



# Disruptive technologies in agricultural operations: a systematic review of AI-driven AgriTech research

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## Abstract

The evolving field of disruptive technologies has recently gained significant interest in various industries, including agriculture. The fourth industrial revolution has reshaped the context of agricultural technology (AgriTech) with applications of artificial intelligence (AI) and a strong focus on data-driven analytical techniques. Motivated by the advances in AgriTech for agrarian operations, the study presents a state-of-the-art review of the research advances which are, evolving in a fast pace over the last decades (due to the disruptive potential of the technological context). Following a systematic literature approach, we develop a categorisation of the various types of AgriTech, as well as the associated AI-driven techniques which form the continuously shifting definition of AgriTech. The contribution primarily draws on the conceptualisation and awareness about AI-driven AgriTech context relevant to the agricultural operations for smart, efficient, and sustainable farming. The study provides a single normative reference for the definition, context and future directions of the field for further research towards the operational context of AgriTech. Our findings indicate that AgriTech research and the disruptive potential of AI in the agricultural sector are still in infancy in Operations Research. Through the systematic review, we also intend to inform a wide range of agricultural stakeholders (farmers, agripreneurs, scholars and practitioners) and to provide research agenda for a growing field with multiple potentialities for the future of the agricultural operations.

**Keywords** Disruptive technologies · Agricultural operations · Agricultural technology (AgriTech) · Artificial intelligence (AI) · Systematic literature review

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## 1 Introduction

The last decade has gone through a data-driven evolution in multiple sectors and fields. The fourth industrial revolution (Industry 4.0) is vast and spans from the rise of social media to smart devices resulting in the development of ground-breaking innovative digital operating models, leading to radical changes to the lifestyle and the daily lives of individuals (George et al. 2014; Knippenberg et al. 2015; Mikalef and Pateli 2017). The data-driven evolution and emergent technologies can generate different kinds of value; value in terms of business and societal goals (Günther et al. 2017; Mikalef et al. 2020), but also can lead to the creation of sustainable societies (Pappas et al. 2018). In the agricultural field, unlike most of the technological disruptions, the transition from conventional operating models of farming to modern but also to smart data-driven ones come out of necessity to feed the ever-growing population coupled with environmental triggers (Yahya 2018). As highlighted in the United Nations Sustainable Development Goals (UN SDGs), food security is a key goal that should bring to the table serious intent and innovative solutions as it is highlighted through subsequent UN reports (2017a, 2017b, 2017c), and recent studies (Sharif and Irani 2017).

The current farming methods and models of conventional agricultural processes, where the focus was on mass production of food, led to an unsustainable solution both for the environment and for the individuals and societies on a long-term basis (Tripicchio et al. 2015). While farming more land will not be a viable solution anymore, alternative ways should be followed in order to increase the yield and crops (Wolfert et al. 2017). Therefore, the arising requirements for a redesign of the farming production call for innovative sustainability-oriented smart solutions applied in the farming fields (Fountas et al. 2015; Lampridi et al. 2019). Within this context, disruptive technologies have a critical role to play, through the development of breakthrough ideas for precise agricultural processes, data analytics and AI techniques (Miranda et al. 2019). Feeding the future population relies highly on a sustainable agricultural system; therefore an optimal solution for the sustainability could be viewed through the applications of smart and precision techniques in agrarian operations (for the problems associated with the arable land and environmental efficiency).

The flourishing field of Agricultural Technology (AgriTech) and the interest in relevant investments come as no surprise, as well as a growing enthusiasm from practitioners and researchers from various fields, with regards to the AI application of AgriTech in the associated operations and practices (Boshkoska et al. 2019; Carayannis et al. 2018; Lezoche et al. 2020). The field of Agriculture has immense potential to benefit from the technological disruption (Kaloxylou et al. 2012; Nukala et al. 2016; Wolfert et al. 2017), through the use of technologies as the Internet of Things (IoT), sensors, smart devices, Big Data Analytics, as well as Machine Learning (ML) and a vast range of techniques of Artificial Intelligence (AI). Recent studies like those of Boshoska et al. (2019) present decision support systems for knowledge dissemination across agri-food value chains and also Lezoche et al. (2020) with an initial scoping survey around the term of Agriculture 4.0, identify the lack of research from an operational perspective and open the way forward for more studies around data-driven technological advances in the fields of agricultural operations. There is still a wide scope in the operations field to explore the processes, practices and the overall disruption of the agricultural sector due to the AI applications of AgriTech. The review of the extant literature will define the term of AgriTech, explore the context, develop a research agenda, and act as a normative reference for future research.

Initially, in this study, the focus is on exploring the AgriTech evolution throughout the last decade, in order to provide a definition of the term “AgriTech” associated with the recent advances of the field and linked to AI-driven applications. Secondly, through a synthesis of 205 studies, the review identifies the various types and techniques applied in the agricultural operations relevant to the context of “technology for the farming operations”. Following this direction, through the pool of studies identified and analysed for the systematic review, the paper iteratively distinguishes the Artificial Intelligence (AI) techniques for the farm management cycle and subsequent implications for the Agricultural Operations. Finally, the study provides a review of the implications of AI-driven AgriTech in Agricultural Operations, potential applications for the Agricultural Sector and the multiple opportunities and challenges for research and practice.

## 2 The evolution of agricultural technology (AgriTech)

The introduction of technology in the agricultural processes originates back to the centuries since the Agricultural Age (ancient years—appx 9000 BC), and dates to the Information Age and the “Big Data” Evolution which recently expands to various sectors. The need for technology in the farming field stems from the strong motivation to feed the world population; which evolved the agricultural area through the years to facilitate modern practices and processes to meet the ever-growing needs (Corallo et al. 2018). Applications of technology in farming are attempting to enhance the agrarian operations through sophisticated information and communication developments (Tsolakis, Bechtsis, and Bochtis 2019; Tsolakis, Bechtsis, and Srai 2019). Aspects of the agricultural industry such as crop cultivation management and control, quality management, transport of food products and food preservation may all be enhanced by taking into account their domain-specific requirements and translating them into the respective functional design, development and applications by ICT experts (Barmounakis et al. 2015; Miranda et al. 2019).

Agricultural Technology (AgriTech) is not defined always in the same way; the current definition is strongly associated with AI applications and refers to the *progression from farming to smart farming*, which flourished in three periods (Miranda et al. 2019; Wolfert et al. 2017). Initially, the Agricultural Evolution which has started from ancient years to approximately 1920s and infers mostly to the pre-industrial agriculture. Characteristics and advancements of this period include the labour intensity and essential subsistence farming in the form of small-scale farms (the agricultural activities as a focus on feeding the farmer’s family). As technology evolved rapidly during the Industrial Evolution, the model of industrial and massive agriculture started to arise, following a high industrialised pattern. The robust industrialisation of agriculture was transformed with technological advances like tractors, harvesters, chemical fertilisers and seeds, and developed the model of the large-scale commercial farms. However, the industrial model of farming was proven unsustainable (Darnhofer et al. 2009; Miranda et al. 2019; Rigby et al. 2001; Wezel et al. 2009, 2014). Recently, new practices were introduced based on data-intensive disruptive ways for solving agricultural problems (Miranda et al. 2019; Wolfert et al. 2017) introducing an unprecedented AI-driven approach for Agricultural Technology (AgriTech). Table 1 illustrates the progression stages from conventional farming to modern and smart farming.

The Information and Data Evolution, as well as Artificial Intelligence (AI) techniques, have entered the smart and precision agriculture, which is characterised by the exploitation of disruptive technologies (e.g. multi-source data, sensors on farm equipment and plants,

**Table 1** The progression from conventional farming to smart farming

	Period	Characteristics	Scope	Advances of technology
Agricultural evolution	Pre-industrial agriculture (ancient years to appx. 1920)	Labour intensity	Essential subsistence farming (small farms)	Manual processes, conventional farming tools
Industrial evolution	Industrial and Massive Agriculture (1920 to appx. 2010)	Industrialisation	Large commercial farms	Tractors, harvesters, chemical fertilisers and seeds
Information and data evolution	Smart and precision agriculture (2010 onwards)	Data intensity	Smart farms (larger or smaller)	Exploiting through AI multi-source data, sensors on farm equipment and plants, satellite images and weather tracking monitoring of water and fertiliser use (precision farming)

satellite images and weather tracking, monitoring of water and fertiliser use) for precision farming. The model of data-intensive agriculture is applied in both large-scale and small-scale farms and transforms the way they operate while providing multiple forms of value for the farmer, consumer, as well as the society (Miranda et al. 2019).

The rapid evolution of AgriTech motivates the study herein, as the technology was always a part of the agricultural practices, even in pre-industrial farming operations. However, the AI applications of disruptive technologies in the agrarian fields and the modern smart farming operating models, present an AI-driven approach of AgriTech that should be further discussed. The study initially has a view to developing a categorisation of the various types and techniques which define the term “AgriTech” within the studies of the last decade and explore a future research agenda for consideration. Numerous studies separately describe AgriTech, mainly from a solution-driven perspective (more than 200 as identified from the systematic review). However, there are only a few of recent AgriTech studies to provide a clear link of AI-applications with a business and operations focus. So far, AgriTech research refers solely on the technical aspects and not the operational background surrounding the applications as a single source of normative text that culminates historical works and, outlines foresight research. Therefore, a systematic review and synthesis of the extant literature will act as a single reference source to motivate new insights of AI-driven AgriTech research and applications from an operations perspective.

### 3 Research methodology

The study follows a systematic review research design to synthesise and present a comprehensive, structured analysis of the normative literature in the scope of “Technology for Agricultural Operations”. Thus, the research builds on the Systematic Literature Review (SLR) methodology proposed by Tranfield et al. (2003) to review the extant field. The evidence-based reviews as proposed by Tranfield et al. (2003) is a successfully employed methodology for a systematic and state-of-the-art comprehensive way to review the literature in the various fields of management (see, e.g. Adams et al. 2015; Colicchia and Strozzi 2012; Delbufalo 2012; Kitchenham et al. 2009; Sivarajah et al. 2017; Spanaki et al. 2018). According to Tranfield et al. (2003), undertaking a literature review to provide *the manifestation for enlightening policy and practice in any discipline*, is a key research objective for the academic and practitioner communities. This further adds to the significance of such literature review papers that may further result in aiding evidence-based decision-making in future research endeavours. The study followed the methodology of evidence-based reviews (Denyer and Tranfield 2009; Tranfield et al. 2003) which differs from the conventional narrative reviews through a systematic, structured and explicit approach in the selection of the studies in Agricultural Technology and Operations area (at every stage in this paper), employing rigorous and reproducible methods of evaluation.

Seminal literature on SLR process (e.g. Delbufalo 2012; Kitchenham et al. 2009, 2012) assert that an SLR is designed to (a) support in generating a sense of joint effort, importance and openness between the research studies in order to impede unproductive recurrence of effort, (b) support in connecting potential research to the queries and issues that have been modelled by previous research studies (e.g. most of those paper reviewed as part of this research exercise) and (c) develop the approaches employed to assemble and synthesise preceding pragmatic evidence. In the interest of parsimony, a meticulous though

not exhaustive SLR was carried out in this paper by following the three-stage approach (Tranfield et al. 2003):

- Stage 1—Planning the review process—defining the research aim and objectives; preparing the proposal and developing the review protocol;
- Stage 2—Conducting the Review Process—Identifying, selecting, evaluating, and synthesising the pertinent research studies; and
- Stage 3—Reporting and Dissemination of the Overall Research Results—Descriptive reporting of results and thematic reporting of journal articles.

Following the three-stage approach, the next Sect. 3.1 summarises the definition of the aim and objectives, including the proposal and Sect. 3.2. summarises the review protocol. Sect. 3.3 describes the Scopus database searching process of the relevant articles. An overview of the selected studies is presented in 3.4, where the study demographics are discussed in brief to provide an initial view of the field. Finally, the reporting and dissemination the overall results will be discussed in the following sections of the paper.

### 3.1 Defining the research aim and objectives and preparing the proposal

As highlighted in the introduction section, this research aims to present a comprehensive systematic review of the Agricultural Technology (AgriTech) applications and techniques theorised/proposed/employed AI for Agricultural Operations to provide a holistic understanding of this landscape with the objective of making sound investment decisions. In doing so, the paper's focus is on systematically analysing and synthesising the extant research published in Agricultural Operations area. More specifically, the authors seek to answer the following three principal questions:

- *Question 1:* What are the various disruptive technologies presented for the operations management processes of the Agricultural sector over the last decades?
- *Question 2:* What are the distinct types and categories of Agricultural Technology (AgriTech)?
- *Question 3:* What is the role of artificial intelligence (AI) for AgriTech applications in agricultural operations?

### 3.2 The review protocol

The review protocol was developed around three questions as mentioned in a previous section (i.e. Q1, Q2 and Q3) by following the prescriptive three-staged approach. Essentially, the responses to the question Q3 results from the review of the 205 papers for Q1 and Q2. The review process ensured that the seven conditions highlighted in Table 2 were strictly adhered to ensure that an effective and reproducible database examining process highlighting the inclusion and exclusion criteria for each of the review process.

### 3.3 Scopus database searching process and results

The use of databases step of the review protocol reports on the steps and activities of the database searching process and demonstrates the outcomes both descriptively and

**Table 2** The review protocol

Review conditions	Description
Use of database	Scopus database was used to undertake the search for published articles in the area of Technology for Agricultural Operations. The rationale for using this database was based on its extensive coverage of journal articles almost reaching 22,800 titles from over 5000 international publishers, including coverage of approximately 21,950 peer-reviewed journals on different areas
Quality control	<i>Inclusion Criteria:</i> To ensure quality, the review considered only published peer-reviewed journal (including articles in press) by selecting the ‘Article’ option from the Document Type option <i>Exclusion Criteria:</i> Grey literature and other document types such as conference articles, trade publications, books series, book or book chapter, and editorials were omitted
Publication year	<i>Inclusion Criteria:</i> The selected articles were published only between 1984 and early 2020, in order to cover the whole transition from AgriTech to AI-driven AgriTech approaches
Publication Language	<i>Inclusion Criteria:</i> Only articles published in the English language were considered <i>Exclusion Criteria:</i> Articles published in any other languages were not considered
Types of publication articles	<i>Inclusion Criteria:</i> The selected articles were only empirical-based (i.e. case-study, survey, results, analytical, etc.), models and conceptual papers <i>Exclusion Criteria:</i> Review papers were excluded; however, these studies were used in Stage 1 (to define the aim and objectives and the proposal)
Article suitability review	<i>Inclusion Criteria:</i> Article suitability process was conducted by ensuring that selected articles contained several key phrases throughout the paper, including, title, abstract, keywords and thereafter the whole paper. This process focuses on those section(s) that explicitly referred to Agricultural Technology and Operations
Finalising articles	Finalising article suitability for the review was done by reading the full remaining article for essential research perspective and manuscripts with empirical data. This process ensured the alignment between the selected articles and the research review objectives

synthetically by searching for relevant articles through the Scopus database (Delbufalo 2012). In order to identify the relevant articles through the Scopus Database, the following keywords search criteria was used following the conditions 2, 3 and 4 of Table 2. This process resulted in 9951 publications, of which 543 were left as relevant after filtering according to the barring conditions.

A title and abstract analysis were thereafter conducted on the extracted articles based on the conditions 5 and 6. At the end of the process, 205 articles were considered for further investigation (Table 3). Finally, the authors followed the quality criteria matrix as adopted by Pittaway et al. (2004). In this step, the selected 205 articles (Appendix II -included studies) were further scanned through the criteria highlighted in conditions 6 and 7. Besides extracting data related to Q1, Q2 and Q3, the descriptive investigation also produced graphs and tables designed to contain the yearly publications, geographical regions of where studies were conducted, the journal outlets and the various AI-driven solutions published in AgriTech research for all 205 articles (Appendix I- publication demographics).

**Table 3** The search process and results

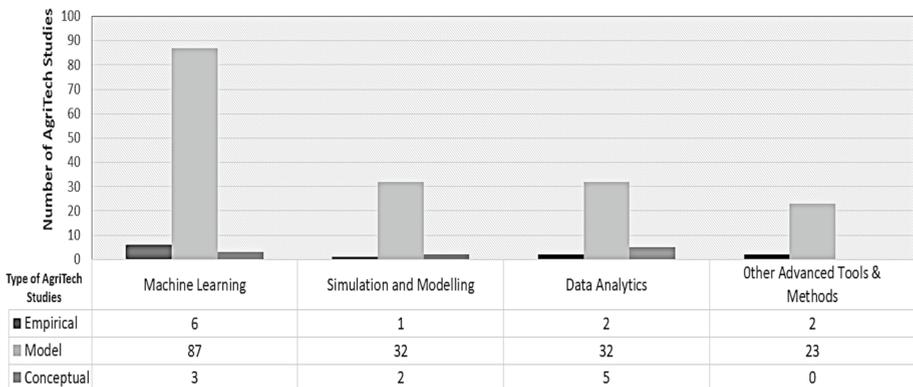
Search process	
Electronic database search	9840 articles
Hand search	76 articles
Citation search	35 articles
Total	9951 articles
<i>Title and abstract review excluded (n = 9408)</i>	
Total	543 articles
<i>Full text analysis excluded (n = 338)</i>	
Total	205 journal articles

### 3.4 Demographics of the selected studies

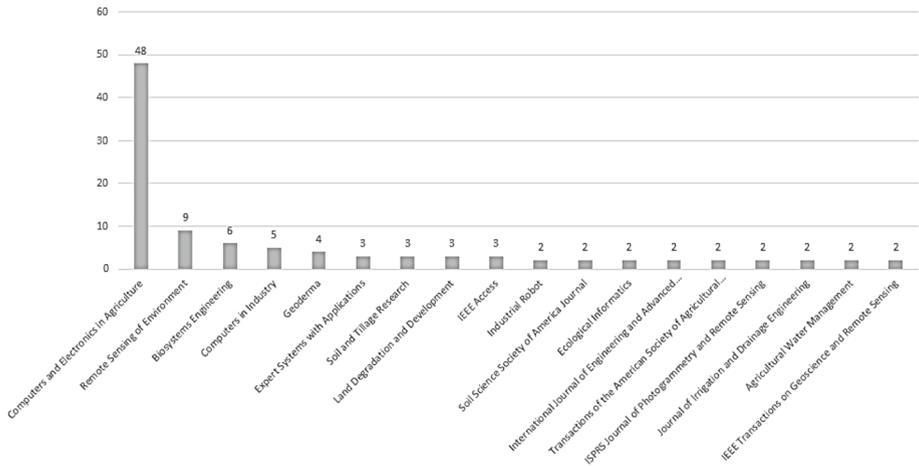
The included research studies of the last decades with a focus on AgriTech, present an evolving rise of AI-driven solutions for the agricultural stakeholders. The potential value of any AgriTech interventions can appear through the application of multiple advanced solutions that could be applied in the farming field. Agricultural stakeholders can apply the AgriTech solutions for processing a large volume of multi-form data and information into meaningful knowledge. There are multiple opportunities nowadays for agricultural stakeholders to apply AgriTech interventions for everyday farming operations, however, in order these interventions to be successful, advanced solutions are required to transform the farming operations in AI-driven approaches. The review of the studies in the field indicated that the top three most applied solutions in the AgriTech research (Fig. 1) consist of AI-driven solutions and they are namely, Machine Learning (ML), Modelling and Simulation, and Data Analytics.

The key journal outlets where the studies in the field of AgriTech and AI have been published appear in Fig. 2.

Many studies have been published in the *Computers and Electronics in Agriculture* outlet (C=48). Unsurprisingly, the findings highlight the majority of the AI-driven AgriTech studies have been published in technical and agriculture-based outlets, such as



**Fig. 1** Number and type of AI-driven AgriTech studies



**Fig. 2** Journals publishing AgriTech research

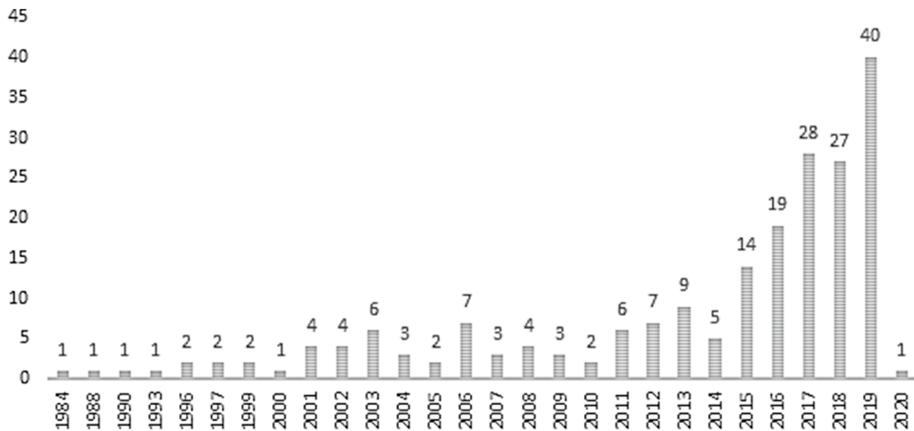
*Biosystems Engineering* and *Remote Sensing of Environment*. There is clear evidence to highlight the need for more research to be published in business, operations and information technology and systems management journals (except a Special Issue in *Computers in Industry*, where 5 studies were published in 2019) that allows exploring organisational and business efficiency-related issues of applying AgriTech.

The yearly studies published in the field of AI-driven AgriTech (Fig. 2) highlight an evolving interest in the field, with the most significant number of publications recorded for the year 2019 (with  $C=40$ , 19.6%), followed by years 2017–18 (with  $C=28$  and 27, 13%). With fewer publications (i.e. below the 10 mark) were recorded from 2015 and a range of one and two articles between 1984 and 2000. Figure 1 below illustrates a rise in the number of journal articles in the AgriTech and AI research area from 2015 onwards until 2019, which is still evolving even in early 2020.

An initial screening of the identified studies revealed three interesting directions of the AgriTech Research:

1. The AgriTech studies are presenting AI-driven solutions from a technical perspective. However, there is a low number of conceptual and empirical studies (Fig. 1 -methodological approaches in the studies).
2. The AgriTech research is flourishing in mostly engineering and biosciences fields, with a lack of research in the field of operations and management (Fig. 2- publication outlets)
3. There is an evolving interest in AgriTech research in the last decade (Fig. 3 -yearly publications).

The demographics of the identified studies show the awareness and importance of this area among the academic community, practitioners, and even governments worldwide. Despite the increase in the number of articles on disruptive technologies for Agriculture, AI-driven AgriTech research is still in infancy, especially in terms of conceptual but also empirical studies. The research domain requires further in-depth conceptual as well as empirical studies, especially case study and survey-based research to explain



**Fig. 3** Publications per year in the field of AgriTech

the implication and the potential social and industrial change and transformation (from business and operations perspectives).

#### 4 Synthesis of the AgriTech operations and applications

The systematic review revealed various types of AgriTech in the analysed studies based on the representative aspects of the disruptive technology which is applied and described in each study. The identification of the types of AgriTech was built initially from the framework of Tsolakis et al. (2019), where three categories were defined according to the aspects of the specific technological application (physical, cyber, and cyber-physical). However, the research synthesis provided here expands the typology of Tsolakis et al. (2019) by scoping the studies on those on AI-driven AgriTech and defining the application type by operation area and the operational challenges that each category could support.

The categorisation in application types by operation area supports future directions for Operations Management by expanding the scope to an operations-oriented and process-based approach. The *physical AgriTech application types* are defined as the disruptive technologies for agricultural operations which can replace not only human labour tasks (e.g. robotic machinery, irrigation systems etc.) but also present physical features as the “hardware” of AgriTech, mostly this category refers to machinery and tools for agricultural tasks. On the other hand, the *cyber aspects of AgriTech* appear as applications which are mostly platform-software related and have a strong link with data analytics and decision support systems for agricultural operations whereas there is also a third category which is the combination of the two previous, the *cyber-physical application* area, which refers mostly to smart agricultural machinery and/ or robotics for the farm which include the hardware and the software for data analysis and predictive/prescriptive tailored decision-making, advice and recommendations. The cyber-physical applications have been developed within the last decade and follow the design and production patterns of the fourth industrial revolution applying disruptive technologies and AI techniques in the farming field.

#### 4.1 AgriTech physical aspects per operation type and application area

The Physical AgriTech aspects can be categorised and related to water operations, aerial operations, land operations and a combination of them based on their relevance with plants or animals (livestock). Table 4 shows the different AgriTech physical applications per operation type, application area and the associated challenges of the agricultural sector addressed by each solution.

Our analysis revealed the existence of only one study for physical aerial operations and the non-existence of water-based physical operations. In terms of studies providing context around the physical aerial operations, Radcliffe et al. (2018) focussed on the tree canopy and sky of an orchard row to be used by an autonomous vehicle platform to navigate through the centre of the tree rows. The research studies on AgriTech physical aspects mostly consider land operations on both plant and animal applications and their implementation using a variety of AgriTech tools and techniques such as satellite imagery, surveillance systems, agricultural machinery, field training, robots, and algorithms for machine learning and data processing.

In terms of the physical applications on plants, Kussul et al. (2017) used architecture to classify land cover and crop types through multi-temporal multi-source satellite imagery (deep learning). Studies as the one of Ennouri et al. (2019) discussed the importance of remote sensing technology, while the study of Seelan et al. (2003) is extending the context of remote sensing and implements a learning community approach for educating farmers with the associated technologies (field training). Other approaches of remote sensing imagery technologies in studies about physical AgriTech for land and aerial operations, present training algorithms to explore image processing techniques (Pydipati et al. 2006) for plant colour features differentiation (data analytics, algorithm). Some studies also show multiple irrigation mapping algorithms through machine learning techniques (Ozdogan and Gutman 2008), but also odometry robotic systems for imagery collection (Ericson and Åstrand 2018). Robotic applications for land surveillance appear in studies such as those of Ko et al. (2015) that presented a mobile robotic platform for agricultural applications, Edan et al. (1993) presented a robot harvester for melons using 3-D, real-time animation, Bayar (2017) developed an autonomous detection mobile robotic system of tree trunks, and

**Table 4** AgriTech physical aspects per operation type and application area

Operation type	No. of studies per application area		Challenges addressed by AgriTech solution
	Plant	Animal (Livestock)	
Water	0	0	
Aerial	1	0	Tree condition checking
Land	11	3	Land and crop classification Land & animal surveillance Farmer education Plant condition assessment Irrigation mapping Crop harvesting Insect infestations assessment Automated feeding of animals Health assessment of animals
Combination	1	0	Environmental parameters monitoring

Kounalakis et al. (2019) with robotic weed recognition for grasslands. From these applications various benefits were archived such as reduced picking time of crops, increase of harvest efficiency, and faster detection of plant health issues.

Regarding the physical aspects of AgriTech in animal-related application areas, the studies focus on automated feeding technologies for pregnant sows (Manteuffel et al. 2011) and surveillance systems for social interaction monitoring in dairy stalls of cows (Guzhva et al. 2016), behaviour and living condition monitoring through an animal-mounted sensor, and automatic surveillance intelligent systems to automatically and continuously monitor the health animals (Yazdanbakhsh et al. 2017). Also, one study with a combination of land, water, and aerial operations was identified (Mesas-Carrascosa et al. 2015), where an open-source hardware system is presented for monitoring different environmental parameters.

## 4.2 AgriTech cyber aspects per operation type and application area

The AgriTech cyber aspects can be categorised into three forms: analytics, virtual/simulation, and algorithmic-based on the different types of tools and techniques applied (which will be explained further in a following designated section). These have been further classified in water, aerial, land operations or a combination of them as well as in terms of their application on animals or plants (see Table 5).

In the analytics categorisation, research directions are often focussed on water applications on plants and with combinations of soft-computing methods, as well as simulations and algorithms to improve the planning and management of water resources and to detect

**Table 5** AgriTech cyber aspects per operation type and application area

Operation type	No. of studies per application area						Challenges addressed by AgriTech solution
	Analytics platforms		Virtual/simulation		Proposed algorithms		
	Plant	Animal	Plant	Animal	Plant	Animal	
Water	3	4	2	0	3	1	Irrigation planning and management Chemicals detection Automated resource collection from animals Climate control of animals housing Water resources allocation Soil assessment Animal condition analysis
Aerial	4	0	0	0	0	0	Image processing for enabling precision agriculture Emissions modelling Air temperature estimation Yield classification
Land	4	1	3	1	7	3	Crop & climatic conditions assessment Animal behaviour prediction Animal disease control
Combination	4	1	1	0	3	1	Yield optimisation Natural resource availability assessment Assessment of soil changes and their implications

chemicals in the water. For example, Gocic et al. (2015) analysed different soft-computing methods, i.e. genetic programming (GP), support vector machine-firefly algorithm (SVM-FFA), artificial neural network (ANN), and support vector machine-wavelet (SVM-Wavelet) to forecast reference evapotranspiration (ET<sub>0</sub>) which is used for planning and managing water resources in agriculture. While, Wang et al. (2006) simulated agriculture derived groundwater nitrate pollution patterns using the artificial neural network (ANN) technique, and Brumbelow and Georgakakos (2007) presented an application of physiologically based crop models to near-optimisation of “‘planning-level” irrigation schedules.

Studies using analytics in water applications for animals use a combination of simulation, optimisation and lab experiments. Halachmi (2009), for example, simulated the hierarchical order and cow queue length in an automatic milking system. Another example appears in the study of Aerts and Berckmans (2004), where a virtual chicken (VirChick) was developed for computer-aided design and engineering of climate controllers for poultry house. On a similar note, Chen et al. (2016) formulated a deterministic optimisation model to alleviate the impact of seasonal drought, which allocates available irrigation water resources to maximise annual returns in a reservoir-pond irrigation system. In the field of animal applications, O’Connell et al. (2015) analysed the animal conditions through artificial insemination in a lab environment.

AgriTech aerial analytics applications on plants are considering autonomous vehicles, meta-models, and image features capturing methods. Several studies used analytics for non-rigid image feature matching in precision agriculture via probabilistic inference with regularisation techniques (e.g. Yu et al. 2017), and meta-models for complex environmental and ecological processes over large geographic areas for emissions modelling of N<sub>2</sub>O/sland, climate (e.g. Perlman et al. 2014). Other studies, such as the study of Sanikhani et al. (2018), analysed the design and application of data-intelligent models for air temperature estimation without climate-based inputs using geographic factors. While in Radcliffe et al. (2018), the authors used an autonomous vehicle platform guided by machine vision system for tree canopy and sky of an orchard row.

There are numerous studies about analytics applications on land for plants that use a wide range of AgriTech, such as mixed spectral responses, neural networks, fuzzy logic, and index development. In this categorisation, some studies include approaches presenting training methods for vector machines (Foody and Mathur 2006), neural networks in combination with fuzzy techniques in the field of agro-ecological modelling (Schultz and Wieland 1997), presence-only geographic species distribution models, i.e. MaxEnt for agricultural crop suitability mapping (Heumann et al. 2011), and IoT- cloud-enabled measurement indexes for temperature and humidity assessment of crops (Mekala and Viswanathan 2019).

A combination of aerial, water and land application studies that used analytics for land and animals adopted a wide range of AgriTech applications. Some of these AgriTech applications are simulation models in combination with geographic information systems and optimisation, as well as algorithms with analytics. For example, McKinion et al. (2001) investigated the use of precision agriculture in combination with simulation models, and geographic information systems in a cotton production system to optimise yields while minimising water and nitrogen inputs. Other studies in the same categorisation evaluated the future impact of soil degradation using simulation and optimisation (Sonneveld and Keyzer 2003). At the same time, other studies used innovative unmanned airborne vehicles to visualise and quantify soil physical changes and their influence on surface morphology at submillimetre resolution (Kaiser et al. 2018) and identify the yield-limiting factors for farmers using real crop data (Paz et al. 2002).

With regards to simulation techniques, the analysis revealed the existence of two studies that used simulation for water and land applications. Specifically, the interest of simulation models is about the agricultural water drainage challenge at the beginning of the cropping season (Jury et al. 2003), and the combination of unsaturated flow and groundwater (Kumar and Singh 2003).

There is also a stream of literature discussing the simulation models problems theoretically as population dynamics and population genetics of *H. zea* in mixed cropping systems (Storer et al. 2003), and the effects of tillage and traffic on crop production in dryland farming systems (Li et al. 2008). While the study of Luecke (2012) developed a virtual reality interface that could be used in operating a combine when harvesting virtual crops. Other simulation models are presented for soil–plant–atmosphere in order to examine the influence of a winter cereal rye cover crop on nitrate–N losses (Feyereisen et al. 2007).

There is a wide range of algorithmic models presented in the reviewed studies for the improvement of water efficiency, optimisation of irrigation planning, and assessment of drainage. Such studies show stochastic dynamic programming models (SDPM) to analyse a farmer’s optimal investment strategy to adopt a water-efficient drip irrigation system or a sprinkler irrigation systems (Heumesser et al. 2012), soil and assessment tool algorithms to relate drainage volume to water table depth (Moriassi et al. 2011), and physiologically based crop models to near-optimisation of “planning-level” irrigation schedules (Brumbe-low and Georgakakos 2007). Only one study was identified with algorithmic water-based applications on animals which used neural network applications to intelligent data analysis in the field of animal science (Fernández et al. 2006).

There are a plethora of studies that developed AgriTech algorithmic applications for land and plants. Some of the studies presented neural networks (Moshou et al. 2001) for the classification of crops and weeds, and hyperspectral imagery for deflection segmentation using classifiers based on Artificial Neural Networks and Decision Trees (Gómez-Sanchis et al. 2012). While studies such as those of Richards et al. (2009) considered the knowledge content of farmer seed systems in the light of a distinction drawn in artificial intelligence research between supervised and unsupervised learning and suggested an alternative approach supported by functional genomic analysis. On a similar note, but using the fuzzy logic approach for decision systems, the review identified a few studies for decisions around specific nitrogen fertilisation (Papadopoulos et al. 2011), hybrid learning of fuzzy cognitive maps for sugarcane yield classification (Natarajan et al. 2016), and flexible irrigation scheduling for different irrigation districts and cases (Yang et al. 2017).

Algorithmic land applications on animals are not that frequent, and most of the studies towards this direction present mostly machine learning techniques and computer programming. In this category, there are research projects applying machine learning techniques to detect oestrus in dairy cows (Scott Mitchell et al. 1996), convolutional neural networks for body condition estimation on cows from depth images (Rodríguez Alvarez et al. 2018), and computer programs for the prototypical knowledge base for cows (Oltjen et al. 1990).

Combinations of water and land algorithmic applications on plants are focusing on soil forecasting and planning. In this category, Keller et al. (2007) developed a new model, ‘SoilFlex-LLWR’, which combines a soil compaction model with the least limiting water range (LLWR) concept. Also, there are models for monthly soil moisture forecasting (Prasad et al. 2018), and machine learning assessments of soil drying for agricultural planning (Coopersmith et al. 2016). While algorithms and models about various applications related to animal and livestock conditions and welfare are very limited. In the few studies of that category, there are examples of studies such as Gonzalez et al. (2015) that developed an algorithm for unsupervised behavioural classification of electronic data collected

at high frequency from collar-mounted motion and GPS sensors in grazing cattle for automatic and real-time monitoring of behaviour with a high spatial and temporal resolution.

### 4.3 AgriTech cyber-physical applications

AgriTech cyber-physical applications refer to applications that combine physical aspects with cyber aspects of AgriTech, e.g. smart tractors, drones connected with sensors at the field, and a number of smart devices for applying AI for agricultural processes. Table 6 presents a summary of the AgriTech cyber-physical applications per application area.

There are numerous studies about AgriTech analytical cyber-physical applications for tasks related to land and plants that develop platforms, algorithms for robots, and decision support systems. These applications are presented as:

- A suboptimal path for agricultural mobile robots combining neural network methods and genetic algorithms (Noguchi and Terao 1997);
- a private Internet of Things (IoT) enabled platform for the research in precision agriculture and ecological monitoring domains (Popović et al. 2017);
- a decision-making system for intelligent chemical control (Guedes et al. 2013);
- a research data collection platform for ISO 11,783 compatible and retrofit farm equipment to control agricultural operations on the farm (Backman et al. 2019);
- a methodology for olive oil traceability to interconnect field and industry to share information (Bayano-Tejero et al. 2019).

There are also several studies about AgriTech cyber-physical analytical applications on land and animals that used sensors, imagery, and algorithms. For example, Manteuffel et al. (2011) implemented a call feeding for pregnant sows which is a modular extension of a conventional electronic feeder and communicates via a network. Another study (Sakai et al. 2019) classified goat behaviours using 9-axis multi-sensor data and a machine learning algorithm. In studies such as Ivushkin et al. (2019), the authors presented a method for livestock mapping of pastured to produce spatial–temporal consistent maps, while Bishop et al. (2019) developed a multi-purpose livestock vocalisation algorithm with machine learning techniques for a continuous acoustic monitoring system. Combination studies about land and water cyber-physical

**Table 6** AgriTech cyber-physical applications per application area

Operation type	No. of studies per application area by technique						Challenges addressed by AgriTech Solution
	Analytics platforms		Virtual/simulation		Proposed algorithms		
	Plant	Animal	Plant	Animal	Plant	Animal	
Water	0	0	0	0	1	0	Mimicking crop irrigation
Aerial	1	0	1	0	1	0	Insect mapping on crops Plant analysis
Land	5	3	2	1	4	3	Traceability enhancement Chemical control Animal feeding Animal condition analysis Livestock mapping
Combination	2	0	0	0	0	0	Soil quantification

analytics for plants are using drones and imagery technologies for soil quantification. Kaiser et al. (2018) used unmanned airborne vehicle to visualise and quantify soil physical changes and their influence on surface morphology at submillimetre resolution. Another research direction quantified soil pore characteristics using a high-resolution X-ray CT scanner linked to soil friability assessed using the drop shatter method (Munkholm et al. 2012). The review indicated that analytics applications of AgriTech in aerial studies of cyber-physical systems for plants are very limited, while for animals are absent. In this research category, there are studies, for example, that present Unmanned Aerial Vehicles (UAVs) to collect imagery about sunflower and maze crops to solve the problem of weed mapping for precision agriculture and proposed a method for pattern selection (Pérez-Ortiz et al. 2016).

Studies about cyber-physical simulation applications focussing on land and plants use Discrete Element Model (DEM) to simulate a deep tillage tool and its interaction with soil to address the stratified soil layers in agricultural fields (Zeng et al. 2017), and simulation of a comprehensive framework that transforms data acquisition platforms and makes possible the ‘‘plug-and-play’’ connection of various sensors (Fernandes et al. 2013). Only one study was identified that considered aerial cyber-physical application using simulation. To be more precise, the study of (Andersen et al. 2005) explored the potential of using area-based binocular stereo vision for three-dimensional (3-D) analysis of single plants and estimation of geometric attributes such as height and total leaf area.

Studies about algorithmic cyber-physical applications on land and plants are focussing on machine learning algorithms and robotics. Such studies present automatic observation systems for wheat heading stage based on computer vision (Zhu et al. 2016) remotely assessing soil conditions (Coopersmith et al. 2016), spiking neural networks (SNNs) for remote sensing spatiotemporal analysis of image time series (Bose et al. 2016), robotic weed recognition applications for precision agriculture in grasslands (Kounalakis et al. 2019).

Cyber-physical algorithms for animals consider machine learning techniques and suggested new algorithmic functions. An example of these is a supervised machine learning technique to classify cattle behaviour patterns recorded using collar systems with 3-axis accelerometer and magnetometer, fitted to individual dairy cows to infer their physical behaviours (Dutta et al. 2015). Cattle behaviours were also classified upon the ‘‘one-vs-all’’ framework (Smith et al. 2016). Studies about conditions for pig development used RGB-D computer vision and machine learning, physical (images from pigs), algorithm (machine learning and RGB-D computer vision) to estimate the muscularity of live pigs (Alshaf et al. 2019). Only one study about cyber-physical water application on plants was found, while studies about water-based applications on animals are non-existent. On that basis, Viani et al. (2017) developed an innovative methodology based on Fuzzy Logic (FL) to mimic the farmers’ experience and best practices for crop irrigation. No cyber-physical studies about aerial applications on animals and plants were found.

## 5 Future considerations and the way forward

The applications of AI and disruptive technologies in Agricultural Operations are providing new ways to increase the yield, optimise the processes and enhance the sustainability of agricultural production (Miranda et al. 2019; Wolfert et al. 2017). The focus of AgriTech and smart farming appears mostly around AI-driven approaches and agricultural data analytics platforms collecting data in order to provide planting advice, tailored recommendations and a general sense-making process of the data stemming from the fields (Boshkoska et al. 2019; Miranda

et al. 2019). The systematic review of AgriTech research has unravelled multiple opportunities for disruptive technologies based on AI-techniques and applications, with a focus mostly on creating value for the Agricultural Sector (Boshkoska et al. 2019; Tzounis et al. 2017).

Through the use of AgriTech and applications of AI, the Agricultural Sector can operate and transform the conventional practices through data analytics and machine learning techniques, which are able to provide targeted advice on each case (Kouadio et al. 2018). The use of the data can envisage competitive advantage even by itself not only for the farmers but also for the whole Agricultural Sector. By collecting data from the field, the farmer can gain knowledge according to each case's requirements, as well as follow prescriptions in advance and provide them as a solution to broader farming problems (Kale and Sonavane 2019; Kouadio et al. 2018; Renuka and Terdal 2019; Tatapudi and Suresh Varma 2019). For instance, this will help farmers in mapping the fields, monitor crop canopy remotely, check for anomalies and take precautionary actions in order to implement more proactive, resilient and sustainable agricultural practices.

AI-driven AgriTech is developed from cross-section disciplines involving a variety of smart and data-intensive approaches, disruptive technologies—spanning from smart devices, sensors, and big data to drone technology and robotics (Miranda et al. 2019; Tsolakis, Bechtsis, and Bochtis 2019). Smart monitoring, irrigation, images and temperature from the field, as well as the soil or livestock conditions, to name a few, can provide a pool of data for tailored recommendations to the farmer and any interested parties (Karim et al. 2017; Manoj Athreya et al. 2019; Tsolakis, Bechtsis, and Bochtis 2019). Data analytics, machine learning, robotics, or any other AI technique applied in the farm through automated practices could provide recommendations, warnings, or even efficiency monitoring and enhance the farming operations, suggesting opportunities for Agriculture to be viable again (Corallo et al. 2018).

The data evolution and cutting-edge, disruptive technologies have shifted the paradigm of conventional and modern agriculture and farming to smart and intelligent approaches. Following data-driven analytical technologies and high-performance computing, the AI context was reshaped and re-emerged in the last decade, creating numerous opportunities for smart and data-intensive solutions in the AgriTech domain. Hence, AgriTech could be defined in today's Agricultural context as the use of data-driven smart technologies and analytical methods for enhancing the farming practices, operations and decision-making in order to achieve in multiple forms and ways the economic efficiency and environmental sustainability of the Agricultural field.

The authors of this research would like to highlight that the findings of this systematic review should be considered within the context of its methodological limitations. It is to be noted that In order to be thorough and conduct an exhaustive search in an SLR research, other notable databases need to be used which helps with being able to cross-check as well as explore in-depth the area of interest. So, the use of only one database (i.e. Scopus) may be considered as a limitation in this research. The authors followed a strict review protocol to conduct a comprehensive search through the Scopus database to mitigate the risks associated with relying on a single database. A summary of the implications of AI-driven AgriTech applications and the associated future research required in the field of operations is highlighted in Table 7.

## 6 Implications to practice

Triggered by the urgency to deal with food security, the digital disruption of Agriculture is unique by its roots and therefore the motivation to adopt AgriTech should be genuine from farmers (CEMA—European Agricultural Machinery 2017). While

**Table 7** Future considerations for AgriTech research

Area of research	Future research considerations
Farm management cycle and operations	<p>How Virtual and Augmented Reality can enhance the applications of precision agriculture?</p> <p>How can Smart Indoor Vertical Farming evolve and support farming production?</p> <p>How can future AgriTech innovations reshape the farming processes?</p>
Analytics platforms	<p>How can farming analytics (Farm to Fork Analytics) contribute to sustainability challenges?</p> <p>How can Farming Analytics provide an advantage to small, medium and larger farms?</p>
Sensor technology	<p>How can IoT-enabled platforms improve farming production for the sustainability of AgriFood sector?</p> <p>How can IoT-enabled regenerative agriculture evolve the next decade?</p> <p>What are the required data sharing policies in order to ensure privacy and competitive advantage for the operations of each farm?</p>
Robotics	<p>What are the next AI and Robotics Ventures (ARV) for socially and environmentally responsible farming?</p> <p>What is the role of AgriTech robots in the new agricultural operations?</p> <p>How can 3D mapping and monitoring contribute to the sustainability goals of each farm?</p> <p>How can hybrid (aerial-ground) drones improve operation management in an unmanned way for agricultural monitoring?</p> <p>How can drones be used for remote agricultural operations in crisis situations?</p> <p>How can hybrid drones and manned aviators collaborate for precision agriculture?</p>

farmers are keen on applying innovative and emerging technologies (e.g. in previous centuries and decades early adopters started with the wheel, tractors, fertilisers etc.) the industrial revolution resulted in large-scale farming and massive production at any cost, in a socially and environmentally unsustainable, and economically inefficient way (Yahya 2018; Zambon et al. 2019). Despite the challenges, already there is a new range of motivated farmers and agricultural start-ups adopting disruptive technologies to manage their operations in digitalised and automated ways. Disruptive technologies in Agricultural Sector, often dubbed as AgriTech, can be widely used by a new generation of farmers but also *Agripreneurs*, a new category of farmer-entrepreneurs trialling AgriTech innovations for the farming field (Carayannis et al. 2018). Agripreneurs consist of a new breed of educated entrepreneurs who merge their knowledge and expertise on agriculture and farming with an acquired business and management approach in order to bridge the gap between farming practices and applied *agribusiness* principles. Among agribusiness principles, sustainability is becoming increasingly crucial for the success of Agrichains. Sustainable Agrichains are dealing with continued complexities of stakeholders' demands on Sustainable Development. As sustainability is becoming more complex, dealing with its challenges are also becoming challenging and costly for Agripreneurs. The initial pragmatic solution is to incorporate Agritech interventions to tackle the sustainability challenges in Agrichains. Over the last decade, advances in Agritech solutions research have made a significant contribution towards the understanding and implementation of sustainability criteria in farming and Agrichains.

In a nutshell, with the application of new AgriTech technologies, every farmer could potentially become an Agripreneur and a champion of sustainability in the near future. Thus, the role of Operations Management is vital to bridge the research gap between

“Agricultural Technology” and “Sustainable Agricultural Operations” and equip the future generation of farmers-agripreneurs.

## 7 Conclusions

Drawing on the recent advances of disruptive technologies for agriculture the review provided interesting insight in the field of AI-driven AgriTech research. The synthesis of the literature can act as a normative reference for the Operations discipline when studying the thematic area of disruptive agricultural technologies. The key findings of this review in line with the initial three research questions are as follows:

- Key Types of Disruptive Technologies and Categories of AgriTech (Q1 and Q2): The analysis highlights that majority of the types of disruptive technologies in the agricultural sector can be categorised into three application areas. The first is (1) *Physical AgriTech application* type which highlights the use of machinery and tools for agricultural operations which can replace not only human labour tasks (e.g. robotic machinery, irrigation systems etc.) but also presents physical features as the “hardware” of AgriTech. The second is (2) *Cyber AgriTech* as applications which are mostly platform-software related and have a strong link with data analytics and decision support systems for agricultural operations. Finally, (3) *Cyber-physical* application area which mainly refers to the use of smart agricultural machinery and/ or robotics for the farm which include the hardware and the software for data analysis and predictive/prescriptive tailored decision-making, advice and recommendations.
- Role of AI applications in Agricultural Operations (Q3): The analysis highlighted that AI-driven AgriTech could disrupt Agricultural Operations and provide new ways of farming practices. There is still an open discussion around various implications and future considerations in the Operations field. The Operations scholars have a key role to play in future AgriTech research in order to define and efficiently design the operational context around AI-driven AgriTech.

The findings of the systematic review will assist both academics and practitioners with interest in the agricultural sector to develop new solutions based on the challenges identified in this paper. Also, it integrates multiple disciplines and approaches for different research fields (spanning from engineering, biotechnology, to data science, cognitive processes of decision-making, etc.). It is evident from the comprehensive review conducted that there is growing interest in the use of AI and data science to support the use of disruptive technologies; motivated to enhance productivity, reduce cost, integrate systems and, promote sustainable farming and food production practice.

## Appendix

See Table 8.

**Table 8** Details of the 205 included studies

Paper ID	References
1	Foody GM, Mathur A (2006) The use of small training sets containing mixed pixels for accurate hard image classification: Training on mixed spectral responses for classification by a SVM. <i>Remote Sens Environ</i> 103:179–189. <a href="https://doi.org/10.1016/j.rse.2006.04.001">https://doi.org/10.1016/j.rse.2006.04.001</a>
2	Kussul N, Lavreniuk M, Skakun S, Shelestov A (2017) Deep Learning Classification of Land Cover and Crop Types Using Remote Sensing Data. <i>IEEE Geosci Remote Sens Lett</i> 14:778–782. <a href="https://doi.org/10.1109/LGRS.2017.2681128">https://doi.org/10.1109/LGRS.2017.2681128</a>
3	Seelan SK, Laguette S, Casady GM, Seielstad GA (2003) Remote sensing applications for precision agriculture: A learning community approach. <i>Remote Sens Environ</i> 88:157–169. <a href="https://doi.org/10.1016/j.rse.2003.04.007">https://doi.org/10.1016/j.rse.2003.04.007</a>
4	Pydipati R, Burks TF, Lee WS (2006) Identification of citrus disease using color texture features and discriminant analysis. <i>Comput Electron Agric</i> 52:49–59. <a href="https://doi.org/10.1016/j.compag.2006.01.004">https://doi.org/10.1016/j.compag.2006.01.004</a>
5	Ozdogan M, Gutman G (2008) A new methodology to map irrigated areas using multi-temporal MODIS and ancillary data: An application example in the continental US. <i>Remote Sens Environ</i> 112:3520–3537. <a href="https://doi.org/10.1016/j.rse.2008.04.010">https://doi.org/10.1016/j.rse.2008.04.010</a>
6	Bourennane H, Douay F, Sterckeman T, et al. (2010) Mapping of anthropogenic trace elements inputs in agricultural topsoil from Northern France using enrichment factors. <i>Geoderma</i> 157:165–174. <a href="https://doi.org/10.1016/j.geoderma.2010.04.009">https://doi.org/10.1016/j.geoderma.2010.04.009</a>
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9	Rushton J, Thornton PK, Otte MJ (1999) Methods of economic impact assessment. <i>OIE Rev Sci Tech</i> 18:315–342. <a href="https://doi.org/10.20506/rst.18.2.1172">https://doi.org/10.20506/rst.18.2.1172</a>
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11	Berenstein R, Shahar OB, Shapiro A, Edan Y (2010) Grape clusters and foliage detection algorithms for autonomous selective vineyard sprayer. <i>Intell Serv Robot</i> 3:233–243. <a href="https://doi.org/10.1007/s11370-010-0078-z">https://doi.org/10.1007/s11370-010-0078-z</a>
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15	Noguchi N, Terao H (1997) Path planning of an agricultural mobile robot by neural network and genetic algorithm. <i>Comput Electron Agric</i> 18:187–204
16	Minervini M, Abdelsamea MM, Tsafaris SA (2014) Image-based plant phenotyping with incremental learning and active contours. <i>Ecol Inform</i> 23:35–48. <a href="https://doi.org/10.1016/j.ecoinf.2013.07.004">https://doi.org/10.1016/j.ecoinf.2013.07.004</a>
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**Table 8** (continued)

Paper ID	References
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21	Dutta R, Smith D, Rawnsley R, et al. (2015) Dynamic cattle behavioural classification using supervised ensemble classifiers. <i>Comput Electron Agric</i> 111:18–28. <a href="https://doi.org/10.1016/j.compag.2014.12.002">https://doi.org/10.1016/j.compag.2014.12.002</a>
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## Compliance with ethical standards

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