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Economic and environmental benefits of digital agricultural technologies in crop production: A review

George Papadopoulos [a,*], Simone Arduini [b], Havva Uyar [a,c], Vasilis Psiroukis [a], Aikaterini Kasimati [a], Spyros Fountas [a]

[a] Laboratory of Agricultural Engineering, Department of Natural Resources Management & Agricultural Engineering, School of Environment and Agricultural Engineering, Agricultural University of Athens, 11855 Athens, Greece

[b] DAFNAE Department, University of Padova, Viale dell'Universita ` 16, Legnaro (PD), 35020, Italy

[c] Research and Development Department, SingularLogic, 14564 Athens, Greece

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ABSTRACT

This comprehensive review delved into the economic and environmental benefits of Digital Agricultural Technologies (DATs) in crop production, synthesising data from 136 peer-reviewed papers and 28 documents with empirical data from relevant EU projects. This analysis highlighted the substantial contribution of DATs across five key categories: Recording and Mapping Technologies (RMT), Guidance and Controlled Traffic Farming (CTF) Technologies, Variable Rate Technologies (VRT), Robotic Systems or Smart Machines (RSSM), and Farm Management Information Systems (FMIS). Specifically, it provided an overview of the various benefits that these technologies can deliver with the most significant ones revealing reductions of up to 80 % in fertiliser usage with RMT and CTF applications, while VRT demonstrated a 60 % decrease in fertiliser usage and up to 80 % reduction in pesticide use. VRT also showed an increase in yield by 62 %. RSSM was able to reduce labour by 97 % and diesel consumption by 50 %. FMIS improved yield by 10 % to 15 %, facilitating simultaneous reductions in labour and input costs, illustrating the critical role of integrated digital solutions in enhancing agricultural efficiency and sustainability. From an environmental point of view, VRT has emerged as a major factor in environmental sustainability, demonstrating water savings of 20 % to 50 % in vineyards and pear orchards and a significant reduction in greenhouse gas emissions. These findings highlighted the significant benefits of DATs on enhancing productivity and promoting environmental sustainability. They provided a compelling case for further investment and research in DATs through quantifiable benefits in crop production.

Introduction

Agriculture plays a pivotal role in the global food production and supply chain, and is constantly adapting to meet the recurring challenges it faces. The adoption of Digital Agricultural Technologies (DATs) has emerged as a prominent aspect of this transformative process, offering a forward-thinking perspective within the agricultural domain [1]. DATs broadly encompass a suite of technologies including precision agriculture, remote sensing, and data analytics. They differ from other technologies by providing an integrated approach that combines various digital tools and platforms to revolutionise traditional farming practices, whereas smart farming often refers to the application of IoT and connectivity solutions, and precision agriculture specifically focuses on the precise management of farm inputs. Together, these advancements facilitate informed decision-making and optimised resource use [2,3].

Digital agriculture encompasses a broad spectrum of technologies, including communication, information, and spatial analysis tools. These technologies enable farmers to efficiently plan, monitor, and manage both the operational and strategic aspects of their production systems. Beyond established technologies like field sensors [4–6], orbital and UAV-embedded remote sensors [7–9], global positioning systems, telemetry, and automation [10], digital agriculture is also characterised by the integration of the Internet and connectivity in crops [11,12], cloud computing, big data, blockchain, and cryptography [13–15], as well as deep learning [16–18], the Internet of Things (IoT) [19], mobile applications, and digital platforms [20,21], and artificial intelligence [22]. These advancements not only support critical pre- and post-production decisions but also promote greater sustainability within

* Corresponding author.
E-mail address: gpapadopoulos@aua.gr (G. Papadopoulos).

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production systems [23,24], offering access to differentiated markets that benefit short food supply chains.

The integration of DATs is critically aligned with global sustainability and food security goals, particularly under the European Green Deal and its 'Farm to Fork Strategy'. These initiatives aim for a radical transformation of the food system towards sustainability, setting ambitious targets for the reduction of chemical pesticides and fertilisers, and the expansion of organic farming by 2030 [25]. DATs, encompassing innovations such as precision agriculture, remote sensing, and data analytics, are at the forefront of this transformation, offering pathways to harmonise economic profitability with environmental stewardship. These technologies enable precision resource application, efficient crop monitoring, and data-driven management, presenting significant advantages in optimising agricultural productivity and reducing ecological footprints [2,23,26,27].

Multiple studies have analysed the adoption trends [28–30], the potential in improving the quality of life for rural populations [31], and the overall resources efficiency of the agri-food sector [32,33]. Researchers have extensively studied the holistic effect of DATs in the form of systematic process-based analyses [34,35], with the environmental footprint of the sector and the potential of DATs in reducing it being at the forefront of numerous studies [36,37].

The evidence supporting the transformative impact of DATs in agriculture is compelling, highlighting their role in enhancing yields, conserving resources, and mitigating environmental impacts. Such outcomes are vital for tackling the challenges of feeding a growing population while preserving natural resources and ecosystems. However, harnessing the full potential of DATs necessitates a comprehensive analysis of their benefits, catering to the informational needs of various stakeholders including policymakers, farmers, and the agricultural industry.

Limited research has been done in combining the environmental and economic parameters associated with the adoption of DATs across the entire agricultural sector, with most existing studies either focusing on a single production system [38] or a single DAT applied in different agricultural cases [39]. This paper aims to provide a comprehensive review covering both the economic and environmental benefits of DATs in a single manuscript, to facilitate decision-making processes, guiding the adoption and implementation of these technologies in line with the sustainability goals of the European Green Deal and the 'Farm to Fork Strategy'.

The EU-funded QuantiFarm project [40], which is dedicated to evaluating the impact of digital agricultural solutions, actively promotes the integration of DATs to increase sustainability and competitiveness. As part of this project, an integrative literature review was conducted to gain a comprehensive understanding of the existing percentage and numerical benefits associated with the economic and environmental aspects of DATs in crop production. Consequently, the primary aim of this paper was to provide a thorough understanding of the economic and environmental impacts of DATs in crop production.

Methodology

The approach followed was grounded on an integrative review of the existing literature, as described by [41]. Integrative reviews offer new perspectives, both theoretical and conceptual, through the synthesis and/or critique of existing research [42]. By using this approach, the outcomes contribute to research by providing a comprehensive perspective on the topic, while also systematically organising the existing knowledge base in a meaningful way.

To guide and clarify the integrative process, the general principles proposed by Tranfield et al. [43] are followed, which include (1) framing the objective, (2) executing the process, and (3) presenting the results [42].

Framing the objective

The overall aim of this review was to provide numerical evidence of the economic and environmental benefits of adopting DATs. By quantifying the benefits associated with each DAT, the aim is to encourage adoption of these technologies amongst farmers, improve their understanding of the benefits and consequently increase their willingness to adopt such innovations in crop production. Consequently, the paper's primary objective was formulated by revisiting the core research questions:

RQ1: What are the economic benefits of integrating DATs into crop production?

RQ2: What environmental benefits arise from the adoption of DATs in crop production?

Categorisation of DATs for crop farming systems

To assess the predefined research questions and to ensure a well-structured search, searches were conducted using specific categories. The categorisation of the DATs of this paper was based on Van Evert et al. [44], which divided Precision Agricultural Technologies into 3 categories, Recording, Guidance and Reacting. For the purpose of this study, these categories have been further expanded to include the wider spectrum of DATs into the following five categories:

Recording and Mapping Technologies (RMT) : Characterised by systems to monitor and map what exists in the crop environment (soil, crop, micro-climate), using yield and soil mapping, Real-Time Location Systems (RTLS) and monitoring mechanisms, these technologies create a bridge between real-time field data and actionable farming strategies [45]. By tracing diverse field metrics, they facilitate the development of detailed field blueprints, thereby guiding agricultural operations in efficient, targeted, and environmentally-friendly directions.

Guidance / Controlled Traffic Farming (CTF) Technologies: These technologies stand as a testament to innovations addressing the adverse impact of random vehicle movement across fields [46]. By localising all vehicular movement to predetermined lanes, CTF combines productivity, sustainability, and profitability, ensuring soil preservation and a favourable environment for crop growth [47].

Variable Rate Technologies (VRT): VRT permits farmers to manage resources with precision. It paves the way for the customised distribution of fertilisers, insecticides, and irrigation, aligning with individual crop needs. This technology has the potential to mitigate the environmental footprint of farming practices while also bolstering resource management, crop yield, and profitability [48].

Robotic Systems or Smart Machines (RSSM): With a combination of Artificial Intelligence (AI), advanced Information and Communications Technology (ICT), Machine-to-Machine (M2M) communication, RSSM mark the digital transformation of agriculture [49]. From drones to machine learning algorithms and robotic systems and vehicles, they represent the union of technology and agriculture, guiding the development of current and future agricultural paradigms.

Farm Management Information Systems (FMIS): Evolving from basic record-keeping systems, today's FMIS platforms and their resulting products, including Decision Support Systems (DSS) and Quality Management Systems (QMS), have evolved into sophisticated holistic platforms. Modern agricultural FMIS allow for automated data processing, by syncing data streams from numerous internet of things (IoT) components (such as sensing devices and cloud services), enabling data-oriented decisions and efficient resource management [50].

Fig. 1 illustrates the categories of DATs applied in the context of crop farming, which are derived from the pre-existing Precision Agriculture Techniques.

Execution of the literature review

The execution step of the literature search strategy was developed

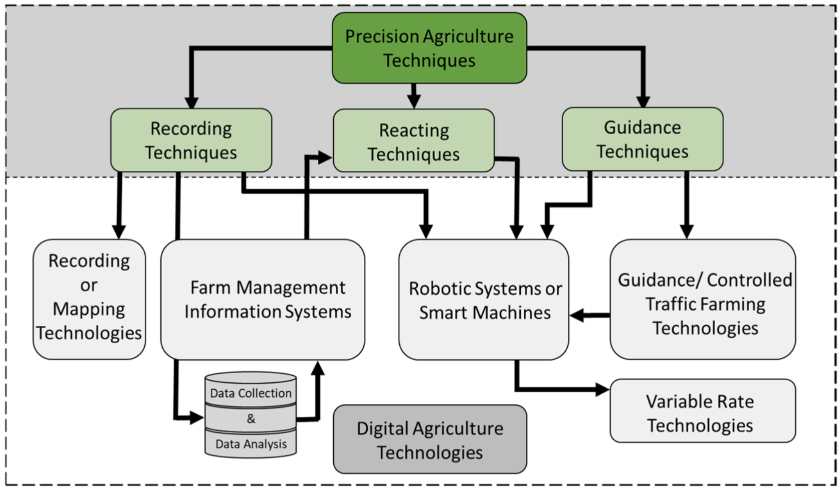

Fig. 1. 'Categories of DATs for Crop Farming'.

performing three actions: (a) identification, (b) screening, and (c) selection. The literature search strategy is represented in Fig. 2.

Identification of studies via databases

Search Strategy

The search for relevant literature was undertaken through Scopus and Web of Science, electronic databases known for their comprehensive coverage of scientific and academic publications [42,51,52]. The search strategy encompassed a range of keywords related to DATs, and the economic and environmental aspects of these technologies. Keyword combinations were structured to target specific DAT categories and their associated economic and environmental benefits.

General Keywords: "agriculture", "farming", "crop production"

DATs Categories Keywords: "Farm Management Information System", "FMIS", "Decision Support System", "DSS", "Guidance", "Controlled Traffic Farming", "CTF", "Variable Rate Technologies", "VRT", "Recording Technologies", "Mapping Technologies", "Robotic Systems", "Smart Machines".

Economic Benefits Keywords: "yield increase", "fertiliser saving", "pesticide saving", "herbicide saving", "labour saving", "fuel saving", "efficiency improvement ", "productivity enhancement", "cost reduction".

Environmental Benefits Keywords: "greenhouse gas emissions", "nitrous oxide", "N2O", "methane emissions", "CH4", "carbon footprint", "groundwater quality", "water quality", "aquatic ecosystem", "soil erosion", "soil emissions", "water runoff", "environmental sustainability".

The conducted literature search resulted in a significant number of potential sources. In order to guarantee the incorporation of the most relevant and updated content, literature selection criteria and a multi-stage screening process was implemented.

Literature Selection Criteria

The formulation of the selection criteria was aimed at ensuring the inclusion of research that is relevant and rigorous. The following criteria were applied throughout the literature search:

Relevance: The inclusion of articles depended on whether they addressed DATs within the context of crop systems, with a focus on their economic and environmental implications.

Publication Date: A preference was given to literature published within the last decade (2013 to 2023) to ensure the incorporation of the most current information.

Language: Inclusion of articles primarily in English, with consideration of articles in other languages if deemed highly relevant and if English translations were available.

Multi-stage screening

At this stage, a review of titles and abstracts of retrieved articles was

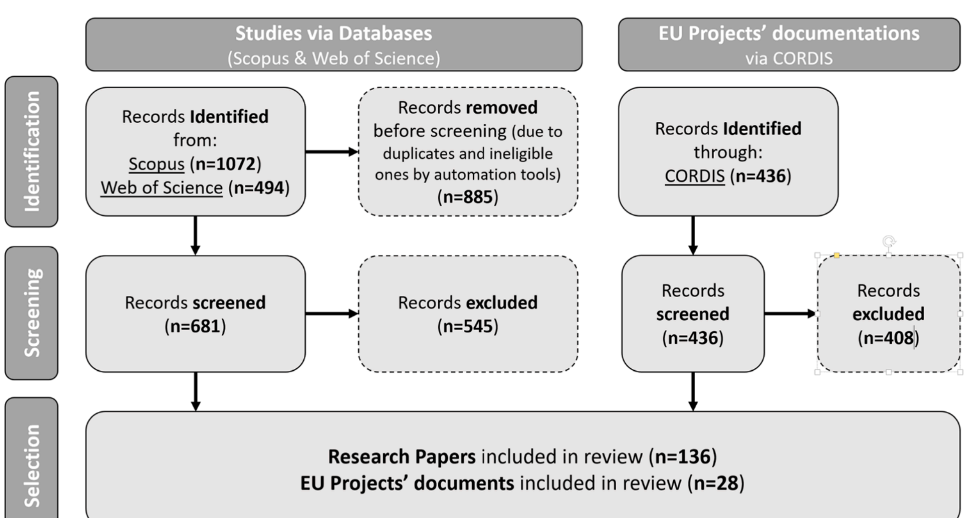

Fig. 2. 'Flow chart of the literature search strategy'.

conducted to evaluate their alignment with the research objectives and inclusion criteria. Subsequently, a comprehensive examination of the full texts of the selected articles was carried out. Studies that did not provide substantial information regarding the economic and environmental aspects of DATs in crop systems, particularly those lacking information on numerical and percentage-based benefits, were excluded. This decision was made in line with the primary aim of the review, which was to record scientific data for economic and environmental benefits as part of the QuantiFarm project to assist farmers in optimising their economic returns and environmental impact.

Identification of EU project documentations via CORDIS

Search Strategy

The search for relevant EU projects was undertaken through CORDIS, the European Commission's central repository for outcomes derived from projects financed by the EU's framework programs. The following keywords were used to gather the projects related to the general context of our research.

Keywords: "smart agriculture", "precision farming", "precision agriculture", "smart farming", "digital agriculture", "digital farming".

In order to manage the large amount of results obtained from CORDIS, a thorough selection process was carried out.

Selection Criteria

The use of specific keywords allowed for the retrieval of relevant materials, resulting in a significant amount of projects and their documentation. All relevant files from CORDIS were downloaded for examination, with a specific focus on extracting quantitative insights into the efficacy of DATs in crop production within the EU context. The initial phase of the selection involved a thorough assessment to eliminate any documents that did not directly contribute to the objectives of our research.

Multi-stage screening

After an initial selection process based on predefined criteria in Section 2.3.1, a multi-stage screening approach was used to further refine the dataset and isolate project documentation that specifically addressed the quantitative benefits of DATs in crop production. A deeper analysis was conducted to extract documents containing specific references to percentages and numerical benefits associated with the implementation of DATs in crop production. This involved reviewing project descriptions, reports, and findings to identify key metrics and data points that illustrate the impact of DATs on crop production.

Presentation of the results

The presentation of the results is structured to offer a comprehensive overview of the economic and environmental impacts of DATs in crop production. Given the diverse nature of DATs and their varied applications in agriculture, the findings are organised into specific categories corresponding to the technology types identified in the methodology: RMT, CTF technologies, VRT, RSSM, and FMIS.

For each category, a dual approach in presenting the results has been adopted:

Quantitative Summary Tables: The number of peer-reviewed papers alongside the number of documents with empirical data from relevant EU projects are synthesised into summary tables. These tables provide a clear, quantified snapshot of the number of papers and documents associated with each DAT category, as well as specific benefits including yield increase, fertiliser savings, pesticide savings, water savings, labour/fuel/cost savings, and environmental benefits (Tables 1–6).

Narrative Synthesis: Complementing the quantitative tables, a narrative synthesis followed to thoroughly examine these findings, presenting a coherent narrative that connects the various pieces of data. This narrative comprehensively examined all notable findings for each DAT category and each specific benefit derived from the literature and projects, presenting a comprehensive perspective on the advantages linked to DATs. It explained the mechanisms through which DATs deliver their advantages and the crop types that the DATs were implemented.

Table 1
Number of References related to DAT Categories.

DAT Categories	Number of relevant Peer-reviewed papers	Number of relevant documents with empirical data from relevant EU projects
Recording and Mapping technologies (RMT)	27	7
Guidance and Controlled Traffic Farming (CTF) technologies	20	2
Reacting or Variable Rate Technologies (VRT)	52	3
Robotic Systems or Smart Machines (inc. Artificial Intelligence (AI))	23	3
Farm Management Information Systems (FMIS)	14	13
Total Number:	**136**	**28**

Results

From the screening process, a total of 160 references were selected, comprising 132 peer-reviewed papers and 28 documents with empirical data from relevant EU projects. These selections were based on their specific contributions to understanding the economic and environmental impacts of DATs. Table 1 below categorises these references according to their relevance to a DAT category and their provision of data on specific benefits. It is important to note that the total number of references included all sources that provided information relevant to one or more DAT categories. Some documents examine more than one DATs category, highlighting the interconnection and multifaceted benefits of DATs in agriculture.

Analysing the table, it is evident that the information provided by scientific articles (136) are more than double that of the European projects (28). Delving into more detail, it is apparent that certain technologies are more extensively studied and analysed than others. For instance, the VRT category provided 48 peer-reviewed articles, ranking first among all categories. From this result, it can be asserted that this category is of fundamental importance in all those agricultural systems whose primary objective is to minimise the misuse of inputs, both for economic reasons and environmental concerns. For this reason most articles in this category referred to the variable rate application of agricultural inputs.

Continuing with the analysis of peer-reviewed articles that garnered significant interest, the 'RMT' category ranked second with 27 articles, followed by the 'RSSM' category in third place with 23 articles. With regard to the results obtained by RMT, this was undoubtedly attributed to the strong presence in today's market of high-performance GPS devices at reasonable costs. This DAT category encompasses several technologies widely adopted in Precision Agriculture and is essential for the proper management of all phases of agricultural management and production. Concerning robotic systems, the significant number of articles was probably due to the growing popularity of these technologies, thanks to the substantial investments currently being made in a sector that is growing not only in agriculture. Finally, the categories 'CTF' and 'FMIS' concluded the ranking with 20 and 14 peer-reviewed articles, respectively. These categories, although used in agriculture for their effectiveness, may be considered less crucial than other technologies analysed, potentially playing a less fundamental role in scientific research.

Regarding the ranking of data obtained from European projects (28), the first position was occupied by data derived from projects related to FMIS technologies. In this case, 13 specific valid data points for this technology were found. This situation demonstrated that the interest in the development of information systems is widely spread and finds space in the agricultural field as well. The second category with the highest number of data is "RMT," which presented 7 European projects. The various technologies falling within this DAT were studied with growing interest. The reason is attributed to the fact that a correct management support system depends on accurate recording of georeferenced data. Finally, the last three categories, "VRT," "RSSM," and "CTF Technologies," produced 3, 3, and 2 data obtained from European projects, respectively.

Recording and mapping technologies (RMT) (inc. monitoring and mapping systems, real-time location systems (RTLS))

Table 2 below provides a detailed and quantified overview of the peer-reviewed papers and documents with empirical data from relevant EU projects associated with the RMT DAT category, detailing the specific benefits observed. These benefits include yield increase, fertiliser savings, pesticide savings, water savings, and savings in labour, fuel, and overall costs, as well as environmental benefits.

Yield Increase: RMT have been instrumental in driving yield increases across various agricultural sectors by enabling more informed and precise farm management decisions. Studies such as that by Paulius et al. [53] have shown yield increases in organic winter wheat grown under low soil performance conditions, with gains ranging from 9.7 % to 13.34 %. Keller et al. [54] observed an 8 % to 12 % yield boost in winter wheat from site-specific weed control, illustrating the potential of targeted agricultural practices.

Yield improvements were also reported by projects like the Added-Value Weeding Data use case of the IOF2020 project, confirming these findings. Through high-resolution camera data processing, this project achieved a 5 % increase in lettuce yield, optimising harvest timings and selective harvesting in organic vegetable farming (Added Value Weeding Data– [55]). Similarly, the Precision Crop Management project, utilising IoT sensors and agronomic models, mirrored these results with a 5 % increase in wheat yield and quality (Precision Crop Management– [56]). This is in line with the results reported by Munnaf et al. [57], where maize grain yield increases led to a gross margin increase of up to $92.67 per hectare.

The Within-Field Management Zoning Baltics initiative, part of the IOF2020 project, utilised hyperspectral imaging, IoT technologies, and AI-driven analytics to enhance crop health in potatoes and wheat. The project achieved substantial yield increases, ranging from 52.5 % to 62.6 % for potatoes and 7.5 % to 8.6 % for wheat, reinforcing the findings of Astanakulov et al. [58] who reported significant wheat yield increases from 4.46 t/ha to 6.24 t/ha using GPS-equipped combines (Within Field Management Zoning Baltics– [59]). Further evidence from Squeri et al. [60] and Haghverdi et al. [61] in viticulture and irrigation management, respectively, with yield increases up to 40 % and 32 %, solidifies the role of RMT in enhancing agricultural productivity.

Table 2
Quantitative Benefits of RMT DAT Category from Peer-Reviewed Papers and EU Projects.

Recording and Mapping technologies (RMT)	Peer-reviewed papers		Documents with empirical data from relevant EU project	
Total Number related to RTLS	27		7	
Economic Benefits	N°	% Range	N°	% Range
Yield Increase	6	8–40 %	3	5–62.6 %
Fertiliser savings	8	1.6–82 %	3	5–70 %
Pesticide savings	7	14–65 %	2	15–30 %
Water savings	2	16–35 %	1	10 %
Labour/Fuel/Cost savings	2		2	
Labour savings		–		5 %
Cost savings		34–46 %		–
Environmental Benefits	2		2	
Global Warming Potential reduction		8.6–17 %		–
CO2 emissions reductions		–		5–20 %

Fertiliser Savings: Advancements in RMT have substantially enhanced fertiliser efficiency. Basso et al. [62] found a 12 % reduction in nitrogen fertiliser use in wheat through spatially variable nitrogen fertilisation in Mediterranean environments. Argento et al. [63] reported a reduction in nitrogen leaching, greenhouse gas (GHG) emissions, and improved nitrogen use efficiency (NUE) by approximately 10 % through site-specific nitrogen management in winter wheat, facilitated by remote sensing and soil data, with fertiliser application reduced by 5–40 %.

Andújar et al. [64] demonstrated an up to 80 % reduction in fertiliser dosage for vineyard crops using aerial imagery and on-ground detection, compared to conventional applications. In greenhouse crops, Vakilian and Massah [65] achieved an 18 % decrease in nitrogen fertiliser consumption with a farmer-assistant robot.

Medel-Jimenez et al. [35] who achieved input savings of 14 % using prescription maps and 23.9 % using sensors. Colaço and Bramley [66], Colaço and Molin [67] and Guerrero and Mouazen [68] also provide literature evidence of nitrogen application reduction, ranging from 1.6 % to 82.0 % with proximal sensors and 6.0 % to 50.0 % with remote sensors.

Empirical data align with these findings. The Precision Crop Management project within IOF2020, utilising IoT sensors and satellite data, achieved a 5 % reduction in nitrogen application (Precision Crop Management– [56]). The Within-Field Management Zoning Baltics use case of IOF2020 employed hyperspectral imaging and machine learning algorithms to precisely assess the nutritional demands of potato and wheat crops, leading to substantial fertiliser cost reductions of €229.5 to €323 per hectare for potatoes and €160 to €224 per hectare for wheat.(Within Field Management Zoning Baltics– [59])

The 'GaiaInFarm' project under HORIZON 2020, using RMT and an FMIS for fruit cultivation, reported a remarkable 50 % to 70 % decrease in fertilisers usage (GAIA InFarm– [69]). This project utilised sensing stations, app technology, and DSS to enhance monitoring and decision-making processes.

Pesticide savings: RMT have made significant strides in Plant Protection Products (PPP) savings across various agricultural practices, as evidenced by both empirical studies and real-world applications. In the realm of literature, Ørum et al. [70] demonstrated that utilising low-dose herbicides through precision application technologies can lead to cost reductions ranging from 20 % to 50 %. Laursen et al. [71] introduced a weed quantification algorithm for maize that significantly reduced herbicide use by 65 %. Yan et al. [72] explored a laser sensor-guided spray control system in greenhouses, achieving a reduction in spray volume by 29.3 % to 51.4 %.Castaldi et al. [73], obtained herbicide savings, based on application map, in the range of 14 % and 39.2 % compared to a uniform application. Gusev et al. [74] observed a 3.6 % reduction in PPP usage by implementing precision farming technologies. De Bortoli et al. [75] reported up to 50 % savings in product usage with the Structure from Linear Motion (SfLM) canopy profiling system for sprayer control. Tewari et al. [76] utilised sonar sensing in orchards, resulting in a 26 % reduction in PPP use.

Complementing these findings, empirical data from projects like SDOP (Smart Detection of Pests) and the EIP-AGRI Focus Group further reinforce these findings. The SDOP project, using optical and acoustic sensors for pest detection, achieved a 20 % reduction in pesticide use by enabling precise and early pest identification, leading to more targeted applications (SDOP– [77]). The EIP-AGRI Focus Group's work on precision fertilisation in fruit production anticipates reductions of 15–20 % in fungicide use for stone fruit and 20–30 % for pome fruit, specifically against powdery mildew [78].

Water savings: Although these systems need more investigation, RMTs contribute to the necessity of water conservation in agriculture. Millán et al. [79] implemented an automatic irrigation scheduling system in a hedgerow olive orchard, leveraging an algorithm that readjusted the water balance based on soil moisture sensor data, resulting in a 24 % reduction in water usage. Similarly, Zhe et al. [80] developed innovative irrigation scheduling software that uses model-predicted crop water stress to determine optimal irrigation timing and quantities, achieving water savings between 16 % and 35 %. These academic findings are mirrored in empirical data from the Precision Crop Management initiative. Utilising a combination of IoT sensors, satellite imagery, and drone technology, this initiative successfully reduced irrigation costs by 10 %, demonstrating effective water-saving strategies and efficient water resource management in wheat cultivation. This real-world application highlights the practical benefits and applicability of RMT in enhancing water conservation in agricultural practices (Precision Crop Management– [56]).

Labour/Fuel/Cost savings: RMT in agriculture, encompassing a range of precision farming tools and methods, have demonstrated substantial efficiencies and cost savings across various aspects of farm management. Gusev et al. [74] explored the impact of precision farming technologies on production and economic indicators in agriculture organisations, identifying a significant 6.3 % reduction in fuel consumption. Concurrently, Strub et al. [81] observed a substantial cost reduction by transitioning from Vertical Shoot Positioning (VSP) to Mechanical Pruning (MP) training systems on steep slopes, achieving an overall cost reduction of 34 % and 46 %, respectively. This decrease was largely attributed to reduced machinery costs.

Complementing these studies, empirical data from the IoF2020 EU-funded project provide real-world evidence of similar benefits. The Added-Value Weeding Data use case within IoF2020, utilising advanced vision systems, achieved a 5 % reduction in machine running hours by optimising image collection and processing (Added Value Weeding Data– [55]). This improvement in efficiency was a direct result of enhanced image analysis capabilities, facilitating more precise weeding operations and reducing the need for extended machine usage. Furthermore, this approach led to a 5 % improvement in labour efficiency, demonstrating how refined image processing can aid in more accurate crop parameter calculation and enhance crop growth predictions, ultimately reducing the manual labour required for weeding and crop monitoring (Added Value Weeding Data– [55]).

Additionally, the Precision Crop Management project within IoF2020, applying IoT-based sensing and advanced analytics, streamlined operations and achieved a 5 % reduction in labour duration (Precision Crop Management– [56]). This efficiency gain underscores the advantages of automated and efficient monitoring methods in saving time and optimising resource allocation, illustrating the practical impact of RMT in enhancing labour, fuel, and cost savings in the agricultural sector.

Environmental Benefits: Environmental benefits derived from RMT have shown promising reductions in GHG emissions and energy use, contributing significantly to the mitigation of global warming potential (GWP). These technologies, particularly when integrated with precision agriculture practices, offer direct environmental benefits through the efficient use of resources and optimization of crop production processes.

Medel-Jiménez et al. [82] quantified the environmental impacts of using optical crop sensors in winter wheat production, revealing an 8.6 % reduction in global warming potential, highlighting the efficacy of crop sensors in reducing the carbon footprint of agricultural operations. Further research by Medel-Jiménez et al. [35] underlined the potential of crop sensors in precision agriculture to cut global warming by 17 %, showcasing their vital role in combating climate change.

Empirical evidence further supports these findings, with the implementation of solar-powered sensors and AI-driven precision farming leading to a 20 % drop in CO_2 emissions (Solar Powered Field Sensors– [83]). This integration of renewable energy sources and advanced analytics into farming practices underscores the potential for significant environmental improvements. Moreover, the Precision Crop Management initiative within the IOF2020 EU-funded project leveraged IoT technology and data-driven decision-making to notably reduce its environmental impact, achieving a 10 % reduction in GHG emissions and a 5 % decrease in energy usage (Precision Crop Management– [56]). These outcomes reflect a strong commitment to environmentally sustainable wheat production practices, illustrating how modern agricultural technologies can lead to considerable environmental benefits.

Guidance and controlled traffic farming (CTF) technologies

Table 3 below provides a detailed and quantified overview of the peer-reviewed papers and documents with empirical data from relevant EU projects associated with the CTF DAT category, detailing the specific benefits observed. These benefits include yield increase, fertiliser savings, pesticide savings, water savings, and savings in labour, fuel, and overall costs, as well as environmental benefits.

Yield increase: CTF technologies have been consistently linked to yield increases in various crops, as evidenced by a range of studies. Hargreaves et al. [84] observed a 13 % increase in dry matter yield due to CTF practices. Galambošová et al. [85] reported that CTF could enhance yields by 35 % compared to multi-pass treatment and 9 % compared to single-pass treatment. In the context of onion production on sandy soils, Pedersen et al. [86] noted 19 % higher yields in CTF simulation plots. Hefner et al. [87] demonstrated significant yield increases in white cabbage, potato, and beetroot of 27 %, 70 %, and 42 %, respectively, associated with CTF. Additionally, Hussein et al. [88] found that CTF outperformed non-CTF practices with a 30 % higher grain yield in average rainfall seasons, and Zhang et al. [89] documented a 16.81 % increase in kiwifruit orchard yields using CTF technologies. The cumulative findings from these studies, including those by Misiewicz & Galambosova [90], indicate that CTF systems can increase yields by 10–15 %, depending on soil type and operation duration. These studies collectively demonstrate the advantages of CTF systems over traditional multi-pass or single-pass treatments.

While empirical data specifically related to yield increases in CTF from field applications are not readily available, the consistency and range of improvements reported in academic studies across different crops and soil conditions strongly suggest the potential benefits of CTF in real-world agricultural scenarios. These benefits are primarily attributed to optimised planting and application processes, reduced soil

Table 3
Quantitative Benefits of CTF DAT Category from Peer-Reviewed Papers and EU Projects.

Guidance and Controlled Traffic Farming (CTF) technologies				
	Peer-reviewed papers		Documents with empirical data from relevant EU project	
Total Number related to CTF	20		2	
Economic Benefits	N°	% Range	N°	% Range
Yield Increase	7	9–70 %	–	–
Fertiliser savings	6	1–26 %	–	–
Pesticide savings	3	1–42 %	1	30 %
Water savings	5	9–42 %	1	30–50 %
Labour/Fuel/Cost savings	8		3	
Fuel savings		2–70 %		10–16 %
Environmental Benefits	4		1	
Reduction in Soil Emissions		21–45 %		–
Reduction in Water Runoff		28–42 %		–
Reduction in Human Toxicity		3–15 %		–
Reduction in Eco-toxicity		11–138 %		–
Reduction in Terrestrial Eutrophication		29 %		–
Reduction in Climate Change Impacts		50 %		–
Reduction in Chemical Runoff		–		99.8 %
GHG Emissions Reduction		–		56 %

compaction, and improved overall agronomic efficiency.

Fertiliser savings: CTF technologies have been identified as effective means for reducing fertiliser usage and costs, a benefit supported by both academic research and empirical data. Balafoutis et al. [38] noted that in CTF systems, where fertilisers are not applied to permanent wheel tracks, there is a potential cost reduction of 10–15 % for narrow-spaced crops. Similarly, Soto et al. [37] reported a 15 % reduction in fertiliser usage through the implementation of CTF. Gasso et al. [91] observed a broader range of fertiliser reduction, between 1 % and 26 %, depending on the context.

Tullberg [92] highlighted an even more significant aspect of CTF: an enhancement in nitrogen efficiency by 40–80 %, attributed to reduced soil compaction and improved soil biological activity. Hussein et al. [88] corroborated this, demonstrating a 1.75 times increase in NUE in CTF compared to non-CTF systems. Furthermore, Misiewicz & Galambosova [90] found a 15 % improvement in fertiliser uptake due to less soil compaction in CTF systems.

Pesticide savings: CTF technologies have shown promising results in reducing PPP usage, as evidenced by both academic research and empirical data. Masters et al. [93] discovered that the combination of controlled traffic and early-banded application in sugarcane farming led to a significant 32–42 % decrease in herbicide losses in runoff, which also contributed to lower input costs. Gasso et al. [91] reported a reduction in pesticide use ranging from 1 % to 26 % in their studies. Furthermore, Tullberg [92] noted that CTF could potentially reduce herbicide requirements by 25 %, attributed mainly to more timely and efficient spraying facilitated by permanent traffic lanes.

Complementing these academic findings, empirical data from innovations like the Wingssprayer, a patented crop spraying technology from the Netherlands, reinforces the fertiliser savings potential in practical applications. The Wingssprayer enables farmers to reduce the use of expensive spraying chemicals by up to 30 % (Wingssprayer– [94]), showcasing the efficiency and environmental benefits of such technologies. This reduction is achieved by focusing on eliminating weeds, insects, and fungi within crops while preventing chemical waste into the surrounding environment.

Water savings: CTF technologies have been identified as key contributors to water savings in agricultural practices, as supported by various studies and empirical data. Bellvert et al. [95] observed water reductions of 13.0 % and 9.0 % for different crops through precision irrigation in CTF systems, highlighting the efficiency of water use. Hussein et al. [88] linked CTF to a 65 % increase in rainfall-use efficiency, leading to reduced runoff and water conservation. This aligns with yield increases, making CTF not only environmentally beneficial but also cost-effective.

Gasso et al. [91], Thomsen et al. [96], and Macák et al. [97] conducted comprehensive reviews and research, consistently finding that CTF resulted in reductions in water runoff by 28 % to 42 % compared to conventional farming practices. These reductions contribute significantly to soil and water conservation by mitigating erosion and preserving water quality.

Empirical evidence supporting these findings comes from the implementation of the Wingssprayer. This technology, while primarily focused on reducing spray agent use, also significantly decreases water usage by 30 % to 50 % due to its efficient spraying method. The Wingssprayer technology, through its unique aerodynamic advantages, enhances the efficiency of spraying, thus contributing to substantial water savings (Wingssprayer– [94]).

Labour/ Fuel/ Cost savings: CTF technologies have demonstrated substantial benefits in reducing labour, fuel, and overall operational costs, as shown by various studies and empirical data. Soto et al. [37] highlighted a 4 % reduction in fuel consumption and a 6.42 % labour saving, attributing these improvements to reduced operator error and fatigue. Nørremark et al. [98] focused on optimising in-field route planning for grain harvest operations, revealing a 7 % reduction in fuel consumption through strategic route planning and operational adjustments. Cheein et al. [99] discussed how service units used in precision agriculture, including path tracking controllers for articulated service units, can significantly improve the efficiency of processes like harvesting and agrochemical application. In their study, time associated with harvesting olives was improved by approximately 42–45 %.

Pedersen et al. [100] found that auto-steer systems enhance planting and fertiliser application efficiency, leading to cost benefits for seed, fertiliser, and tractor fuel. Hameed et al. [101] reported that the interpretation of data in specific algorithms could reduce tractor usage costs by 2–14 %. Gasso et al. [91] showed a 23 % reduction in fuel use, while Tullberg [92] found that CTF significantly reduces tractor fuel requirements by 40 % and 70 % in different tillage scenarios compared to conventional tillage. Misiewicz & Galambosova [90] noted a 25 % fuel saving due to reduced soil compaction in CTF systems.

Empirical data further supports these findings. The Wingssprayer does not require extra fuel to pump spray fluid, leading to additional fuel savings of 10 to 20 litres per hour (Wingssprayer– [94]). The EIP-AGRI Focus Group on "Mainstreaming Precision Farming" confirmed that CTF reduces fuel consumption by 10 % by avoiding overlapping [78]. Additionally, the SIEUSOIL project documented that optimised routes for farm machinery, developed using specific algorithms, were about 14 % shorter than reference trajectories, with turning costs reduced by up to 16 % [102].

Environmental Benefits: CTF technologies have been identified as a pivotal strategy for reducing GHG emissions and enhancing environmental stewardship in agriculture. These technologies facilitate significant reductions in fuel consumption, soil emissions of nitrous oxide (N2O), methane (CH4), and water runoff, underscoring their role in promoting sustainable agricultural practices.

Research conducted by Gasso et al. [91] revealed that the adoption of CTF could result in fuel savings of up to 23 %, showcasing the system's efficiency in energy use. Additionally, the study highlighted a reduction in soil emissions of nitrous oxide by 21–45 %, which plays a crucial role in diminishing the overall GHG emissions associated with farming activities. Moreover, studies from Australia and China, as documented by Macák et al. [97], demonstrated that CTF could significantly reduce water runoff by 28–42 %, thereby preventing soil erosion and protecting aquatic ecosystems from sedimentation.

A comparative Life Cycle Assessment (LCA) conducted by Gasso et al. [103] between CTF and random traffic farming (RTF) in Denmark illustrated CTF's broad environmental advantages. The study showed reductions across various impact categories, including human toxicity by 3–15 %, eco-toxicity by 11–138 %, terrestrial eutrophication by 29 %, and climate change by 50 %, underscoring CTF's potential to mitigate environmental impacts through precise management and reduction of agricultural inputs.

Empirical data further supports these findings. The Wingssprayer technology, a component of CTF, has been demonstrated to prevent waste effectively, reducing runoff to the ground by 56 %. This innovation ensures minimal spray agent penetration into the groundwater, aligning with environmental protection goals. Furthermore, the Wingssprayer's design, which blocks wind, has led to a drastic reduction in drift by 99.8 %, substantially minimising the risk of chemical dispersal into non-target areas (Wingssprayer– [94]).

Reacting or variable rate technologies (VRT)

Table 4 below provides a detailed and quantified overview of the peer-reviewed papers and documents with empirical data from relevant EU projects associated with the VRT DAT category, detailing the specific benefits observed. These benefits include yield increase, fertiliser savings, pesticide savings, water savings, and savings in labour, fuel, and overall costs, as well as environmental benefits.

Yield increase: VRT have demonstrated significant yield increases across a variety of crops, showcasing the efficiency and effectiveness of precision agriculture. In studies focusing on irrigation, Sui et al. [104]

Table 4
Quantitative Benefits of VRT DAT Category from Peer-Reviewed Papers and EU Projects.

Reacting or Variable Rate Technologies (VRT)				
	Peer-reviewed papers		Documents with empirical data from relevant EU project	
Total Number related to VRT	52		3	
Economic Benefits	N°	% Range	N°	% Range
Yield Increase	13	0.8–33 %	1	2 %
Fertiliser savings	12	5–59 %	2	22–30 %
Pesticide savings	20	8–52 %	3	15–53 %
Water savings	13	2.5–50 %	2	5–34 %
Labour/Fuel/Cost savings	6		1	
Cost savings		2.3–7.6 %		18.28–25 %
Fuel savings		2.8–28 %		26–29 %
Labour savings		28 %		–
Environmental Benefits	6		1	
GHG Emissions Reduction		15.2–17.2 %		26–29 %
Reduction in Soil N2O Emissions		10 %		–
Reduction in NH3 Volatilization		23 %		–
Reduction in NO3 Leaching		16 %		–
Reduction in CO2 Emissions		22.6 %		26 %
Reduction in NO emissions		42 %		–

and Balafoutis et al. [38] noted a 2.8 % increase in soybean yield and 0.8 % in corn yield through VRI management. The potential of VRT extends to diverse crops, as evidenced by Samborski et al. [105] and Amaral et al. [106] who conducted studies on VRNA, achieving yield increases of 6.25 % and 30 %, respectively. Guerrero et al. [107] observed an increase in yields of up to 10 %, Bergerman et al. [108] recorded a 33 % increase in corn yield with VRF,) and Esau et al. [109] reported a 31 % higher yield in wild blueberries using a variable-rate (VR) fungicide application. Casa et al. [110] highlighted a 28 % increase in silage maize yields through the use of variable rate nitrogen fertilisation (VRNF) driven by multi-temporal clustering of archives guided by satellite data.

In the context of vineyards, Sanchez et al. [111] achieved a 10 % increase in yield through VRI, while Nadav & Schweitzer [112] implemented Variable Rate Drip Irrigation (VRDI), resulting in a 17 % increase in total yield. Further supporting the benefits of VRT, Vellidis et al. [113] introduced a dynamic control system for VRI, leading to an 8.4 % increase in yields. Additionally, Munnaf et al. [114] utilised a multi-sensor data fusion approach for site-specific seeding in potato production, achieving a substantial 21.94 % increase in yield. Corassa et al. [115] found that reducing seeding rates by 18 % did not compromise yields, offering tangible economic benefits in terms of seed savings.

Empirical support for these findings comes from the Within Field Management Zoning project of IOF2020, where a 2 % increase in yield was achieved through precise field management and customised VR application strategies (Within Field Management Zoning– [59]). This project exemplifies the practical application of VRT in enhancing crop productivity.

Fertiliser savings: VRT has proven to be a significant tool in reducing fertiliser usage across a variety of agricultural settings, as evidenced by numerous studies. Basso et al. [62] observed a 12 % reduction in nitrogen fertiliser use in Mediterranean environments, demonstrating the efficiency of spatially variable application. Similarly, Li et al. [116] reduced N fertiliser use by 11 % without decreasing grain yield, while Guerrero et al. [107] reported a substantial reduction of 19 % in nitrogen consumption through site-specific management in cereal crops. Argento et al. [63] also achieved notable decreases in nitrogen leaching and GHG emissions, along with improved NUE, reducing fertiliser application by 5–40 % in winter wheat. Liakos et al. [117] showed substantial savings in a Greek apple orchard, with 59.6 % and 63.4 % less fertiliser used compared to uniform application using VRA based on yield-based mathematical formulae.

Further research by Colaço and Molin [67] led to a 13.1 % increase in citrus yield alongside a significant reduction in potassium and nitrogen applications. Chattha et al. [118] developed a VR spreader for wild blueberries, achieving fertiliser savings between 30 % and 50 %. Van Evert et al. [44] applied VRT in olive production, cutting down the use of various fertilisers by substantial margins, including a 31 % reduction in potassium fertilisers and 59 % in phosphate. Saleem et al. [119] highlighted a 50 % reduction in fertiliser use in wild blueberries, also noting decreased water contamination. Soto et al. [37] emphasised the broader impacts of precision agriculture, achieving an 8 % reduction in nitrogen fertiliser use. Stamatiadis et al. [120] reduced total nitrogen application by 38 % in winter wheat, translating to a 58 % increase in NUE. Additionally, Vatsanidou et al. [121] successfully implemented nitrogen VRT in a pear orchard, leading to a 56 % and 50 % reduction in nitrogen fertiliser usage.

Empirical data aligns with these academic findings. The Within Field Management Zoning project of IOF2020 demonstrated a 22–30 % reduction in nitrogen fertiliser use, highlighting the potential of VRT for efficient resource utilisation and cost savings (Within Field Management Zoning– [59]). The TARGIS-VRA system, adaptable to traditional agricultural machines, achieved 25 % to 30 % fertiliser conservation, confirming that precision farming can be both effective and economically viable, even for smaller scale operations (TARGIS-VRA– [122]).

Pesticide savings: Recent advancements in VRT have shown significant potential for PPP savings in agriculture. These technologies, leveraging sensor-based systems and precision agriculture techniques, have been effective in various studies and empirical data.

Tackenberg et al. [123] achieved an 8 % fungicide savings in winter wheat using sensor-based variable-rate application (VRA). Zhang et al. [124] reported a 51.9 % reduction in spray volume for air-assisted spraying based on real-time disease spot identification. Román et al. [125] implemented geostatistical optimisation for PPP application, resulting in approximately 25 % savings. Gil et al. [126] and Campos et al. [127] conducted vineyard experiments, achieving PPP reductions of 21.9 % and over 40 %, respectively, through VR spraying. Dammer [128] reported annual herbicide savings ranging from 30 % to 43 % in carrot fields using a real-time VRA system.

Keller et al. [54] explored site-specific weed control, achieving herbicide savings of 40 %, 29 %, and 71 % for different types of weeds, with overall savings of 36 %. Maghsoudi et al. [129] and Nackley et al. [130] focused on precision spraying in pistachio orchards and deciduous perennial crops, respectively, reducing PPP use by about 34.5 % and between 67 and 80 %. Rodriguez-Lizana et al. [131] and Li et al. [132] explored variable PPP application in olive groves and orchards, with savings ranging from 21 % to 38 % and a 46 % reduction in spraying volume. Kempenaar et al. [133] and Fessler et al. [134] showed average savings of about 25 % and 54 %, respectively. Fountas et al. [50], Ørum et al. [70] and Gonzalez-de-Soto et al. [135] reported substantial herbicide savings of 20–50 % and 66 %, respectively, through precision herbicide application technologies.

Additionally, Tewari et al. [136] developed a microcontroller-based herbicide applicator for field crops, which utilised a camera and MATLAB software for image processing to control herbicide application. Their system resulted in an average of 50 % savings in herbicide usage, with a weeding efficiency of 90 %. Vorotnikova et al. [137] evaluated a web-based expert system for precision fungicide management in strawberry production. The Strawberry Advisory System (SAS) led to significant reductions in crop losses (23.7 % for anthracnose and 20 % for Botrytis) and decreased fungicide use by 47 % for anthracnose and 49 % for Botrytis, while increasing profit by 41.6 % and 16.8 %, respectively. Zhu et al. [80] tested a laser-guided VR air-assisted sprayer in commercial nurseries, achieving reductions in spray volume and chemicals by 60 % to 77.6 %, depending on the pest and nursery. Xun et al. [138] demonstrated that advanced spraying systems in apple orchards could reduce PPP application by 12 % to 43 % compared to conventional methods.

Empirical evidence from various projects supports these findings. The Within-Field Management Zoning Use Case within the IOF2020 project achieved substantial PPP savings by utilising advanced sensor-based technologies, resulting in a 43 % to 53 % reduction in haulm killing herbicide use, a 17 % decrease in weed control herbicide, and a 20 % to 25 % reduction in overall herbicide and fungicide use (Within-Field Management Zoning– [59]). The TOAS initiative developed intelligent drones for weed detection in crops, leading to a 15–35 % decrease in herbicide use (TOAS - [139]). The Smart Sprayer OPTIMA, part of the EU Horizon 2020 research project, achieved a 23 % reduction in PPP usage [78]. The EU LIFE project Life-F3 demonstrated a reduction of spray volume by 17.65 % [78], and the Agricultural Mechanization Unit of the Polytechnical University of Catalonia's OPTIMA smart sprayer achieved a 23 % reduction in pesticide use [78]. Additional trials with high-end Fede sprayers in Poland saved 25 % of water and PPPs [78]. A project involving Rota Unica utilised sensors and cameras in orchards, leading to a 20 % to 30 % reduction in PPP use [78].

Water savings: Recent developments in VRT have demonstrated their potential in significantly reducing water consumption in agricultural practices. These technologies, which employ precision agriculture techniques and sensor-based systems, have been validated through various studies and empirical data.

Balafoutis et al. [38] conducted computer simulations showing variable water savings up to 26 % with optimised specific zone control in centre-pivot irrigation. Vellidis et al. [140] introduced a soil moisture sensor-based irrigation scheduling system, achieving water savings ranging from 7.5 % to 19 %. Sui et al. [104] revealed that VRI systems can reduce irrigation water use by 8–20 % for soybeans and 25 % for corn. Sanchez et al. [111] reported up to a 17 % gain in water use efficiency with VRI in California vineyards.

Nadav & Schweitzer [112] implemented VRDI in vineyards, achieving a 20 % reduction in water consumption. Modina et al. [141] successfully applied VRI in vineyards and orchards, reducing water usage by 20 % in vineyards and 50 % in pear orchards. Campos et al. [127] developed canopy vigour maps using UAVs for site-specific management, resulting in over 40 % water savings during vineyard spraying. Bohman et al. [142] evaluated variable rate nitrogen (VRN) and reduced irrigation management in potato production, achieving a 15 % reduction in irrigation water use.

Martello et al. [143] assessed a VRI system integrated with soil sensor technologies, indicating improvements in irrigation water use efficiency with increases of 35 % and 10 % in different zones. Ortuani et al. [144] and Turker et al. [145] explored the feasibility of VRI, reporting water savings of 18 % and a range from 2.56 % to 7.3 %, respectively. Mendes et al. [146] presented a feasibility study of a fuzzy VRI control system, achieving a 27 % reduction in irrigation water use. Gutiérrez et al. [147] developed an automated irrigation system optimising water use for agricultural crops, achieving water savings of up to 90 % compared with traditional irrigation practices.

Empirical data further supports these findings. The HydroSense project applied VRI in cotton fields in Greece, showing 5 to 34 % savings in water consumption [148]. The EU LIFE project Life-F3 demonstrated a reduction in spray volume of plant protection products and water by 17.65 %, maintaining effective coverage [78].

Labour/Fuel/Cost savings: Recent studies have highlighted the economic benefits of Reacting or VRT in agriculture. These technologies optimise resource usage, leading to significant reductions in input costs, fuel consumption, and labour hours, thereby enhancing farm profitability and environmental sustainability.

Velandia et al. [140] found that VR systems could reduce the cost of sowing by 3.5 to 22.9€/ha, which includes avoiding the need for replanting. Kuang et al. [149] compared traditional and VR approaches in Danish spring barley and observed an increase in lime consumption but also an increase in yield, resulting in a net profit of €3.61/ha for the VR approach. Daccache et al. [150] estimated the benefits to lettuce growers in Cambridge, UK, from using VRI to be around 30 €/ha, especially in over-irrigated areas in humid climates. Liakos et al. [117], based on yield-based mathematical formulas, implemented variable-rate fertilisation (VRF) resulting in cost savings ranging from 2.3 % to 7.6 %

Soto et al. [37] noted that VRN Technology led to a 2.8 % reduction in fuel consumption, illustrating the economic and environmental benefits of precision agriculture. Manandhar et al. [151] conducted a techno-economic evaluation of a laser-guided VR spraying system in apple orchards, finding a significant reduction in labour hours and fuel consumption by approximately 28 %.

Empirical data from projects like the EU LIFE project Life-F3 further supports these findings. The project demonstrated savings by using FEDE's Smartomizer H3O, which improved work performance by around 26 % (from 2.25 ha/h to 3 ha/h) due to increased tractor speed while maintaining similar fuel consumption. This led to both labour cost savings and a 26 % reduction in fuel use. The cost savings from using the Smartomizer H3O compared to the reference sprayer were approximately 18.28 % [78]. Additionally, a high-end Fede sprayer tested in an apple field resulted in a 29 % reduction in spraying hours, a 25 % cost reduction, and a 29 % fuel saving. The cost-benefit analysis for this situation indicated financial savings of around 760 € per hectare per year [78].

Environmental Benefits: VRT have emerged as significant contributors to environmental sustainability in agriculture by offering precise application of inputs like water, fertilisers, and pesticides, thus enhancing resource efficiency. Studies have underscored the environmental benefits of VRT, particularly in reducing GHG emissions and optimising water use, marking a positive shift towards sustainable farming practices. Li et al. [116] demonstrated the environmental benefits of implementing a proximal sensor for VRNA achieving a 10 % reduction in soil N2O emissions,reduction in volatilization of NH3 by 23 % and last of all 16 % reduction in NO3 leaching.Bohman et al. [142] highlighted a 15 % reduction in GHG emissions through the implementation of VRN and Reduced Irrigation Management in potato production. El Chami et al. [152] demonstrated the superiority of precision irrigation systems over conventional methods by achieving a 22.6 % reduction in CO2 emissions and a 23.0 % decrease in water use. McCarthy et al. [153], Abalos et al. [154], and Balafoutis et al. [38] further supported these findings, with reductions in GHGs emissions by 15.2 %, a 42 % decrease in NO emissions, and a 17.2 % reduction in GHGs emissions, respectively. These studies collectively affirm the role of VRT in reducing the environmental footprint of agriculture by significantly cutting down on emissions and resource use.

Empirical data further corroborates the environmental benefits of employing VRT in agricultural practices. A field test involving a high-end Fede sprayer equipped with crop sensing capabilities on an apple farm led to a 29 % reduction in GHG emissions, mirroring a similar decrease in fuel consumption [78]. Another practical application at an olive farm in Portugal utilised FEDE's Smartomizer H3O, which not only improved work performance by 26 % but also achieved a 26 % decrease in GHG emissions. This reduction was accompanied by significant economic savings, moving from a cost of 332 €/ha per year to 271.35 €/ha per year with the Smartomizer H3O, highlighting an 18.28 % cost-saving [78]

Robotic systems or smart machines (RSSM) (inc. artificial intelligence (AI))

Table 5 below provides a detailed and quantified overview of the peer-reviewed papers and documents with empirical data from relevant EU projects associated with the RSSM DAT category, detailing the specific benefits observed. These benefits include yield increase, fertiliser savings, pesticide savings, water savings, and savings in labour, fuel, and overall costs, as well as environmental benefits.

Yield increase: The studies conducted by Munnaf et al. [155] and Kitić et al. [156] on the use of sensors for site-specific silage seeding and real-time soil analysis using robotic systems have resulted in an increase

Table 5
Quantitative Benefits of RSSM DAT Category from Peer-Reviewed Papers and EU Projects.

Robotic Systems or Smart Machines (RSSM) (inc. Artificial Intelligence (AI))				
	Peer-reviewed papers		Documents with empirical data from relevant EU project	
Total Number related to RSSM	23		3	
Economic Benefits	N°	% Range	N°	% Range
Yield Increase	4	1.7–50 %	–	–
Fertiliser savings	3	7.5–18 %	–	–
Pesticide savings	11	9.9–90 %	3	13–95 %
Water savings	2	17–75 %	1	14–26 %
Labour/Fuel/Cost savings	7		2	
Labour savings		37.75–62 %		–
Cost savings		17 %		40 %
Fuel savings		22.15–49.14 %		55 %
Environmental Benefits	–		3	
Reduction in GHG emissions		–		26 %
Reduction in PPP usage		–		17.65 %
Reductions in CO2 emissions		–		29.3 %
Reductions in CH4 emissions		–		29.3 %
Reductions in NO2 emissions		–		29.3 %
Reduction in spray drift		–		48 %

in yield of 4.4 % and 1.76 %, respectively. Regarding orchards, the robotic systems studied by Nagasaki et al. [157] for harvesting and by Rose & Bhattacharya [158] for precision forecasting have led to yield increases of 50 % and 15 %, respectively. In the case of the study conducted by Rose & Bhattacharya [158], a 10 % saving in used land was achieved, with a 20 % reduction in damaged fruit. These developments underscore the significant impact of advanced agricultural technologies on yield enhancement and operational efficiency.

Fertiliser savings: The autonomous robotic systems for real-time soil analysis studied by Kitic et al. [156] allowed for a saving of 7.5 % in KAN fertiliser (Potassium, Ammonium, Nitrate). In the fruit cultivation field, the study conducted by Esau et al. [159] on the use of machine vision smart sprayers for targeted agrochemical distribution in wild blueberry fields resulted in a fertiliser saving ranging from 10 % to 12.6 %. Finally, the study conducted by Vakilian and Massah [65] on machine vision smart sprayers for targeted agrochemical distribution in wild blueberry fields achieved an 18 % saving in nitrogen fertiliser. These advancements are not only boosting productivity but also promoting sustainable agricultural practices by curbing unnecessary resource use.

Pesticide savings: The integration of RSSM, incorporating AI, into modern agricultural practices has led to substantial PPP savings, highlighting significant strides towards sustainability. These technologies, through precise weed detection, spot application, and sensor fusion, have markedly reduced PPP usage, demonstrating both environmental and economic benefits. Gonzalez-de-Soto et al. [135] showcased an autonomous system achieving 66 % herbicide savings through precise weed detection and spraying. Pérez-Ruiz et al. [160] observed a 45 % reduction in applied spray volume with autonomous crop protection technologies. Zaman et al. [161] reported fungicide savings ranging from 9.9 % to 51.22 % with automated prototype VR sprayers in wild blueberry fields. Partel et al. [162] highlighted a 28 % reduction in spraying volume using sensor fusion and AI in smart tree crop sprayers. Oberti et al. [163] noted PPP use reductions between 65 % to 85 % with CROPS robots in grapevine spraying, while Biocca et al. [164] achieved a 43 % reduction in copper-based PPP use with the Rovitis 4.0 autonomous robot. Hussain et al. [165] demonstrated savings of 42 % and 43 % in spray liquid during weed and simulated diseased plant detection experiments with AI-based VR sprayers. Sanchez-Hermosilla et al. [166] observed herbicide savings of 34.39 % and 35.15 % across two seasons with leaf area estimation technologies. Rose & Bhattacharya [158] achieved a 90 % reduction in fungicide usage with autonomous UVC disease treatment robots in the soft fruit sector. Tewari et al. [76] reported a 26 % reduction in PPP usage with sonar sensing-based automatic spraying technology. Berenstein & Edan [167] achieved a 45 % reduction in PPP material with an automatic adjustable spraying device.

Empirical data further supports these advancements. The Smart Orchard Spray Application, integrated within IOF2020, recommended precise treatment parameters based on crop conditions, leading to a 13 % to 26 % decrease in PPPs and spray volume (Smart Orchard Treatment– [168]). The EU-FP7 project CROPS developed a precision spraying robot for viniculture, achieving an 84 % pesticide reduction in greenhouse tests and demonstrating the potential for up to 90 % reduction with selective spraying [169]. The EU-funded Asterix project's autonomous robot, AX-1, applies eco-friendly biopesticides sparingly, reducing weed killer usage by up to 95 % and suggesting a yield increase up to 45 % in parsley root [170].

Water savings: The integration of RSSM, powered by AI, into agricultural practices has demonstrated significant potential for water savings. These advanced technologies, by enabling precise irrigation management, have shown to markedly improve water use efficiency in agriculture. Viani et al. [171] introduced a scalable smart irrigation system for precision agriculture, utilising a fuzzy logic strategy integrated with a distributed monitoring system based on wireless sensor network technology. This system, experimentally validated in an apple orchard, enhanced irrigation efficiency by more than 40 % compared to standard irrigation methods. The approach led to more accurate water exploitation, stabilising soil moisture levels, which positively impacted crop health and product quality. Dobbs et al. [172] explored sensor-based automatic irrigation, achieving water savings of up to 75 %. Their study highlighted the effectiveness of using automatic rain sensors, soil water sensors (SWS), and evapotranspiration controllers (ET) over traditional automatic timer treatments. These technologies applied significantly less water, with reductions ranging from 17 to 49 %, 64–75 %, and 66–70 %, respectively, demonstrating substantial improvements in water conservation.

Empirical evidence further supports the water-saving capabilities of these technologies. Within the IOF2020 project, the Smart Orchard Spray Application showcased water savings between 14 % to 26 % through strategic application and IoT-driven precision. By optimising spray parameters and targeting specific areas, this innovation significantly reduced water consumption in orchard irrigation, contributing to efficient resource utilisation and sustainable agricultural practices (Smart Orchard Treatment– [168]).

Labour/Fuel/Cost savings: The deployment of robotics in precision agriculture, specifically in arable farming, vineyards, and soft fruit sectors, has evidenced considerable economic benefits, marking a significant advancement towards efficient resource management. Lampridi et al. [173] conducted an economic evaluation of robotics in precision arable farming, finding that a 5 % increase in field efficiency of robots led to a 17 % reduction in total cost per unit of time, and a labour saving of 37.75 % by reducing the required units from four to three. Pérez-Ruíz et al. [174] demonstrated a 57.5 % reduction in labour time with a co-robotic intra-row weed control system, significantly decreasing the time spent on hand hoeing in the intra-row region. On the contrary, Bochtis et al. [175] demonstrated that the use of deterministic behaviour robotic systems (AMS) in path planning reduced non-working time from 10.7 % to 32.4 % in inter- and intra-row operations in orchards. Lopez-Castro et al. [176] developed a Vineyard Terrestrial Robot, achieving a 97 % reduction in labour required for fumigation processes, while Bechar et al. [177] highlighted that agricultural robots could reduce manual labour required in vineyard mechanisation by 45–62 %. Tziolas et al. [178] revealed fuel savings between 22.15 % and 49.14 % through the use of Collaborative Robots in Greek viticulture. Rose & Bhattacharya [158] noted substantial labour reductions in the soft fruit sector, with packhouse labour down by 30 % and farm labour by 40 %, attributing additional savings to logistic support robots.

Empirical data further underscores these advancements. The Smart

Orchard Spray Application, integrating IoT-enabled airblast atomizing sprayers, achieved a 55 % reduction in fuel consumption, equating to €517 in fuel savings per hectare annually (Smart Orchard Treatment– [168]). This system optimises crop protection efficiency in cherry, apple, and almond production, minimising environmental impacts while enhancing cost control and decision-making. Additionally, the EU-FP7 project CROPS aims to develop modular, adaptable robotic systems that promise to reduce harvest costs by 40 %, showcasing the potential of intelligent tools in agriculture [169].

Environmental Benefits: RSSM, incorporating AI showcased remarkable environmental benefits, particularly in the reduction of green missions and PPP use. EIP-AGRI Focus Group reported a 26 % decrease in GHG emissions alongside a 17.65 % reduction in PPP usage. Furthermore, the same study noted a significant 29.3 % reduction in CO2, CH4, and NO2 emissions per sprayer per year, highlighting the potential of smart technologies to mitigate environmental impact in agricultural practices [78].

Empirical evidence supports these findings, with the Smart Orchard Spray Application within the IOF2020 initiative demonstrating a substantial 22 % to 39 % reduction in GHG emissions. This achievement was facilitated by the adoption of precise, IoT-enabled smart sprayers that optimise PPP application, focusing treatment on specific zones to minimise unnecessary usage and thereby reduce emissions. This approach not only enhances environmental sustainability in orchard farming but also results in a 48 % reduction in spray drift, further contributing to the conservation of surrounding ecosystems and reducing the potential for environmental contamination (Smart Orchard Treatment - [168]; Smart Orchard Spray Application - [179]).

Farm management information systems (FMIS)

Table 6 below provides a detailed and quantified overview of the peer-reviewed papers and documents with empirical data from relevant EU projects associated with the FMIS DAT category, detailing the specific benefits observed. These benefits include yield increase, fertiliser savings, pesticide savings, water savings, and savings in labour, fuel, and overall costs, as well as environmental benefits.

Yield increase: FMIS has led to notable yield increases across various agricultural sectors by harnessing the power of IoT, data analytics, and precision agriculture techniques. Sapkota et al. [180], demonstrated how the application of the DSS Nutrient Expert® enabled farmers to implement site-specific nutrient management (SSNM) for wheat. This adoption resulted in a 14 % increase in yield and 9 % increase in biomass compared to conventional farming practices. Cui et al. [181] conducted field trials across China, utilising a decision-support program that resulted in an average yield increase of 10.8 % to 11.5 % for major crops such as maize, rice, and wheat. Karydas et al. [182] further demonstrated the economic benefits of PreFer services in Greece, where 33 farmers experienced significant yield improvements up to 15 % across 1864 hectares of rice, maize, cotton, and wheat cultivation.

Empirical evidence from the IoF2020 EU-funded project has significantly demonstrated the benefits of IoT-driven monitoring and precision control across various agricultural domains. The "Fresh Table Grapes Chain" use case has shown a notable improvement in the quality and yield of organic table grapes, with a 10 % increase in grape size and a 5 % enhancement in sugar content (Fresh Table Grapes Chain– [183]). Similarly, the "Soya Protein Management" initiative capitalised on sensor-driven technologies and a DSS to enhance soybean protein quality by 5 % and increase overall yield by the same margin, thanks to precise irrigation management and tailored seed density applications.

In the realm of potato production, the "Data-Driven Potato Production" initiative utilised IoT data analytics and advisory systems to facilitate a 10 % increase in product quality, thereby boosting yield through informed decision-making processes (Data-driven Potato Farming– [184]). The "Chain-Integrated Greenhouse Production" use case, which implemented IoT-based DSS and data amalgamation, achieved a significant rise in crop harvested per square metre per year, ranging between 6.9 % and 8.3 %, specifically in greenhouse tomato cultivation (Chain Integrated Greenhouse Production - [185]).

Furthermore, the "Automated Olive Chain'' demonstrated how a comprehensive IoT infrastructure could effectively monitor and adjust irrigation and fertilisation, culminating in a 10 % increase in yield per hectare (Automated Olive Chain - [186]). The AREAS (Agriculture Remote Aerial Sensing) project, leveraging remote sensing and machine learning, provided timely decision-making data that led to a 10 % yield increase (AREAS - [187]). Lastly, TeamDev's Agricolus DSS, a cloud application designed for precision agriculture, utilised NDVI analysis to predict the occurrence and spread of pests, thereby aiding in quick disease management and potentially safeguarding yields [188].

Fertiliser savings: Integrating FMIS into agricultural practices has led to significant fertiliser savings, demonstrating the power of technology in enhancing resource use efficiency and sustainability. The research conducted by Cui et al. [181] across China's major agro-ecological zones employed a robust decision-support program, which resulted in nitrogen application reductions by 14.7 % to 18.1 %. Gallardo et al. [189] explored the FERTIRRIGERE V2.11 DSS for optimising fertigation management in drip-irrigated tomatoes in Italy, achieving a 46 % average reduction in nitrogen application while maintaining production and quality standards. Li et al. [190] reported a 40 % decrease in chemical fertiliser use through a systematic water-saving management system based on the IoT, and Cheng et al. [191] introduced a surrogate model-assisted multiobjective algorithmic framework for precision agriculture, demonstrating a 37 % reduction in nitrogen application. These improvements not only contribute to cost reduction but also align with environmentally sustainable practices.

Empirical evidence from various initiatives underscores the impact of FMIS on fertiliser savings. The "Fresh Table Grapes Chain" within the IoF2020 EU-funded project demonstrated a reduction in fertiliser usage by 15 % per kilogram of grapes annually, illustrating the system's effectiveness in promoting resource efficiency and eco-friendly agricultural practices (Fresh Table Grapes Chain - [183]). Similarly, the "Soya Protein Management" initiative realised a substantial 10 % decrease in fertiliser use through the implementation of advanced sensor-based technologies and precision farming practices. This reduction signifies a notable advancement towards sustainable agriculture,

Table 6
Quantitative Benefits of FMIS DAT Category from Peer-Reviewed Papers and EU Projects.

Farm Management Information Systems (FMIS)	Peer-reviewed papers		Documents with empirical data from relevant EU project	
Total Number related to FMIS	14		13	
Economic Benefits	N°	% Range	N°	% Range
Yield Increase	3	9–14 %	6	5–10 %
Fertiliser savings	4	14.7–46 %	8	5–70 %
Pesticide savings	4	20–61 %	6	5–15 %
Water savings	8	10–50 %	11	4.3–60 %
Labour/Fuel/Cost savings	1		10	
Labour savings		–		10–15 %
Cost savings		20 %		5–20 %
Environmental Benefits	1		4	
Input factors & Energy savings		20–30 %		–
Reduction in energy consumption		–		10–15 %
Energy efficiency improvement		–		2.7–4.8 %
Reduction in water contamination		–		5.3 %
Reduction in carbon footprint		–		15 %
Reduction in environmental impacts & Disease risk		–		20 %

facilitated by informed decision-making based on sensor data (Soya Protein Management - [192]).

Furthermore, the "Big Wine Optimization" project achieved significant fertiliser cost savings of 15 %, translating to 13€ per hectare. This initiative leveraged data analytics to optimise soil fertility and vine health, thereby streamlining fertiliser applications and promoting cost efficiency alongside sustainable viticulture practices (Big Wine Optimisation - [193]). In the "Data-Driven Potato Production" use case of the IoF2020 project, the integration of IoT technology and satellite data resulted in fertiliser cost savings ranging from 5 % to 15 %, alongside a remarkable 15 % improvement in NUE. This optimisation of resource allocation underscores the benefits of precise farming practices (Data-driven Potato Farming - [184]). The "Automated Olive Chain" utilised IoT-based monitoring and tailored recommendations to achieve a significant 10 % decrease in fertiliser use. This approach guided farmers in precise and efficient fertiliser application, enhancing sustainability and reducing costs (Automated Olive Chain - [186]). GAIA InFarm, powered by GAIAtrons IoT devices, offers a holistic smart farming solution that significantly cuts fertiliser usage by 50–70 %, supporting small farmers in optimising farming practices for better yields and environmental conservation (GAIA InFarm - [69]).

Lastly, the Agricolus DSS developed by TeamDev provides a cloud-based precision farming system that aids farmers and agronomists in reducing over-fertilisation by 12–22 %, showcasing the application's utility in enhancing agronomic decisions [188]. The EU's Horizon 2020 program, IoF2020, facilitated the adoption of smart solutions among potato farmers in Poland, Cyprus, and Ukraine. These solutions, spanning irrigation, pest management, and fertilisation, make strategic use of telemetry IoT stations, satellite data, and tailored scientific models based on regional geographical characteristics. The GAIA sense smart farming solution drives data-driven potato predictions, integrating advanced technologies like IoT, Big Data, Earth Observation, context-based decision support, and machine learning.The GAIA sense solution is enhanced with FIWARE-powered data exchange mechanisms, promoting interoperability and openness between systems. The impact of this technology includes a 15 % improvement in NUE (Data-driven Potato Production - [194])

Pesticide savings: Research and empirical evidence have highlighted the effectiveness of these technologies in optimising PPP application, leading to significant savings and environmental benefits. Ørum et al. [70] emphasised the economic efficiency of utilising low-dose herbicides, with potential cost reductions ranging from 20 % to 50 %. Li et al. [190] observed a 61.67 % decrease in PPP use in strawberry cultivation with a systematic water-saving management system based on the IoT, which also resulted in a 32.48 % reduction in PPP costs. Román et al. [125] reported about 25 % in PPP savings from precise, map-based variable-dose treatments in vineyards, showcasing the advantages of DSS in disease management.

Crop Protection Online (CPO), a DSS described by Kudsk et al. [195], integrates decision algorithms and a herbicide dose model to optimise herbicide choice and dosage, achieving substantial herbicide reductions (about 60 % measured as the Treatment Frequency Index (TFI)) in spring barley through field experiments in Denmark. This demonstrates that decision support can significantly contribute to sustainable weed management.

Empirical evidence from the IoF2020 EU-funded project further underscores the impact of FMIS. The "Fresh Table Grapes Chain" use case illustrated a 6 % decrease in PPP application per kilogram of grapes annually, leveraging innovative IoT technologies for sustainable pest management (Fresh Table Grapes Chain - [183]). The "Digital Ecosystem Utilisation" use case utilised sensor-based data and predictive analytics to monitor environmental conditions correlated with pest occurrence, leading to a significant 5 % to 10 % decrease in the usage of PPPs (Digital Ecosystem Utilisation - [196]). The "Big Wine Optimisation" initiative realised a substantial 15 % reduction in PPP costs, equating to savings of 120€ per hectare by leveraging predictive analytics (Big Wine Optimisation - [193]). The "Data-Driven Potato Production" use case effectively lowered PPP costs by 10 % up to 15 %, showcasing efficient pest management strategies (Data-driven Potato Farming - [184]). Employing weather forecasts and fertigation models within the "Chain-Integrated Greenhouse Production" use case under the IOF2020 project resulted in a 5.3 % decrease in PPP use, fostering environmentally conscious practices (Chain Integrated Greenhouse Production - [185]). The Horizon 2020 program's support for smart solutions in potato farming has facilitated a 15 % reduction in PPP consumption by integrating telemetric IoT stations, satellite data, and scientific models (Data-driven Potato Production - [194]).

Water savings: Research has demonstrated the impact of these systems on water conservation. The integration of IoT for water-saving management in strawberry cultivation reported by Li et al. [190] resulted in a 128 % improvement in water use efficiency. Tsirogiannis et al. [197] showed that a participatory DSS for irrigation management in wine grapevines led to improved crop water productivity (WPC) by 20–44 %. Mirás-Avalos et al. [198] introduced the Irrigation-Advisor for vegetable crops, achieving a 42.1 % reduction in water use. Fotia et al. [199] indicated water savings of up to 13 % in olive cultivation, and Cayuela et al. [200] demonstrated how FMIS could reduce water use by 20 % in oranges and tomatoes with controlled deficit irrigation strategies. Cheng et al. [191] reported a 44 % reduction in water consumption through precision agriculture management. Buono et al. [201] found that a DSS for kiwifruit farming saved 20–25 % of water, and Tamirat and Pedersen [202] highlighted water-saving benefits ranging from 10 % to 50 % in orchards.

Empirical evidence from the IoF2020 EU-funded project further supports these findings. The "Fresh Table Grapes Chain" use case achieved a 20 % reduction in irrigation water usage annually by employing IoT-enabled precision control (Fresh Table Grapes Chain - [183]). The "Digital Ecosystem Utilisation" use case optimised irrigation schedules through sensor data, leading to a 5 % to 10 % reduction in water consumption (Digital Ecosystem Utilisation - [196]). The "Soya Protein Management" initiative reduced irrigation costs by 10 % (Soya Protein Management - [192]), while the "Big Wine Optimisation" project saw a 10 % reduction in water consumption (Big Wine Optimisation - [193]). The "Data-Driven Potato Production" use case accomplished a 25 % reduction in water consumption (Data-driven Potato Farming - [184]), and the "Chain-Integrated Greenhouse Production" use case curtailed water usage by 4.3 % to 5.6 % (Chain Integrated Greenhouse Production - [185]). The "Automated Olive Chain" facilitated a 15 % reduction in water consumption through intelligent water management (Automated Olive Chain - [186]). GAIA InFarm, with its IoT-driven solution, slashes irrigation water usage by up to 25 % (GAIA InFarm - [69]). The FIGARO project estimates that its DSS can save 20–60 % of irrigation water ([203].), and SMARTAGRIFOOD2's irrigation advice application helps farmers reduce irrigation costs by up to 30 % [204]. Lastly, the Agricolus DSS supports decisions leading to a 20 % reduction in water stress for crops [188].

Labour/Fuel/Cost savings: FMIS, including DSS and QMS, have demonstrated considerable benefits in terms of labour, fuel, and cost savings across the agricultural sector. These systems optimise farm operations, leading to enhanced productivity and efficiency while significantly reducing operational costs. Karydas et al. [182] showcased the economic benefits of PreFer, an FMIS offering site-specific prescription maps for fertilisation. Farmers utilising PreFer reported yield increases up to 15 % and input cost reductions up to 20 %, highlighting the system's effectiveness in simplifying fertilisation planning and application processes.

Empirical evidence further corroborates the advantages of FMIS and related technologies. The "Fresh Table Grapes Chain" within the IoF2020 EU-funded project optimized operations, leading to a 15 % reduction in labour hours per kilogram of grapes harvested annually and a 20 % decrease in irrigation costs per year (Fresh Table Grapes Chain - [183]). The "Digital Ecosystem Utilisation" use case leveraged IoT devices and data analytics to streamline farm management practices, reducing the need for physical field visits by 20 % and achieving a 10 % cost reduction per kilogram input (Digital Ecosystem Utilisation - [196]; Digital Ecosystem Utilisation - [205]).In soybean cultivation, the "Soya Protein Management" initiative employed advanced sensor technologies and a tailored DSS, resulting in a 5 % reduction in production costs and work time (Soya Protein Management - [192]). The "Big Wine Optimisation" use case utilised tractor-mounted camera systems and multispectral imagery to achieve a 5 % reduction in treatment frequency, indicating significant labour savings (Big Wine Optimisation - [193]).

Furthermore, the "Data-Driven Potato Production" use case demonstrated reductions in irrigation costs by 5 % to 25 % and total inputs costs by 18.6 %, highlighting the efficiency of IoT stations and satellite information in potato cultivation (Data-driven Potato Farming - [184]; Data-driven Potato Production - [194]). The "Chain-Integrated Greenhouse Production" project achieved a 5.2 % reduction in crop cultivation expenses through innovative IoT technologies and robust data analysis (Chain Integrated Greenhouse Production - [185]).The "Automated Olive Chain" optimised processes, reducing labor time by 10 % per kilogram produced and production costs by 15 %, demonstrating the impact of IoT-powered analytics and streamlined automation on operational efficiency (Automated Olive Chain - [186]). TeamDev's development of the Agricolus DSS aims to support farmers and agronomists in making informed decisions, leading to an increase in farm productivity by 5–10 % and cost savings of 504€ per hectare, potentially saving farms an average of 10,000€ [188].

Environmental Benefits: FMIS, including DSS and QMS, present direct environmental benefits, notably in reducing GHG emissions and enhancing sustainability in agricultural practices. Barradas et al. [206] discussed the DSS-FS fertigation simulator, designed to optimise irrigation and fertigation systems, increasing their environmental sustainability. This system, as reported by users, boosts production significantly while saving 20–30 % in input factors and energy, illustrating the positive impact of FMIS on environmental sustainability.

Empirical evidence further supports the environmental benefits of FMIS. The Big Wine Optimisation initiative, by installing electricity metres and optimising power usage within cellars and wine production areas, achieved a 10 % reduction in energy consumption. This was realised through meticulous monitoring, control, and optimisation of resource consumption, enhancing operational efficiency while reducing environmental impact (Big Wine Optimisation - [193]). The Chain-Integrated Greenhouse Production use case within the IOF2020 project improved energy efficiency by 2.7 % to 4.8 % and reduced water contamination by 5.3 %, mitigating adverse ecological effects associated with intensive greenhouse farming (Chain Integrated Greenhouse Production - [185]). The Automated Olive Chain, by integrating IoT technologies, managed energy consumption across operations, resulting in a 15 % reduction. This system provided farmers with actionable insights, enabling them to optimise energy usage and contribute to a more sustainable farming environment (Automated Olive Chain - [186]). The Agricolus DSS, developed by TeamDev, offers a cloud application to support farmers and agronomists in making informed agronomic decisions. This project claims to mitigate the carbon footprint by 15 %, thereby reducing environmental impacts and disease risk by 20 % for issues like Olive Fruit Fly and Phytophthora [188].

Discussion

Recording and mapping technologies (RMT) (inc. monitoring systems, real-time location systems (RTLS))

In this category, 34 articles were identified, of which 27 were peer-reviewed articles, and 7 were attributed to European projects. This category of DATs is of fundamental relevance in the context of Precision Agriculture, and the quantity of data obtained demonstrates it. Among the numerous peer-reviewed articles, the most evident benefits were attributed to savings and increased efficiency in fertiliser use, with the identification of 8 valid studies. Among these, Andújar et al. [64] achieved the most remarkable result, managing an 80 % reduction in fertiliser doses applied in a vineyard through the use of aerial imagery and ground detection, optimising input usage without compromising crop yield.

Additional benefits of RMT were found in further studies. Squeri et al. [60] achieved a 40 % yield increase in viticulture, thanks to vegetative indices based on prescription maps obtained from satellite images. Based on data from recordings and mappings, Laursen et al. [71] introduced a weed quantification algorithm for maize that significantly reduced herbicide use by 65 %, with positive environmental and economic impacts. The use of recording systems was also studied by Millan et al. [79], managing to use soil moisture sensors to reduce water usage by 24 %. Finally, Medel-Jiménez et al. [35] highlighted the potential of crop sensors in precision agriculture to reduce global warming by −17.04 %, compared to a conventional agricultural management scheme.

Regarding European projects relevant to the investigation, once again, the most significant data is attributed to fertiliser savings. In particular, the 'GaiaInFarm' project under HORIZON 2020, using RMT and an FMIS application for fruit cultivation, was able to achieve a decrease in fertiliser usage between 50 % and 70 %. It should be noted that the project utilised sensing stations, app technology, and Decision Support Systems (DSS) to enhance monitoring and decision-making processes. Based on what has emerged, it can be stated that the proper use of these technologies is capable of bringing concrete benefits, such as the use of a lower quantity of fertilisers. Furthermore, the widespread availability of images and data (both satellite and non-satellite), if correctly interpreted, translates into an economic benefit that contributes to higher farmer's profits.

Guidance and controlled traffic farming (CTF) technologies

Similarly to the previous category, this category has also provided a significant number of articles, totalling 20, while the number of projects was the lowest among all the technologies analysed, only 2. The most significant results in terms of benefits were found in the field of fertiliser and fuel use and savings. The study that stands out the most for the quality of the results achieved is the one conducted by Tullberg in 2014. The study stated that CTF systems can improve soil biological activity due to reduced compaction. This also leads to an improvement in Nitrogen Use Efficiency (NUE) between 40 % and 80 %, resulting in a lower demand for fertilisers [92]. The study also attributed to CTF a reduction in fuel consumption between 40 % and 70 % during all soil cultivation operations, making this technology less impactful in terms of consumption and sustainability [92].

Additional benefits were found in the study conducted by Hefner et al. [87] regarding the increase in yields of white cabbage, potatoes, and beetroots, which reached increases of 27 %, 70 %, and 42 %, respectively, thanks to the use of CTF. The benefits of this technology were also highlighted in the study by Hussein et al. [88], which reported a 175 % increase in NUE and a 65 % increase in rainfall-use efficiency due to reduced soil compaction. The use of CTF has also demonstrated the ability to reduce herbicide requirements by 25 % [92] and decrease soil emissions of nitrous oxide (21–45 %), as demonstrated by Gasso et al. [91]. Regarding European projects, the best result was achieved in terms of drift reduction. Specifically, the "Wingssprayer" project was able to achieve a 99.8 % reduction in drift, minimising the risk of chemical dispersal into non-target areas (Wingssprayer - [94]).

In light of the analysis, it is evident that crop management through CTF technologies is crucial to reduce the amount of fertilisers used and optimise the quality of operations performed. Furthermore, what has been highlighted is indispensable within a cropping system that can be defined as technological and sustainable. Therefore, these technologies must be further developed and adopted on a large scale.

Reacting or variable rate technologies (VRT)

This category has encountered the highest number of relevant peer-reviewed articles (52), while only 3 European projects have addressed the topic. Certainly, within a cropping system aiming to be efficient, sustainable, and technologically accurate, this technology is vital to reduce any kind of waste, whether it be inputs or economic resources. This technology has also proven to generate the most significant environmental benefit, precisely due to its ability to reduce the quantity of PPPs used during crop operations. Thanks to the wealth of data obtained, it has been possible to attribute the main benefits to two categories, namely PPP savings and water savings. Regarding PPP use, two studies have proven highly valid, with encouraging results: the study conducted by Tewari et al. [136] led to the creation of a system capable of achieving a 50 % savings in herbicide use, with a weeding efficiency of 90 %. Similarly, Zhu et al.'s [80] study allowed for a reduction in pesticide volume between 60 % and 77.6 %. The best water management was found in the study conducted by Modina et al. [141], where the use of a Variable Rate Technology (VRT) irrigation system allowed for savings of 20 % and 50 % respectively for a vineyard and a pear orchard. In addition to these, other studies have highlighted the benefits of variable-rate technologies. The use of variable-rate fertilisation allowed Bergerman et al. [108] to record a 33 % increase in wheat yield compared to conventional fertilisation.

Regarding fertiliser consumption, Van Evert et al. [44] were able to achieve a significant reduction in potassium-based fertiliser of 31 % and a reduction in phosphate consumption of 59 %. All these benefits cannot be classified solely as fertiliser savings but must also be considered as economic savings and more sustainable agricultural management. Finally, although the number of European projects in this field was not satisfactory, the "Life-F3″ project, using a high-end Fede sprayer tested in an apple field, resulted in a 29 % reduction in spraying hours, a 25 % cost reduction, and a 29 % fuel saving (which translates into a decrease in greenhouse gas emissions by 29 %). The cost-benefit analysis for this situation indicated financial savings of around €760 per hectare per year [78]. In light of the knowledge gained, it can be said that the wise application of VRT has the potential to produce significant environmental benefits. The amount of PPPs saved through these operations should not be underestimated, as it contributes significantly to both pollution mitigation and economic savings. This underlines the importance of adopting precision farming practices, not only for environmental sustainability but also for the economic efficiency they bring to farming operations.

Robotic systems or smart machines (RSSM) (inc. artificial intelligence (AI))

Within this category, it was possible to identify 23 peer-reviewed articles and 3 European projects. The results from various research studies and European projects focusing on RSSM have demonstrated a significant positive impact, primarily emphasising savings in PPPs and water. The experiment conducted by Oberti et al. [163], using the "CROPS" robot, led to a reduction in vineyard PPP usage between 65 % and 85 %. A slightly higher result is reported by Rose & Bhattacharya [158], achieving a 90 % reduction in fungicide usage with autonomous UVC disease treatment robots in the soft fruit sector.

Regarding water conservation, Dobbs et al. [172] explored sensor-based automatic irrigation, achieving water savings of up to 75 %. Their study highlighted the effectiveness of using automatic rain sensors, SWS, and ET compared to traditional automatic timer systems. Furthermore, the research and projects developed have significantly contributed to reducing the required labour and have led to appreciable environmental benefits. Lopez-Castro et al. [176] developed a Vineyard Terrestrial Robot, resulting in a 97 % reduction in labour required for fumigation processes.

From the point of view of yield increase, not many studies have been found, apart from the one carried out by Nagasaki et al. [157] who found a 50 % increase in yield by using a robotic harvesting system in an orchard. Additionally, the Smart Orchard Spray application within the IOF2020 initiative demonstrated a substantial 22 % to 39 % reduction in GHG emissions (Smart Orchard Spray Application - [179]). In summary, the analysis of the RSSM category reveals a positive impact in agricultural sectors. The data on which the study is based highlights significant savings both in PPPs and in water usage. The highlighted examples underscore the importance of such technologies.

Farm management information systems (FMIS)

The conducted research has yielded a substantial amount of data, both concerning peer-reviewed articles (14) and, especially, European projects (13). The lower presence of peer-reviewed articles might be attributed to the fact that many companies and farmers do not consider this technology crucial for better crop management, likely because they prefer to invest in technologies with a more significant impact on their operations, such as VRT or guidance systems. As for the analysis of data obtained from European projects, it is noteworthy that data from projects related to FMIS rank first. This is evidently due to the fact that these technologies intersect with the realms of data management and data reception, elements that currently find ample space within startups and new computing projects.

Among the many studies and projects analysed, those that have sparked the most interest cover a range of topics, from fertiliser savings to improved work efficiency. For instance, the DSS explored by Gallardo et al. [189] was able to reduce nitrogen application by 46 % through a fertigation system. In the same context, the "GAIA InFarm" project enabled a reduction in fertiliser use by 50 % to 70 %, supporting small farmers in optimising farming practices for better yields and environmental conservation. From a water management perspective, Tsirogiannis et al. [197] demonstrated that a participatory DSS for irrigation management in wine grapevines led to improved crop water productivity (WPC) by 20–44 %.

Regarding the savings of PPPs, Li et al. [190] observed a 61.67 % decrease in PPP use in strawberry cultivation with a systematic water-saving management system based on the IoT, which also resulted in a 32.48 % reduction in PPP costs. In economic terms, European projects have shown the most interest in study. The "Big Wine Optimisation" initiative achieved a substantial 15 % reduction in PPP costs, equivalent to savings of €120 per hectare, leveraging predictive analytics (Big Wine Optimisation - [193]). Similarly, the study conducted by Karydas et al. [182] demonstrated the economic benefits of PreFer, an FMIS offering site-specific prescription maps for fertilisation. Farmers utilising PreFer reported yield increases up to 15 % and input cost reductions up to 20 %, highlighting the system's effectiveness in simplifying fertilisation planning and application processes.

TeamDev's development of the Agricolus DSS aims to support farmers and agronomists in making informed decisions, leading to an increase in farm productivity by 5–10 % and cost savings of €504 per hectare, potentially saving farms an average of €10,000 [188]. The same Agricolus DSS project also claims to be able to mitigate the carbon footprint by 15 %, demonstrating itself as a valuable environmental resource. The highlighted studies and projects mainly focus on the theme of fertiliser savings and all the related environmental and economic benefits.

In conclusion, the research has provided significant contributions through peer-reviewed articles and European projects. The latter additionally underscore an increasing significance placed on data management and acquisition within the framework of contemporary computing environments. This growing emphasis reflects a recognition of the pivotal role that effective data handling plays in the success and advancement of technological initiatives. As these projects unfold, they not only contribute to specific objectives but also contribute to the broader understanding of the pivotal role data management holds in driving innovation and efficiency in diverse sectors. This trend aligns with the evolving landscape of technological advancements, where informed and strategic data usage is increasingly recognised as a key determinant of success in various fields.

Conclusion

This paper presented an integrative literature review on the economic and environmental impacts of DATs in crop production, emphasising their transformative potential across various categories, including RMT, CTF, VRT, RSSM, and FMIS. The analysis, grounded in peer-reviewed papers and documents with empirical data from relevant EU projects, demonstrates that DATs offer substantial economic benefits, such as yield increases, cost savings in fertilisers, pesticides, water, labour, and fuel, alongside notable environmental advantages by minimising the use of chemical inputs and optimising resource utilisation.

Economically, DATs have demonstrated significant benefits across various agricultural practices, directly impacting yield outputs and input cost savings. Specifically, RMT has shown a potential yield increase ranging from 9.7 % to 62.6 % across different crops, highlighting their effectiveness in enhancing crop production efficiency. Furthermore, advancements in CTF technologies have been linked to yield increases of up to 70 %, demonstrating the positive impact of optimised field operations on crop productivity. In terms of input cost savings, VRT has led to substantial reductions in the use of fertilisers and pesticides, with studies reporting fertiliser savings of up to 59.6 % and pesticide savings ranging between 8 % and 80 %. These reductions not only lower the operational costs for farmers but also contribute to more targeted and efficient resource use. Additionally, RSSM have facilitated labour and fuel savings, with autonomous systems achieving a reduction in labour time by up to 97 % in specific tasks and fuel savings between 22.15 % and 49.14 % through optimised machinery use. The implementation of FMIS has further enhanced economic efficiency by enabling better decision-making and resource allocation, leading to a reduction in water consumption by up to 60 % and a decrease in fertiliser use by 50–70 % in various case studies. These systems support the strategic management of agricultural inputs, optimising the application of water, fertilisers, and pesticides, thereby reducing excess use and minimising costs.

From an environmental perspective, the analysis showcases DATs' capacity to markedly improve resource use efficiency and reduce the ecological footprint of farming practices. Specifically, the deployment of RMT and VRT has been associated with substantial reductions in pesticide usage, ranging from 20 % to 50 %, and fertiliser savings up to 80 %, mitigating soil and water pollution. CTF technologies contribute to soil structure preservation and reduce greenhouse gas emissions by optimising field operations and minimising unnecessary soil compaction. Furthermore, the adoption of RSSM and FMIS emphasises precision in application and resource management, leading to notable decreases in water usage by up to 40 % and enhancing the sustainability of water resources.

The review has established that the economic and environmental benefits of DATs are closely linked, with gains in efficiency directly contributing to reduced environmental impacts. These benefits illustrate the pivotal role of DATs in facilitating a transition toward agricultural systems that are both more sustainable and economically viable. However, the maximisation of these benefits necessitates overcoming barriers to adoption, such as the need for improved integration across DAT platforms, the development of user-friendly interfaces for a diverse range of users, and the creation of supportive policy environments. To address these needs, future research should focus on developing holistic and interoperable DAT solutions that can seamlessly integrate into various agricultural practices. Additionally, creating policies that support the adoption and scaling of these technologies will be crucial for their widespread implementation.

In summarising the main objectives and findings, it is clear that DATs offer valuable opportunities to enhance both the sustainability and efficiency of crop production, providing tangible economic benefits alongside significant contributions to environmental conservation. As the agricultural sector evolves to meet the challenges of the 21st century, the strategic deployment of DATs will be essential in securing food security, economic resilience, and environmental sustainability. Importantly, the deployment of DATs aligns with and is essential for achieving the ambitious objectives of the European Green Deal and the Common Agricultural Policy, which seek to transform the EU into a fair and prosperous society with a modern, resource-efficient, and competitive economy. This review calls for continued innovation and the broader adoption of DATs, urging stakeholders to embrace digital agriculture's potential in transforming farming into a more efficient, sustainable, and productive sector.

CRediT authorship contribution statement

George Papadopoulos: Writing – review & editing, Writing – original draft, Supervision, Project administration, Funding acquisition, Conceptualization. **Simone Arduini:** Writing – original draft, Resources, Investigation, Formal analysis. **Havva Uyar:** Writing – original draft, Methodology, Investigation, Formal analysis. **Vasilis Psiroukis:** Writing – review & editing, Methodology. **Aikaterini Kasimati:** Writing – review & editing, Validation, Resources, Methodology. **Spyros Fountas:** Writing – review & editing, Supervision.

Declaration of competing interest

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

Data availability

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

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Ethics Statement

Not applicable.

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