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Review

Review and Assessment of Crop-Related Digital Tools for Agroecology

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Academic Editor: Frank Liebisch

Received: 22 September 2025
Revised: 30 October 2025
Accepted: 4 November 2025
Published: 12 November 2025

Citation: Anastasiou, E.; Kasimati, A.; Papadopoulos, G.; Vatsanidou, A.; Gemtou, M.; Kantelhardt, J.; Gabriel, A.; Schwierz, F.; Matavel, C.E.; Meyer-Aurich, A.; et al. Review and Assessment of Crop-Related Digital Tools for Agroecology. *Agronomy* **2025**, *15*, 2600. https://doi.org/10.3390/agronomy15112600

Abstract

The use of digital tools in agroecological crop production can help mitigate current farming challenges such as labour shortage and climate change. The aim of this study was to map digital tools used in crop production, assess their impacts across economic, environmental, and social dimensions, and determine their potential as enablers of agroecology. A systematic search and screening process, following the Preferred Reporting Items for Systematic reviews and Meta-Analyses methodology, identified 453 relevant studies. The results showed that most digital tools are applied for crop monitoring (83.4%), with unmanned aerial vehicles (37.7%) and camera sensors (75.2% combined) being the most frequently used technologies. Farm Management Information Systems (57.6%) and Decision Support Systems (25.2%) dominated the tool categories, while platforms for market access, social networking, and collaborative learning were rare. Most tools addressed the first tier of agroecology, which refers to input reduction, highlighting a strong focus on efficiency improvements rather than systemic redesign. Although digital tools demonstrated positive contributions to social, environmental, and economic dimensions, studies concentrated mainly on economic benefits. Future research should investigate the potential role of digital technologies in advancing higher tiers of agroecology, emphasising participatory design, agroecosystem services, and broader coverage of the agricultural value chain.

Keywords: crop production; tiers of agroecology; digitalization; systematic map; smart farming

1. Introduction

During the previous decades, the world exhibited rapid technological and economic growth in all sectors [1]. However, this growth was conducted without taking into consideration the limited available resources that the planet offers as well as the environmental consequences that may arise by using unsustainable production methods [2,3]. Thus, various issues have arisen from this approach, including climate change, environmental pollution, health risks, demographic changes, and biodiversity decline [4–8]. The agricultural sector has not been an exception to this. Heavy dependence on chemical pesticides and synthetic fertilisers has resulted in health problems due to the consumption of unhealthy food, as well as water, soil, and air pollution [9]. Moreover, the use of heavy machinery has led to soil degradation [10], while urban migration has also led to the abandonment of rural areas [11]. Furthermore, farmers' aging may further limit the ability to feed an increasing population in coming years [12].

Thus, there is a need for more sustainable and socially just agricultural production systems. Many initiatives have started in the previous years at national and international levels (e.g., European Union's Green Deal [13], United Nations' Sustainable Development Goals [14], and Paris Agreement [15]) that apply to agriculture and promote an economically, socially, and environmentally sustainable future. Adoption of agroecology can contribute to this future. Agroecology refers to a holistic approach that combines social, economic, and environmental elements that can lead to sustainable agricultural production [16]. Agroecology can contribute to both incremental and transformational changes in agriculture. According to previous research, adoption of agroecological practices can be categorised into five different tiers, namely: Tier One: input reduction; Tier Two: substitution with sustainable inputs; Tier Three: incorporation of biodiversity through agricultural system redesign; Tier Four: reconnection of producers and consumers; and Tier Five: creation of a just and equitable global food system [17].

The path of agroecology is not the only one that can lead to a more sustainable future. Smart farming can also contribute to this future. Many studies have indicated the incremental and transformational power of the adoption of digital tools that are applied in agriculture. Digital tools refer to offline or online software-based systems (e.g., programs, applications, platforms, and other computational resources) that are used on computers, mobile, or other devices for the completion of tasks through the utilisation of digital information [18]. Digital tools applied in agriculture include various sensors like red-green-blue (RGB), red-green-blue-depth (RGB-D), multispectral, hyperspectral, and thermal cameras, light detection and ranging (LiDAR), Internet of Things (IoT)-based weather sensors (air temperature, air humidity, precipitation, wind velocity and direction), smart traps, soil sensors (moisture, temperature, soil electrical conductivity) and actuators, soil electrical conductivity sensors, synthetic aperture radar (SAR), Global Navigation Satellite Systems (GNSSs), proximal canopy sensors, and others. These are mounted on satellites, crewed and uncrewed terrestrial or aerial vehicles, or stationary platforms [19–21]. The data collected from these sensors are analysed using artificial intelligence (AI) and machine learning (ML) methods to provide insights to optimise crop production [22,23].

Although the aims of smart farming and digitalisation in agriculture are consistent with the scope of agroecology, their relationship is still relatively new and underexplored [24,25]. Furthermore, there is a huge debate among advocates and opponents of using digitisation for agroecological transformation. The first supports this by emphasising improved yields and optimal decision-making, whereas the latter refers to restricted autonomy in decision-making and disenfranchisement [26]. Consequently, the primary goal of this study was to map digital tools utilised in crop production and analyse their economic, environmental, and social impacts in order to determine their potential as agroecology enablers.

2. Materials and Methods

2.1. Search Strategy and Query Design

A systematic literature search using the Web of Science database was conducted to identify relevant digital tools that were applied in crop production over the past ten years and that could enable the transition to agroecology. The reason for selecting Web of Science as the sole database is that it is one of the leading research article databases, covering more than 34,000 journals and containing over 270 million records [27]. Additionally, the long time span helps reduce potential biases caused by the limited number of studies included in the analysis. A structured query was applied on 28 February 2025 to the search engine to identify relevant research articles (Table 1). The query was developed for identifying relevant information for crop, animal, and agroforestry production as part of the Horizon Europe and Innovate UK co-funded project Digitalisation for Agroecology (D4AgEcol) [28]. The outcomes of this query were further screened to extract relevant studies with a focus on crop production.

Table 1. Query used in the Web of Science database to identify relevant publications [28].

Web of Science Database Query
(TS=("Internet of Things") OR TS=("cloud computing") OR TS=("big data") OR TS=("artificial intelligence") OR TS=("machine learning") OR TS=("simulation") OR TS=("augmented reality") OR TS=("additive manufacturing") OR TS=("horizontal and vertical system integration") OR TS=("autonomous robo*") OR TS=("cybersecurity") OR TS=("DSS") OR TS=("decision support") OR TS=("sens*") OR TS=("databas*") OR TS=("ICT") OR TS=("robo*") OR TS=("GPS") OR TS=("GNSS") OR TS=("information syste*") OR TS=("image analys?s") OR TS=("image processing") OR TS=("camera*") OR TS=("video") OR TS=("RFID") OR TS=("eID") OR TS=("ruminal bolus") OR TS=("drafting") OR TS=("walk over weight") OR TS=("thermistore*") OR TS=("smart trap*") OR TS=("e?trap*") OR TS=("insect trap*") OR TS=("UAV*") OR TS=("UAS*") OR TS=("accelerometer*") OR TS=("pedometer*") OR TS=("virtual fencing") OR TS=("RGB") OR TS=("multispectral") OR TS=("hyperspectral") OR TS=("thermal") OR TS=("LIDAR") OR TS=("RADAR") OR TS=("EMI") OR TS=("satellite") OR TS=("UGV*") OR TS=("recording") OR TS=("guidance") OR TS=("steering") OR TS=("reacting") OR TS=("variable rate") OR TS=("monitoring") OR TS=("social network*") OR TS=("social platform*") OR TS=("social media") OR TS=("platform*") OR TS=("aerial") OR TS=("proximal") OR TS=("ground") OR TS=("FMIS") OR TS=("farm management information syste*") OR TS=("blockchain") OR TS=("marketplace*") OR TS=("load cell*") OR TS=("flow meter*") OR TS=("microphone*") OR TS=("feeder*") OR TS=("drinker*") OR TS=("body temperature device") OR TS=("photoelectric sensor") OR TS=("scale") OR TS=("force plat*")) AND (TS=("diversit*") OR TS=("knowledge AND (co-creat* OR shar*)") OR TS=("synerg*") OR TS=("efficien*") OR TS=("recycl*") OR TS=("value* AND (human OR social)") OR TS=("cultur*") OR TS=("food AND tradition*") OR TS=("responsib* AND govern*") OR TS=("economy AND (circular OR solidarity)")) AND (TS=("digital agriculture") OR TS=("digital farming") OR TS=("agroecolog*") OR TS=("agro-ecolog*") OR TS=("sustainable agriculture") OR TS=("precision agriculture") OR TS=("smart farming") OR TS=("smart agriculture") OR TS=("precision livestock farming")) AND (TS=("crop*") OR TS=("vineyard*") OR TS=("vegetable*") OR TS=("orchard*") OR TS=("arable") OR TS=("livestock") OR TS=("poultry") OR TS=("chicken") OR TS=("hen") OR TS=("ruminant*") OR TS=("pig*") OR TS=("goat*") OR TS=("sheep") OR TS=("lamb*") OR TS=("cow*") OR TS=("cattle"))

2.2. Results Filtering

The selected research articles were published between 2012 and December 2024 in order to concentrate on recent research publications. To map the pertinent research papers and guarantee a methodical and transparent approach, the literature review adhered to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) methodology. PRISMA is an evidence-based minimum set of items for reporting in systematic reviews and meta-analyses [29].

The aforementioned query yielded 2412 research articles, which were reviewed by people with prior experience on the topics of this study. The systematic map targeted research articles in English with a focus on digital tools applied to arable, vegetable, and orchard crops, as well as vineyards. Consequently, studies related to livestock, agroforestry, or livestock–crop farming systems were excluded, as well as studies with a focus on genetics and mechanised interventions without the use of digital tools. Each record was screened independently by two reviewers at the stages of screening and eligibility. Conflicts at either stage were resolved by a third reviewer, who adjudicated and issued the final decision. As a result, the first outcomes were filtered to exclude articles that, based on the title and abstract, were unrelated to the study's goal. On this basis, 1531 of the retrieved items were omitted. The subsequent screening round was applied on the remaining 881 articles and excluded inaccessible items as well as articles that were irrelevant to the study scope based on the entire text. The final number of suitable articles that were evaluated in depth for this study was 453 (Figure 1).

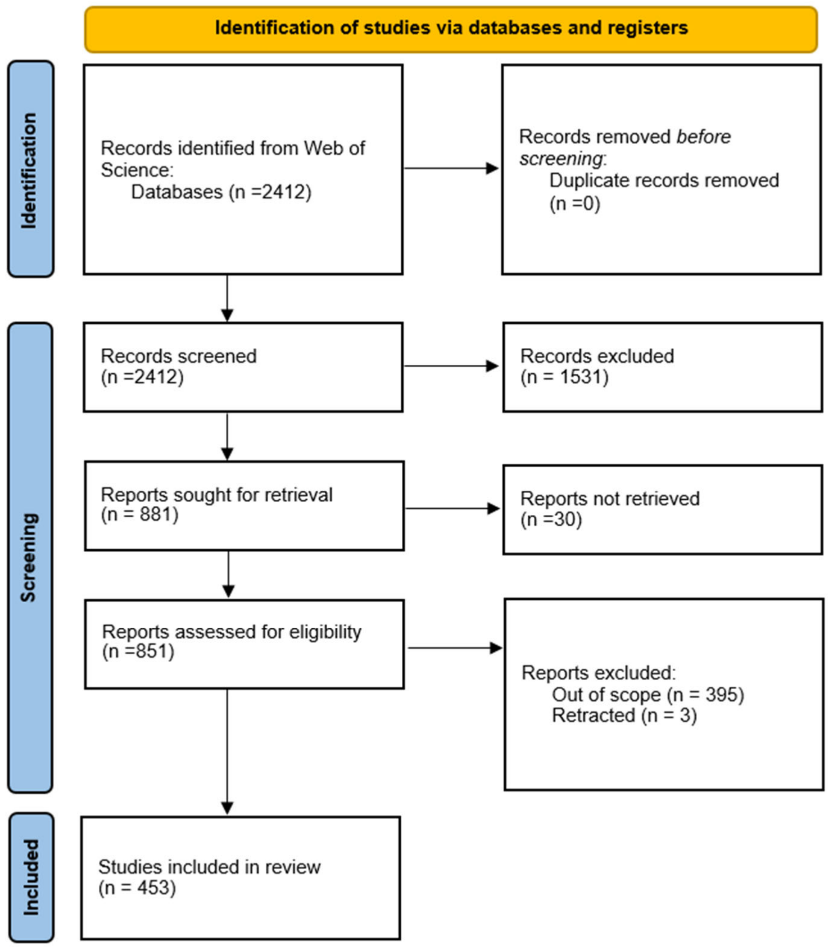

Figure 1. The PRISMA workflow diagram of the research articles search.

2.3. Classification

The selected articles were categorised into three generic classes and several subclasses based on relevant research [17,19–21,30–32]. Each article followed a consistent methodology for categorisation, involving two reviewers for assessment and a third reviewer to resolve any conflicts. The classification into agroecology tiers was based on the following criteria. Articles focusing on digital tools aimed at increasing the efficiency of agricultural operations at the field level (e.g., variable rate nitrogen application [33], decision support system for pest monitoring [34]) were assigned to Tier One, "reduce inputs." When digital tools were referenced in conjunction with sustainable inputs (e.g., organic fertilisers [35], or other sustainable practices like mechanical pruning [36]), the articles were classified under Tier Two, "substitute with sustainable inputs." Tier Three, "redesign agricultural systems to incorporate biodiversity," included articles addressing holistic management approaches at the regional level (e.g., land suitability tools [37], risk assessment for heavy metal pollution in soils [38]). Articles related to applications that enhance crop yield characteristics to better meet consumer needs (e.g., plant phenotyping [39]), contribute to food safety (e.g., yield prediction [40]), or improve traceability [41] were assigned to Tier Four, "reconnect producers and consumers." Tier Five, "create a just and equitable global food system," comprised articles focusing on regional-level food systems (e.g., [42,43]). The final selection of studies was subjected to qualitative and statistical analysis to extract key insights into existing digital tools for the crop sector (Table 2). One article can be categorised into multiple keywords, resulting in percentages of each keyword contribution, not summing up to 100%.

Table 2. Technical aspect keywords used in the literature review.

Classes	**Options**
Crop-related characteristics and applications	
Farming Type	Arable Crops; Vegetable Crops; Orchard Crops; Vineyards
Farming System Type	Conventional; Organic; Integrated Management
Operation Type	Land Preparation; Irrigation; Fertilisation; Pest Control; Weeding; Harvest; Monitoring; Marketing; Breeding
Characteristics and use of digital tools on crops	
Application Type	Guidance/Steering; Recording/Monitoring/Mapping; Reacting/VRA (Variable Rate Application)/Control; Information/Knowledge Sharing
Platform	Satellite; UAV (Uncrewed Aerial Vehicle); UGV (Uncrewed Ground Vehicle); Crewed Ground Vehicles; Stationary; Wearable; Mobile Ground; Crewed Aerial Vehicles
Sensors	Hyperspectral; Multispectral; Thermal; RGB/RGB-D; LIDAR; Weather Station; Load Cell; Sound Sensor; Flow Meter; Temperature Sensor; Weight Sensor; Soil Sensor; Stem Water Potential Sensor; NIRS (Near- Infrared Spectroscopy; Smart Trap; Synthetic Aperture Radar; GNSS; Soil Electrical Conductivity Sensor; Canopy Sensor; Fluorescence; Water Quality Sensor; Ground-Penetrating Radar; Soil Cutting Resistance Sensor; Electronic Plate Meter; Force Plate; pH Sensor
Software	Software; FMIS (Farm Management Information System); DSS (Decision Support System); Social Platform; Digital Marketplace
Contribution to transition to agroecology	
Tier of Agroecology	Tier One: reduce inputs; Tier Two: substitute with sustainable inputs; Tier Three: redesign agricultural systems to incorporate biodiversity; Tier Four: reconnect producers and consumers; Tier Five: create a just and equitable global food system

2.4. Impact Categorisation

The collected records were assessed in terms of different impacts, and specifically environmental, economic, and social impacts. The impacts were based on the work performed by Wolters et al. [44] (Table 3).

Table 3. Impacts used for the assessment of the selected research articles [28].

Impact Type	Impact
Economic Impact	Productivity Revenue, profit, farm income Input costs Shelf life of product Product quality Product wastage
Environmental Impact	Air protection Soil protection Water protection Biodiversity protection GHG emission
Social Impact	Labour time Stress for farmer Amount of heavy physical labour Number and/or severity of personal injury accidents Number and/or severity of accidents resulting in spills, property damage, incorrect application of inputs, etc. Human exposure to chemicals

An "Impact Scale" with a simple grading was used to analyse the impact of digital tools for agroecology found in the research articles. This scale, ranging from "Large Decrease" to "Large Increase," was used to assess the impact of digital technologies on the aforementioned economic, environmental, and social variables [28]. The aim of using this scale was to classify the effect of each solution allowing, for a disciplined and uniform way of measuring the possible advantages or drawbacks. The scale's categorical nature allowed for a clear delineation of impact, highlighting tools that might substantially improve conditions or those that could possibly pose risks or challenges across the assessed areas. Numerical values were assigned for each impact based on each category with the aim of making the impact of digital tools, which present heterogeneous evidence, easily comparable (Table 4). Each digital tool was accounted for once, regardless of its application system. In case one publication introduced several tools, the impact scale was created for the combined use of the digital tools. Two reviewers with relevant experience assigned the numeric values to each record, where if there was a conflict, a third reviewer made the final decision.

Table 4. Numeric values assigned per impact type [28].

Impact	Numeric Value				
	Large Decrease	Small Decrease	No Effect	Small Increase	Large Increase
Economic Impacts					
Productivity	−2	−1	0	+1	+2
Revenue, profit, farm income	−2	−1	0	+1	+2
Input costs	+2	+1	0	−1	−2
Shelf life of product	−2	−1	0	+1	+2
Product quality	−2	−1	0	+1	+2
Product wastage	+2	+1	0	−1	−2

Table 4. *Cont.*

Impact	Numeric Value				
	Large Decrease	Small Decrease	No Effect	Small Increase	Large Increase
Environmental Impacts					
Air protection	−2	−1	0	1	+2
Soil protection	−2	−1	0	1	+2
Water protection	−2	−1	0	1	+2
Biodiversity protection	−2	−1	0	+1	+2
GHG emission	+2	+1	0	−1	−2
Social Impacts					
Labour time	+2	+1	0	−1	−2
Stress for farmer	+2	+1	0	−1	−2
Amount of heavy physical labour	+2	+1	0	−1	−2
Number and/or severity of personal injury accidents	+2	+1	0	−1	−2
Number and/or severity of accidents resulting in spills, property damage, incorrect application of inputs, etc.	+2	+1	0	−1	−2
Human exposure to chemicals	+2	+1	0	−1	−2

After evaluating the economic, environmental, and social impact, the overall score for each category was calculated by summing the scores for each type of impact. A similar technique was used to assess the combined economic and environmental impact, as well as the overall impact, which considered economic, environmental, and social impacts. This was conducted to provide a more holistic assessment, since economic, environmental, and social dimensions are often interdependent and can influence one another. However, the combinations of economic with social and environmental with social were not considered, as these pairs do not provide the same level of complementary insight. In these evaluations, weights were used to normalise the numbers to account for the fact that the environmental effect category has one fewer type of impact than the economic and social categories [28,45]. Specifically, the weights in the Table 5 were assigned to ensure comparability across categories and to avoid over-representing any single dimension when impacts were combined. For the economic, environmental, and social categories, a weight of 1 was used, since each represents a distinct and independent type of impact. In contrast, combined categories such as economic and environmental and the overall impact (economic, environmental, and social) were given smaller weights (0.5 and 0.33 for each impact, respectively) to normalise their scores. In this way, balanced scores for the combined categories in relation to the single-dimension scores was ensured (Table 5).

Table 5. Weights and categorisation rules per impact category [28].

Impact Type	Weight for Each Impact Type	Numeric Values		
		Low Impact	Medium Impact	High Impact
Economic	1	<4	≥4 and <8	≥8
Environmental	1	<3	≥3 and <7	≥7
Social	1	<4	≥4 and <8	≥8
Economic and Environmental *	0.5	<4	≥4 and <8	≥8
Overall **	0.33	<4	≥4 and <8	≥8

* Each impact (economic and environmental) was assigned 0.5 to result in normalised values. ** Each impact (economic, environmental, and social) was assigned 0.33 to result in normalised values.

The distribution of the overall scores was used to provide a standardised and data-driven way of defining thresholds to assign each record to low, medium, or high impact [28]. Specifically, values falling in the lower numeric values range were categorised as low impact, mid-range values as medium impact, and upper numeric values as high impact (Table 5).

2.5. Analysis

The statistical analysis included the number of research studies published annually. In addition, frequency analysis was performed for the crop characteristics (type, operation, and farming system), the digital tools (scope of use, sensors, and platforms), the agroecology tier, and the impact assessment. The PRISMA checklist, the classification and analysis of the selected research articles are presented in the Supplementary Materials [33–43,46–487].

3. Results

3.1. Annual Publications

Between 2012 and 2024, there was a significant and consistent increase in the number of published research articles on digital tools for crop production that could support the transition to agroecology. Starting with a negligible number of articles in 2012, the research output shows a gradual rise until 2017, after which there is an exponential growth, culminating in over 100 articles in 2024 (Figure 2).

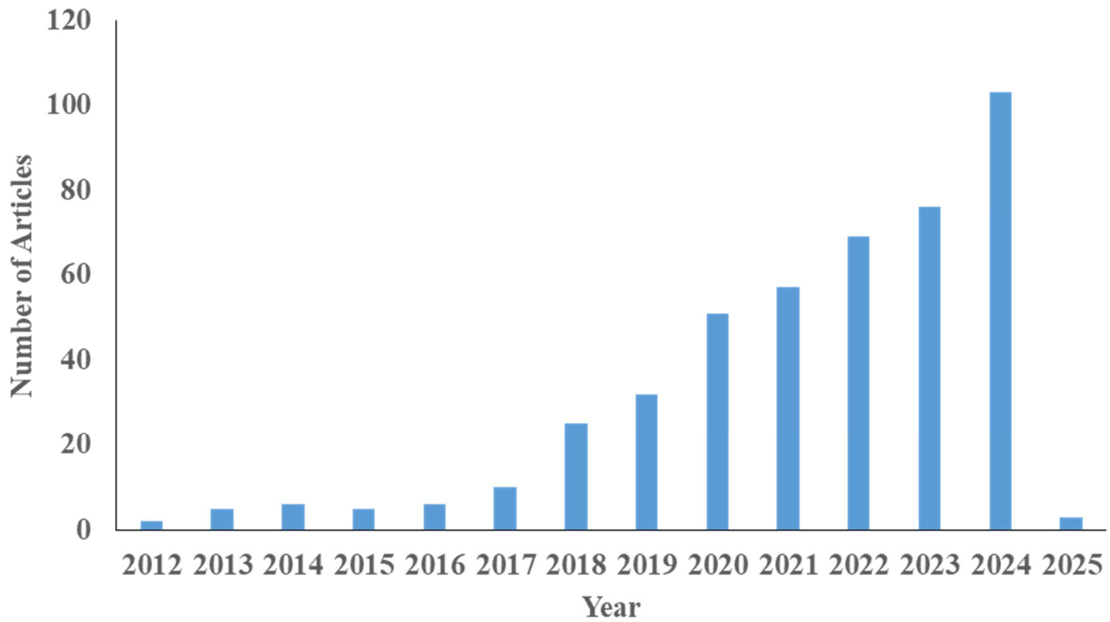

Figure 2. Number of articles per year (the 2025 bar represents articles that were accepted in 2024, published in 2025, and subsequently included in the database).

3.2. Crop-Related Characteristics and Applications of Digital Tools

The percentages of research articles that correspond to different agricultural management systems are presented in Figure 3. According to the analysis, the conventional agricultural management overwhelmingly dominates the discourse, with digital tools being applied in 99.3% of relevant articles. In contrast, "Integrated Management" and "Organic" farming systems show significantly lower percentages, at 74.2% and 57.4%, respectively. While "Integrated Management" still features digital tools in a substantial portion of its research, the gap between this and "Conventional" is considerable. "Organic" agriculture, which aligns most closely with agroecological principles, has the lowest mention of digital tools.

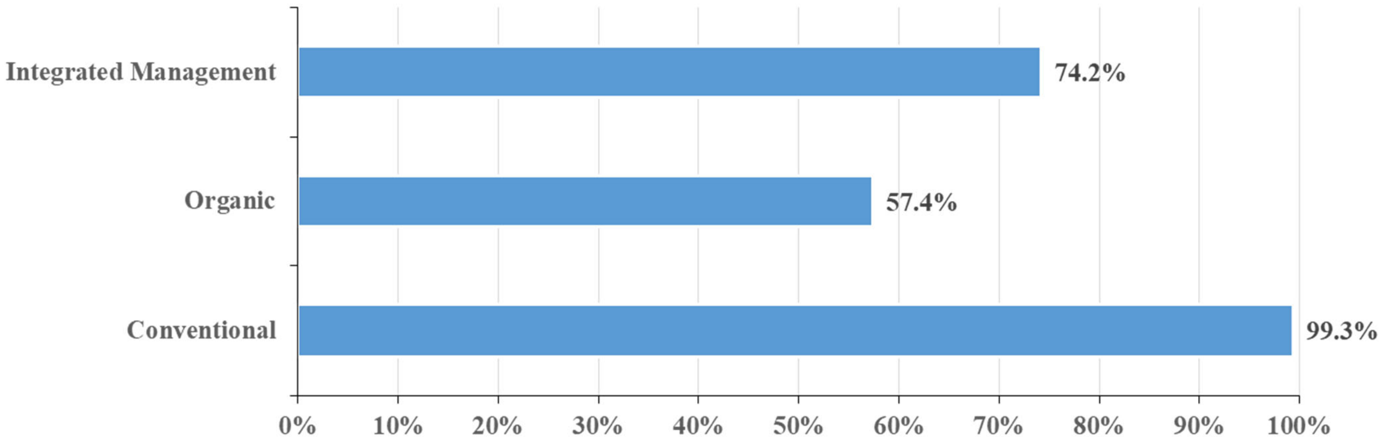

Figure 3. Percentage of relevant articles per system.

The percentage of research articles that use digital tools in crop production across different crop categories is presented in Figure 4. The results indicate that "Arable Crops" dominate the research landscape, accounting for 61.8% of the articles. In contrast, "Vegetable Crops" and "Orchard Crops" receive considerably less attention, representing 24.1% and 22.3% of the articles, respectively. While still a notable portion, their combined share is less than that of arable crops. Finally, "Vineyards" receive the lowest percentage, representing only 15.0% of the research articles.

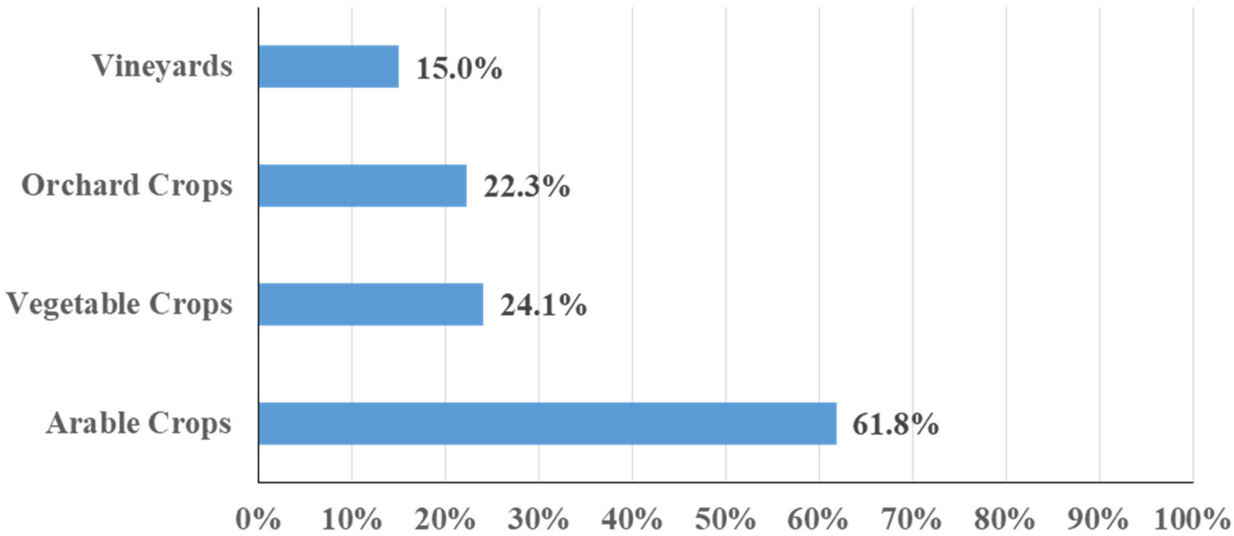

Figure 4. Percentage of relevant articles per crop type.

Regarding the application of digital tools in crop production across various farming operations, "Monitoring" overwhelmingly dominates the research landscape, accounting for 83.4% of the articles. "Fertilisation" and "Harvest" are the next most researched areas, at 22.7% and 19.0%, respectively. "Irrigation" and "Pest Control" ranked fourth and fifth, also receiving substantial attention in 18.5% and 12.8% of the articles, respectively. "Weeding," "Land Preparation," "Breeding," and "Marketing" have comparatively lower percentages at 9.7%, 7.1%, 5.7%, and 1.1%, respectively (Figure 5).

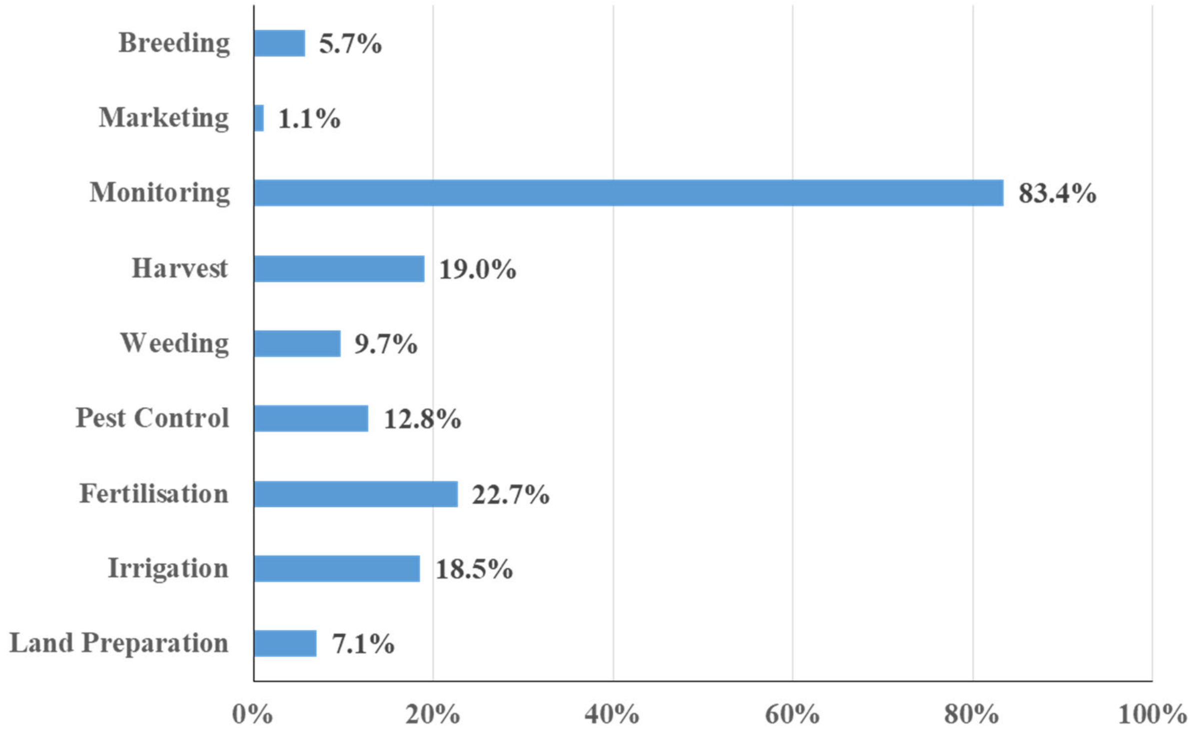

Figure 5. Percentage of relevant articles per operation type.

3.3. Characteristics and Use of Digital Tools on Crops

As presented in Figure 6, regarding the application type of digital tools on crops, "Recording/Monitoring/Mapping" stands out as the predominant use, accounting for a remarkable 85.7% of the research articles. "Reacting/VRA/control" is the second most common use of digital tools in crops, but at a significantly lower percentage (14.8%). This category involves using data gathered from monitoring devices to trigger specific actions, such as automatically adjusting irrigation, applying fertilisers at variable rates, or controlling machinery. Finally, "Information/Knowledge Sharing" at 6.6% and "Guidance/Steering" at 4.6% were the least frequent application type categories.

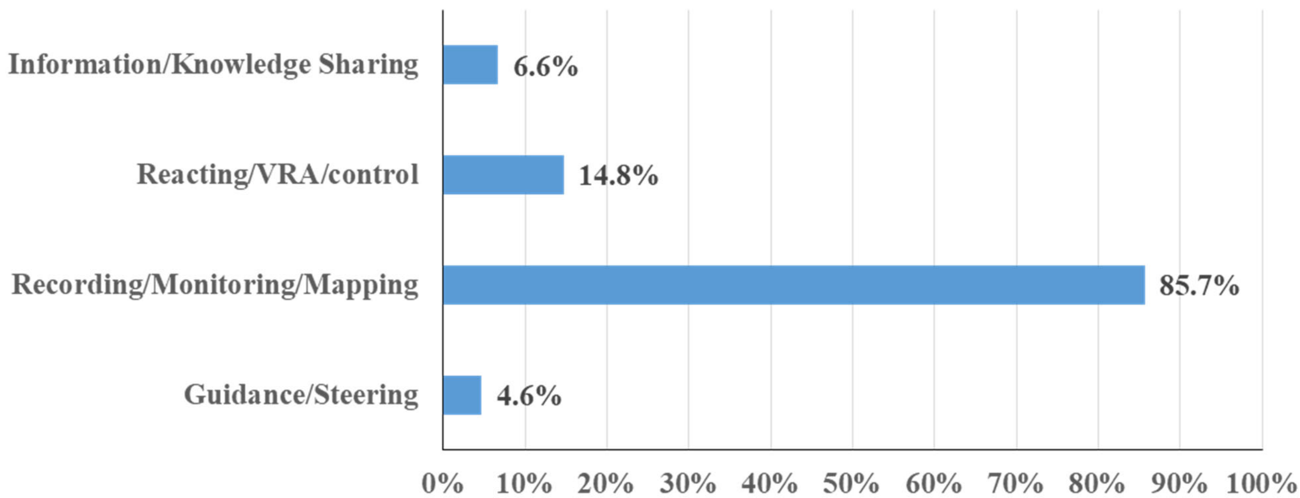

Figure 6. Percentage of relevant articles per application type.

Figure 7 shows the percentage distribution of different sensor types used in the selected research articles. According to the analysis, there is a diverse but uneven focus across various sensing technologies. "Multispectral" and "RGB/RGB-D" sensors are clearly the most prominent, used in 33.6% and 28.3% of the selected research articles, respectively. Following these, "Hyperspectral" sensors (9.1%) and "Soil Sensor" (9.7%) also show significant usage. "Weather Station" (7.1%), "Canopy sensor" (6.6%), "LiDAR" (5.1%) and Thermal" (4.2%), represent another tier of commonly used sensors. Many other sensor types, such as "Soil Electrical Conductivity Sensor" (4.2%), "Fluorescence" (1.1%), and "GNSS" (0.9%), are present but with much lower percentages, reflecting their more specialised applications or their role as components within larger digital systems rather than primary data collection tools for crop parameters (e.g., GNSS for location, not direct crop sensing). A large number of sensor types, including "load cell," "sound sensor," "flow meter," "weight sensor," "stem water potential sensor," "NIRS," "smart trap," "Synthetic Aperture Radar," "water quality sensor," "ground-penetrating radar," "soil cutting resistance sensor," "electronic plate meter," "force plate," and "pH sensor" were rarely mentioned (mostly under 2% and many under 1%).

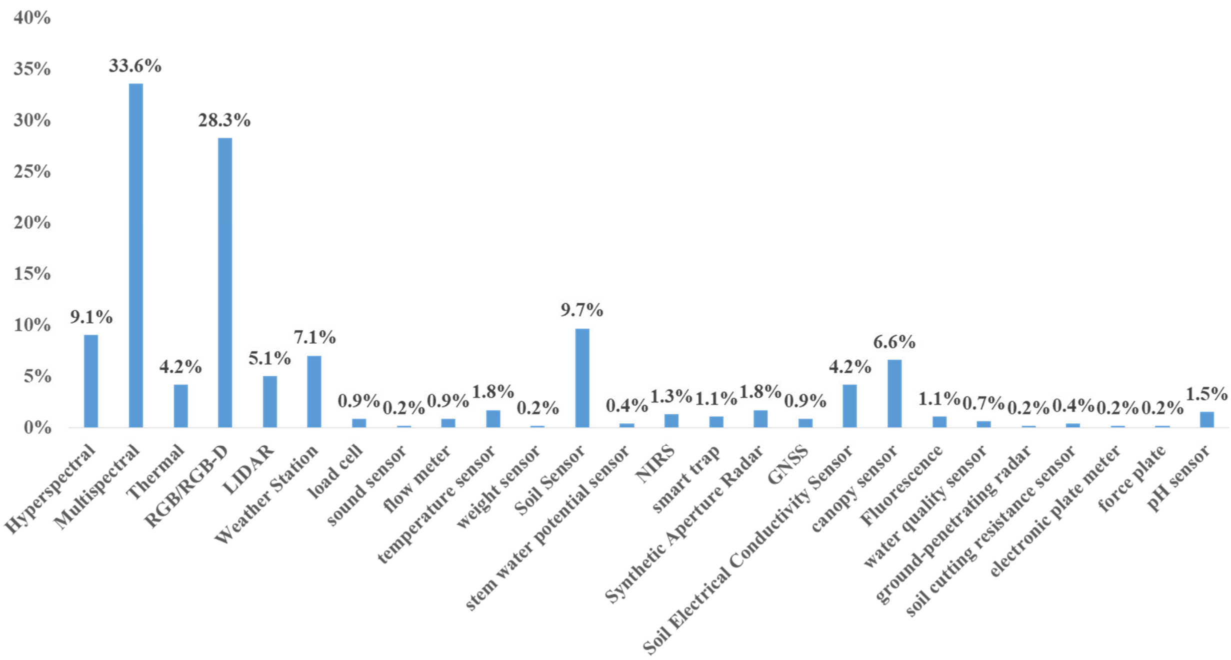

Figure 7. Percentage of relevant articles per sensor type.

In Figure 8, the percentage of articles per platform type is presented. According to the results, "UAV" ranked first as the most frequently researched platform, accounting for 37.7% of the articles. "Stationary" platforms ranked second at 22.3%, "Mobile Ground" platforms ranked third at 21.6%, and "Satellite" platforms ranked fourth at 19.6%. The remaining platform types showed significantly lower percentages, specifically, "Crewed Ground Vehicles" at 8.2%, "UGV" at 4.9%, "Crewed Aerial Vehicles" at 1.1%, and "Wearable" devices at 0.7%.

Regarding the distribution of research articles per software type, "FMIS" (Farm Management Information Systems) was by far the most prominent system type in the screened research, accounting for 57.6% of the articles, with "DSS" following as the second most common system type, representing 25.2% of the articles. On the contrary, "Social Platform" and "Digital Marketplace" showed low percentages, at 1.1% and 0.9%, respectively (Figure 9).

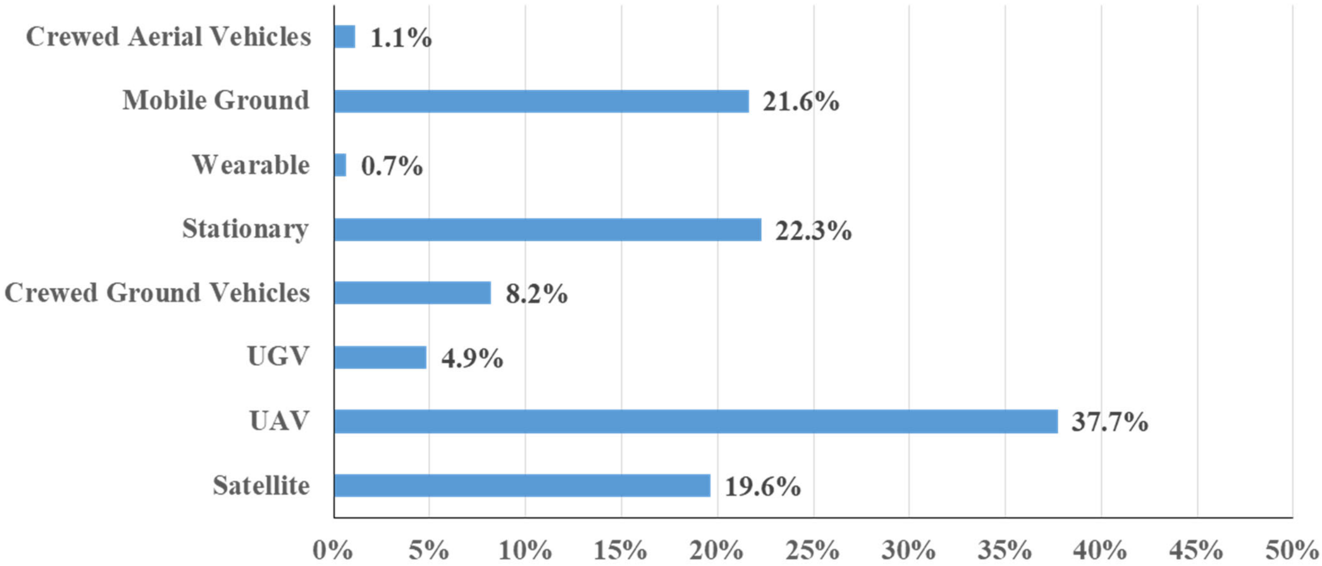

Figure 8. Percentage of relevant articles per platform type.

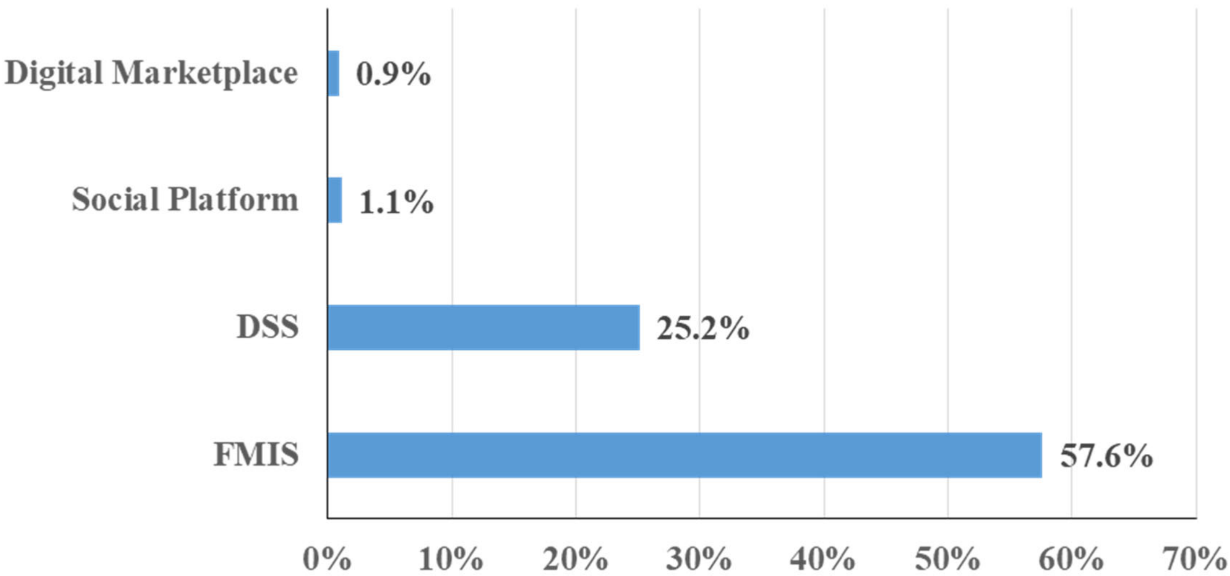

Figure 9. Percentage of relevant articles per software type.

3.4. Crop-Related Digital Tools and Contribution to Transition to Agroecology

As presented in Figure 10, regarding the distribution of research articles on digital tools in crop production across the five different "tiers" of agroecological transformation, "Tier One: reduce inputs" received the most research focus, accounting for 66.9% (303 from 453) of the articles, followed by "Tier Three: redesign agricultural systems to incorporate biodiversity" at 24.7% (112 from 453) and "Tier Two: substitute with sustainable inputs" at 12.4% (56 from 453) of the articles. "Tier Five: create a just and equitable global food system" and "Tier Four: reconnect producers and consumers" exhibited very low percentages, at 6.4% (29 from 456) and 2.4% (11 from 453), respectively.

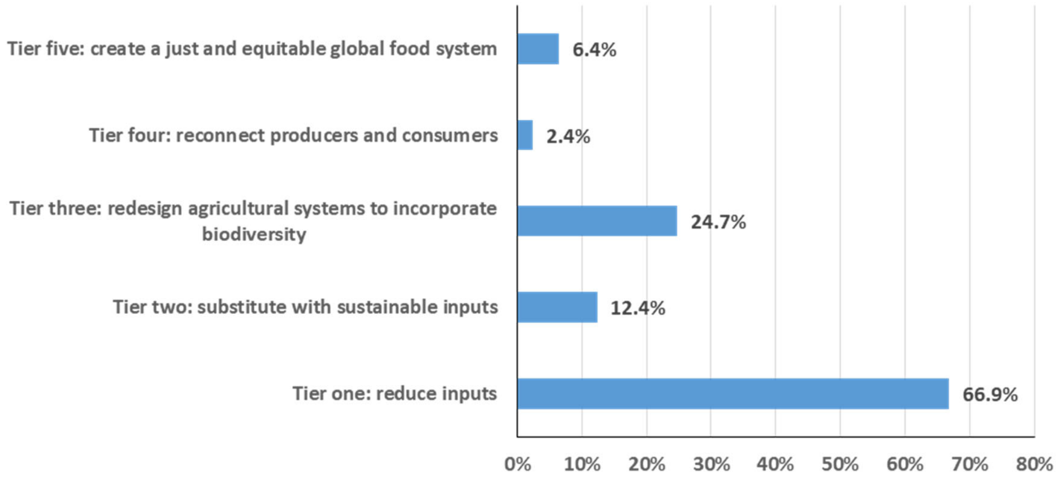

Figure 10. Percentage of relevant articles per tier of agroecology.

3.5. Impact Assessment of Application of Digital Tools on Crops

According to the results of the impact assessment analysis, the use of digital tools in crop production contributes to positive economic, environmental, and social impacts (Figure 11). Specifically, from an economic perspective, the impact of digital tools in crop production is positive. Digital tools can contribute to large increases in productivity and farm income. Additionally, the digital tools found in the research articles contributed to a decrease in input costs and product wastage. Furthermore, the use of digital tools was associated with "Some" or a "Large Increase" in product quality (70%). Most digital tools showed little to no impact on the product's shelf life.

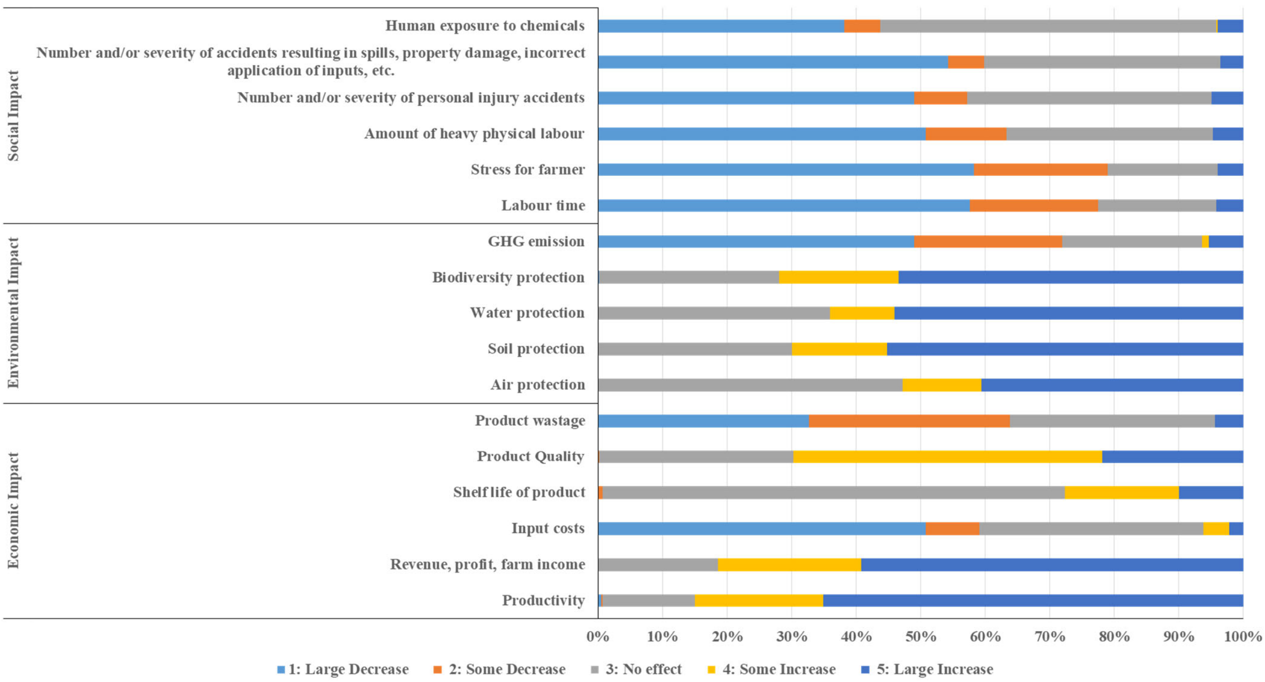

Figure 11. Distribution of perceived societal, environmental, and economic impact levels of digital tools adoption in agriculture.

Regarding the environmental benefits of digital tools, the results indicated that the use of digital tools in crop production can contribute to increased protection of biodiversity, water, soil, and air. However, no contribution ("No Effect") to environmental protection may also be experienced by using digital tools, according to the results. Regarding greenhouse gas emissions, more than 70% of the applications of digital tools in crop production can contribute to "Some" or a "Large Decrease."

In the social dimension, digital tools can contribute to a reduction in the amount of heavy physical labour, stress for farmers, accidents leading to spills or property damage, and personal injury accidents. Most of the applications of digital tools led to "No Effect" regarding human exposure to chemicals (more than 50%). Finally, most of the articles indicated "Some" or a "Large Decrease" in labour time.

For the accumulated economic impact, the results indicated that digital tools can mainly result in "High Impact" (46.1%). Digital tools exhibited "Medium Impact" and "Low Impact" at 27.4% and 26.5% of the studies, respectively. With regard to environmental impact, digital tools exhibited "High Impact," "Medium Impact," and "Low Impact" at 44.8%, 21.2%, and 34.0% of the research articles, respectively. Similar results were found for the social impact with "High Impact" at 51.0%, "Medium Impact" at 13.7%, and "Low Impact" at 35.3% of the research articles. Considering the "Economic and Environmental Impacts," the results presented "High Impact" at 44.8%, "Medium Impact" at 21.9%, and "Low Impact" at 33.3% of the research articles. Finally, for "All Impacts," the distribution was at 43.3% for "High Impact," 21.0% for "Medium Impact," and 35.8% for "Low Impact" regarding the use of digital tools in crop production (Figure 12).

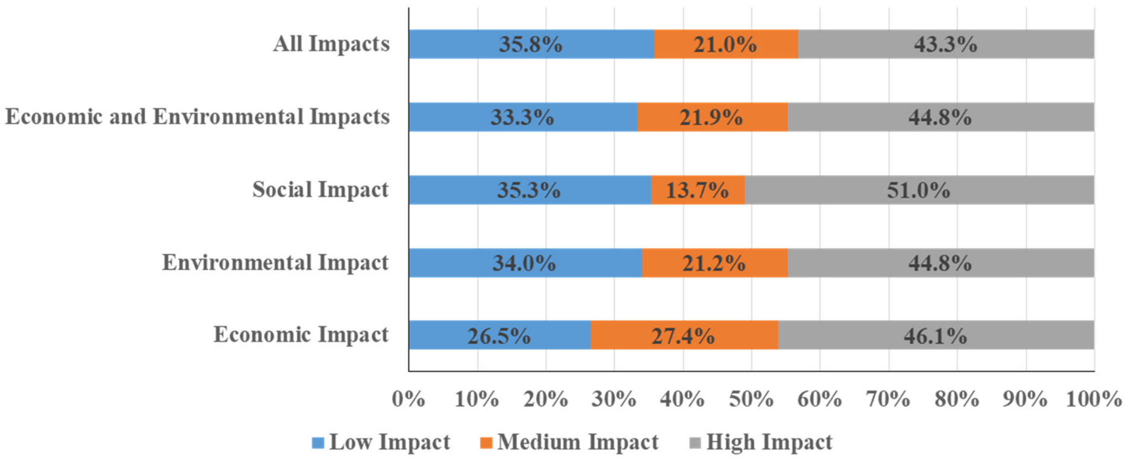

Figure 12. Distribution of perceived impact levels (low, medium, high) of digital tools in crop production across social, environmental, and economic dimensions.

4. Discussion

4.1. Number of Publications

The increase in research article publications on the use of crop-related digital tools for agroecology, particularly from 2018 onwards, can be justified by several factors. One of the reasons is the increasing urgency of sustainable agriculture due to climate change and environmental degradation [488,489]. Also, the growing maturity and accessibility of digital technologies (such as AI, IoT, and remote sensing) applicable to agriculture can justify this trend [19,21]. Moreover, the scientific community is increasingly recognising the potential of agroecology in ensuring food security and promoting ecological sustainability [490,491].

4.2. Crop Characteristics

The high percentage of studies on conventional farming systems indicates that the vast majority of research on digital tools in crop production is still focused on optimising and enhancing traditional, input-intensive farming practices. This can be justified by the historical prevalence of conventional agriculture, by the existing infrastructure and relatively small market for organic farming technologies, and the immediate economic incentives for maximising yields through technological means in established systems [492]. Regarding "Organic" and "Integrated Management," the lower values suggest that the integration of digital technologies into more sustainable and agroecological approaches is still in its nascent stages [493]. The lower figures for Integrated and Organic management could be justified by several factors. These include the inherent complexity of agroecological systems, which may not be easily amenable to conventional digital optimisation [494], and the debate within these movements towards open-source and simple solutions specifically tailored for their unique requirements [26,495].

Regarding the results on crop types, the predominance of tools used in arable crops is justified by the vast cultivated area dedicated to arable crops (e.g., cereals, oilseeds, and pulses), their critical role in global food security, and the significant economic scale of their production [496–500], which incentivises the adoption and research of digital technologies for efficiency and yield optimisation [501]. Regarding the lower percentage in vegetables and orchards, this can be justified by their generally smaller individual farm sizes, more specialised cultivation practices, and sometimes exhibiting higher operation complexity compared with large-scale arable farming, which might lead to different priorities for digital tool development [502–504]. Similarly for the vineyards, the lower percentage can be justified given that viticulture is a highly specialised and often regionalised agricultural sector compared with the rest of the crops while requiring higher operational complexity [505,506].

The high percentage of articles that address "Monitoring" operations is well justified given that this operation is foundational to smart farming and enables data-driven decision-making across almost all other farming operations. Digital tools like sensors, drones, and satellite imagery are crucial for data collection on crop health, soil conditions, and environmental factors. Processed data from these sensors can lead to timely and accurate decisions for all operations [507–510]. The emphasis on "Fertilisation" reflects the economic and environmental importance of optimising nutrient application, where digital tools (e.g., variable rate spreaders, IoT sensors for nutrient analysis) can be used for optimising application of nutrients based on crop needs due to better detection of crops (<5% error) and can achieve savings of >8% depending on the nutrients compared with traditional practices [511,512]. Accordingly, digital tools for "Harvest" are used to improve efficiency, reduce losses, and optimise timing for quality and yield by achieving yield prediction of >90% [513]. Similarly, "Pest Control" and "Irrigation" benefit significantly from digital solutions for optimised pest management and water application due to the fact that they can reduce chemical use and resource waste by >70% according to the pesticide type through the use of prescription maps and >10% in irrigation water by coupling weather, soil, and crop data to assess the specific needs [21,514]. Regarding the low percentages of "Weeding" and "Land preparation," these can be justified by the fact that these operations are of high importance, mainly in arable crops. Digital tools can save >20% herbicides through spot spraying due to high accuracy in weed detection (>90%), while >50% fuel savings and >0.6 tonnes reduction of air pollution can be achieved due to trajectory optimisation and path following through the use of autosteering and appropriate tillage depth compared with traditional practices [501,515,516]. The low focus on "Breeding" can be justified by it being a longer-term, more scientific process that is not as directly impacted by real-time digital tools in the field [517]. The very low percentage for "Marketing" suggests that research on digital tools in crop production predominantly focuses on the production aspects within the farm gate, with less emphasis on post-harvest value chain and market access strategies using digital technologies, while this aspect is of higher interest in urban agriculture [518,519].

The main focus on the "Recording/Monitoring/Mapping" application can be justified by the fact that digital tools are mainly used to monitor and map the agricultural environment and provide the essential data layer for all other advanced digital farming applications [507–510]. Accordingly, "Reacting/VRA/control," while crucial for optimising inputs and outputs, inherently relies on the preceding "Recording/Monitoring/Mapping" phase, which justifies its lower percentage [20]. "Information/Knowledge Sharing," while important for knowledge transfer and community building, does not exhibit immediate and measurable results [520]. Similarly, the low percentage of "Guidance" can be justified by its niche application to specific machinery operations, compared with the broad utility of monitoring, although it is vital for precision and efficiency in field operations [521,522].

4.3. Digital Tools

Our study showed that imaging sensors can provide a higher volume of information compared with other sensors, and for this reason they were selected in the field studies, in accordance with preceding studies. Specifically, multispectral imaging captures specific light bands to assess crop health, nutrients, and stress, while thermal imaging measures temperature variations to detect water stress and disease. Both are key in remote sensing for large-area monitoring [523,524]. RGB/RGB-D cameras support visual inspection (e.g., weed, pest, crop), 3D mapping, and agricultural robotics [525,526]. Hyperspectral imaging provides even richer spectral detail for advanced plant analysis, though it is less common due to higher cost and data complexity [527,528]. Additionally, soil sensors are fundamental for precise irrigation and fertilisation, measuring parameters like moisture, pH, and nutrient levels, directly impacting resource efficiency [529]. LiDAR provides highly accurate 3D structural information of crops and fields, useful for canopy volume, plant height, and terrain mapping that can be used for optimising application of nutrients and plant protection products, pruning, and yield prediction [530]. Canopy sensors directly measure plant properties, often relating to nitrogen status or biomass. These sensors support more specific or detailed analyses compared with broad-area remote sensing [531]. Regarding the low use of the rest of the sensors in crops, the results can be justified by the fact that these sensors are used in specific agricultural applications. Also, they are less frequently the primary focus of research articles on digital tools in crop production compared with the more broadly applicable and widely adopted imaging and soil sensing technologies. Finally, these sensors provide limited benefit in comparison with the other sensor types [19,21].

The high percentage of "UAV" in the category platform is well justified by the unique advantages of UAVs in agriculture, namely their ability to provide high-resolution, on-demand imagery, flexibility in deployment, and capacity to cover significant areas quickly and cost effectively for application and monitoring compared with ground-based methods. They are particularly valuable for monitoring and mapping, which, as seen in a previous analysis, is the dominant use of digital tools [532]. "Stationary platforms" includes fixed-position sensors and actuators (e.g., soil sensors, solenoid valves) and weather stations. Their significant presence is justified by the need for continuous, long-term, and precise data collection at specific points within the field, providing a stable and reliable data source for various agricultural parameters [533]. "Mobile Ground" platforms encompass a range of handheld devices, mainly used for monitoring and mapping. Their importance lies in their ability to perform close-range sensing, detailed sampling, and precise application of inputs, complementing aerial data with ground-truth information [531]. "Satellites" offer broad-area coverage and frequent revisit times, but their resolution can be lower than UAVs, and cloud cover can be an issue when using optical data. Also, satellites are used for enabling accurate positioning, and consequently, allowing accurate navigation and application of crop robots. However, their ability to cover vast regions makes them economically crucial for large-scale monitoring and regional analysis, justifying their substantial, though not leading, share [534]. "Crewed Ground Vehicles" and "Crewed Aerial Vehicles" represent traditional human-driven machinery and aircraft, which are less the focus of novel digital tool research compared with autonomous or remote systems, justifying their lower percentages due to safety and less work effort for the operators [19,21]. The "UGV" category, while promising for precision tasks and reducing labour, are still in earlier stages of adoption and research compared with UAVs, explaining their modest share due to regulations and higher manufacturing costs [535]. "Wearable" devices, while useful, are currently less central to the automated data collection and application processes that dominate digital agriculture research. Hence, they exhibited limited use in crop-related studies, although they are widely used in the livestock sector [536,537].

Regarding the results on software types, the high percentage of "FMIS" is highly justified because the systems are comprehensive software platforms designed to integrate and manage various aspects of farm operations, from planning and record-keeping to resource management and financial analysis. They serve as the central hub for data collected by sensors and other digital tools, enabling holistic decision-making and operational efficiency. The strong emphasis on FMIS aligns with the previous findings that "monitoring" is the dominant use of digital tools, as FMISs are crucial for processing and utilising these monitored data [538–540]. DSS are specialised computer programs that analyse data to provide recommendations or assist farmers in making informed decisions regarding, for example, optimal fertilisation, irrigation scheduling, or pest control. Their substantial presence is logical, as they represent the analytical and actionable layer built upon the data foundation provided by FMIS and monitoring tools [541]. In contrast, "Social Platform" and "Digital Marketplace" percentages indicate that research has very little focus on platforms designed for farmer-to-farmer interaction, knowledge exchange, or direct buying and selling of agricultural products. This could be justified by the fact that the core of precision agriculture research is typically centred on in-field production efficiency and optimisation, rather than on social aspects or broader supply chain and market dynamics where the farmers are utilising traditional platforms [542–545].

4.4. Transition to Agroecology

The application of digital tools in agriculture presented the strongest focus on "Tier One: input reduction," where digital tools optimise fertilisers, pesticides, water, and energy use to cut waste and environmental impact while maintaining yields, aligning with precision agriculture goals [546]. Accordingly, digital tools that address "Tier Two: substitution with sustainable inputs" received less focus, because most tools are designed to improve the efficiency of existing inputs rather than replacing them, although in some cases they can be used for the application of sustainable crop inputs (e.g., organic fertilisers and pesticides) [547]. Similarly, digital tools for "Tier Three: incorporation of biodiversity through agricultural system redesign" received less focus due to the need for more complicated systems [548]. "Tier Four: reconnection of producers and consumers" and "Tier Five: creation of a just and equitable global food system" received minimal research, as current digital agriculture efforts remain centred on on-farm production [542–545]. The results can be justified by the fact that Tiers Four and Five aim at value chains as well as complicated food systems. These involve interconnected activities and actors that make it challenging to develop and assess solutions [549]. Moreover, incremental changes like the ones that correspond to Tiers One, Two, and Three are more preferable due to lower risk, shorter adoption and adaptation periods, and a lower number of conflicts compared with the radical changes that correspond to Tiers Four and Five [550]. Also, different barriers have been identified for the adoption of informatics technologies in agri-food chains that are relevant to production processing and commercialisation and include data privacy and security, high costs to connectivity, training, interoperability, data standards, scalability, governance, technological and infrastructure gaps, technological readiness, farm size, time consumption, and age [551]. Thus, appropriate policies and practices should be implemented to address these barriers and enable the development of radical digital tools that address Tier Four and Tier Five.

4.5. Impact Assessment

Regarding the results on the impacts, these are in alignment with other studies that found that there are economic, environmental, and societal benefits to the use of digital tools in agriculture. Digital tools are expected to reduce product wastage, improve product quality and shelf life, cut input costs, and boost revenue, profit, farm income, and productivity. These gains derive from better timing, resource optimisation, and targeted application of inputs indicating that the adoption of digital tools can provide direct economic benefits [547,552–554]. Accordingly, environmental impacts were also beneficial. Digital tools contribute to decreased GHG emissions by optimising fuel and fertiliser use. Many studies referred to increases in biodiversity, water, and air protection, with some seeing no effect. Soil protection trends are positive, reflecting benefits from the use of digital tools [555–557]. Moreover, the social impacts of digital tools in agriculture were also in alignment with the rest of the results from the other impacts. Digital tools can contribute to reduced human exposure to chemicals through precision operations (e.g., spraying, fertilisation) and automation, and they also tend to slightly lower the number and severity of accidents and personal injuries. The amount of heavy physical labour is widely expected to decrease due to the use of robots and other automated systems, although they may add pressures from data management, complexity, and financial costs [21,558–560].

Digital tool use in agriculture is generally seen as positive by the reviewers of the database across economic, environmental, and social dimensions, with the strongest consensus around significant economic benefits such as increased productivity, revenue, and reduced input costs, and very few studies rating the impact as low. However, concerns have been raised that productivity gains might not cover the capital costs of investments, for instance in site-specific management [561]. Environmental impacts are also widely seen as beneficial, though the scale of these benefits is slightly lower than for economic gains. Social impacts, despite mixed assessments, also received a high proportion of high-impact ratings, likely reflecting a broader recognition that digital tools can substantially reshape labour needs. Combined assessments showed that economic and environmental impacts together are rated as high in 44.7%, medium in 21.9%, and low in 33.3% of the research articles, while all impacts combined (economic, environmental, and social) receive high, medium, and low ratings in 43.2%, 21.1%, and 35.7% of the cases, respectively. The slight drop in high-impact ratings when all dimensions are considered suggests that lower-impact perceptions in certain social aspects diluted the strong economic and environmental scores. This is justified by the limited focus of the research on digital tools in the social impact category [518,519].

4.6. Future Directions

The findings highlight a significant opportunity and need for increased research and development into digital tools that genuinely support and enable the transition towards more sustainable and agroecological farming systems, rather than predominantly reinforcing conventional methods. Specifically, the identified digital tools prioritise crop yield and input optimisation rather than contributing to radical agroecological transformation.

Thus, there is a need to support whole-system transformation and social innovation such as polyculture, agribusiness diversification strategies, and community-based networks [561]. Additionally, the wide use of FMIS and DSS platforms reflects that there is a focus on farm-level decision-making. However, agroecology emphasises the co-creation of knowledge, participatory learning, and stronger relations across value chains, and for this reason, these should be further investigated [562]. For example, the integration of blockchain technologies can promote environmental sustainability and efficient resource contribution and enhance trust and traceability while optimising inventory and distribution [563], and thus, it should be further developed. Similarly, different types of sensors should be developed to provide a richer picture of agroecosystem functions (e.g., pollinator activity through insect traps with camera sensors, multi-sensor integrated approaches for soil nutrient cycles monitoring) [564–566] along with robotics and automation platforms that are better adapted to agroecological environments and handle multicultural systems [132]. From the abovementioned discussion, it is clear that a better coupling between digitalisation and agroecology at socio-technical levels through participatory design is needed to empower all actors across value chains under the principles of agroecology [24,562,567]. Also, the socio-cultural drivers and barriers that affect the adoption level of digital tools that can be utilised as enablers of agroecology should be further investigated at regional, cultural, and traditional levels [568,569], along with the suggested technologies referred to above.

5. Study Limitations

The present literature review, while providing valuable insights into the intersection of digital tools and agroecology in crop production, is subject to several limitations that warrant consideration. Firstly, the query structure employed, relying on specific keywords, inherently narrowed the scope of included articles. This approach, while necessary for focus, may have inadvertently excluded relevant studies that utilised alternative terminologies, focused on related but not directly matched concepts, or were published in disciplines less accustomed to the precise phrasing used in the search string, particularly at the nuanced interface of "digital tools" and "agroecology." Secondly, the review's reliance on a defined number of years (2012 to 2024 as seen in the initial analysis) means that foundational research published prior to this period, or very recent, cutting-edge developments that have not yet been indexed or widely disseminated, may have been omitted. Thirdly, the exclusive use of one database for article retrieval introduces a potential bias, as different academic databases index varying sets of journals across diverse disciplines and geographical regions. This singular source might not fully capture the global breadth and depth of research, leading to an incomplete representation of the existing literature [570]. Additionally, the broad focus of this survey did not allow narrowing of the focus to the most significant cases where digital tools have the most impact [571]. Finally, the inherent subjectivity in interpreting and categorising information from diverse research articles and impact assessments, coupled with the rapidly evolving nature of digital agriculture, means that the findings represent a snapshot in time and may not fully capture the dynamic landscape of this interdisciplinary field [572].

6. Conclusions

As it was presented above, crop-related digital tools are more focused on input reduction, which corresponds to the first tier of agroecology. This indicates that current developments remain primarily efficiency-oriented and do not fully integrate systemic agroecological approaches that can be radical and transformative across value chains and regions. Accordingly, the impact assessment revealed that although the digital tools can contribute positively to economic, environmental, and social dimensions, the majority of studies focused on economic outcomes, with limited evaluation of environmental and social impacts.

Thus, future research on the digitalisation of crop production should place greater emphasis on assessing and enhancing the environmental and social contributions of digital tools, integrating appropriate agroecological frameworks into their development. Efforts should also explore the potential of underutilised technologies, such as ground-based robots, wearable sensors, and diversified environmental monitoring systems, across a wider range of production stages, including breeding, land preparation, and post-harvest marketing. More databases (e.g., IEEE, Scopus, Google Scholar) should be included in future studies to better map the relevant technologies. Finally, digital tools should be co-designed with farmers and other stakeholders to identify potential socio-cultural drivers and barriers that may differ and to consequently ensure social acceptability, foster participatory knowledge exchange, and support transitions toward higher tiers of agroecology.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/agronomy15112600/s1, Supplementary File: The PRISMA checklist and the supporting information on the scientific literature review assessment.

Author Contributions: E.A.: Writing—Review and Editing, Writing—Original Draft, Visualisation, Methodology, Investigation, Formal Analysis, Data Curation, Conceptualisation, Supervision; A.K.: Writing—Original Draft, Methodology, Investigation, Data Curation; G.P.: Writing—Original Draft, Visualisation, Investigation, Data Curation; A.V.: Writing—Review and Editing, Investigation, Data Curation; M.G.: Writing—Review and Editing, Investigation, Data Curation; J.K.: Investigation, Data Curation; A.G.: Investigation, Data Curation; C.E.M.: Investigation, Data Curation; E.M.: Writing—Review and Editing, Investigation, Data Curation; K.B.: Writing—Review and Editing, Investigation, Data Curation; A.M.: Investigation, Data Curation; S.D.B.-K.: Writing—Review and Editing, Investigation, Data Curation; S.M.P.: Writing—Review and Editing, Investigation, Data Curation; A.L.: Writing—Review and Editing, Investigation, Data Curation; L.P.: Writing—Review and Editing, Investigation, Data Curation; J.R.: Investigation, Data Curation; M.K.: Investigation, Data Curation; H.D.: Investigation, Data Curation; F.S.: Investigation, Data Curation; Project Administration; A.M.-A.: Writing—Review and Editing, Investigation, Data Curation; Project Administration; S.F.: Writing—Review and Editing, Conceptualisation, Supervision. All authors have read and agreed to the published version of the manuscript.

Funding: The research has been funded by the European Union project D4AgEcol: 'DIGITALISATION FOR AGROECOLOGY', under Grant Agreement No.: 101060759. The research has been co-funded by UK Research and Innovation (UKRI Reference No. 10037994).

Data Availability Statement: The original contributions presented in this study are included in the Supplementary Materials. Further inquiries can be directed to the corresponding author.

Acknowledgments: We would like to thank Karl Reimand and Andreas Niedermayr for their valuable help in the investigation. During the preparation of this manuscript/study, the authors used Quillbot for the purposes of grammar. The authors have reviewed and edited the output and take full responsibility for the content of this publication.

Conflicts of Interest: Authors Junia Rojic, Minkyeong Kim and Heiner Denzer were employed by the company Pessl Instruments GmbH. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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