A., Yule, I.J., Grift, T.E., and Balasundram, S.K., et al. (2018). Research and development in agricultural robotics: a perspective of digital farming. *International*

Journal of Agricultural and Biological Engineering, 11(4): 1–14, https://doi.org/10.25165/j.ijabe.20181104.4278

Tilman, D. (1998). The greening of the green revolution. *Nature*, 396(6708): 211–212.

Tilman, D., Cassman, K.G., Matson, P.A., Naylor, R., and Polasky, S. (2002). Agricultural sustainability and intensive production practices. *Nature*, 418(6898): 671–677.

Tricco, A.C., Lillie, E., Zarin, W., O'Brien, K.K., Colquhoun, H., and Levac, D., et al. (2018). PRISMA extension for scoping reviews (PRISMA-ScR): checklist and explanation. *Annals of Internal Medicine*, 169(7): 467–473, https://doi.org/10.7326/M18-0850

Verdouw, C., Robbemond, R., Verwaart, T., and Wolfert, S. (2021). Digital twins in smart farming. *Agricultural Systems*, 189: 103046, https://doi.org/10.1016/j.agsy.2020.103046

Wang, L. (2024). Digital twins in agriculture: a review of recent progress and open issues. *Electronics*, 13(11): 2209, https://doi.org/10.3390/electronics13112209

Wolfert, S., Ge, L., Verdouw, C., and Bogaardt, M.J. (2017). Big data in smart farming: a review. *Agricultural Systems*, 153: 69–80.

Yarovenko, H., Ohol, D., Ashirbekova, L., and Popp, J. (2025). Digital transformation and economic development in Europe: classical and machine-oriented approaches. *Journal of International Studies*, 18(4): 256–284, https://doi.org/10.14254/2071-8330.2025/18-4/13