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Towards smart farming: Systems, frameworks and exploitation of multiple sources

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A B S T R A C T

Agriculture is by its nature a complicated scientific field, related to a wide range of expertise, skills, methods and processes which can be effectively supported by computerized systems. There have been many efforts towards the establishment of an automated agriculture framework, capable to control both the incoming data and the corresponding processes. The recent advances in the Information and Communication Technologies (ICT) domain have the capability to collect, process and analyze data from different sources while materializing the concept of agriculture intelligence. The thriving environment for the implementation of different agriculture systems is justified by a series of technologies that offer the prospect of improving agricultural productivity through the intensive use of data. The concept of big data in agriculture is not exclusively related to big volume, but also on the variety and velocity of the collected data. Big data is a key concept for the future development of agriculture as it offers unprecedented capabilities and it enables various tools and services capable to change its current status.

This survey paper covers the state-of-the-art agriculture systems and big data architectures both in research and commercial status in an effort to bridge the knowledge gap between agriculture systems and exploitation of big data. The first part of the paper is devoted to the exploration of the existing agriculture systems, providing the necessary background information for their evolution until they have reached the current status, able to support different platforms and handle multiple sources of information. The second part of the survey is focused on the exploitation of multiple sources of information, providing information for both the nature of the data and the combination of different sources of data in order to explore the full potential of ICT systems in agriculture.

1. Introduction

The concept of agriculture includes a series of different scientific fields, where some of them are directly connected to land cultivation (water control, crop growing, harvesting, etc.) [1,2], while some other are the natural expansion of the agriculture model (engineering, economics, management, etc.) [3,4]. Advances in different areas of the Information and Communication Technologies (ICT) domain in combination with the need for improvement of agriculture productivity [5], both for food security issues and environmental impact, have created the field of smart agriculture.

Precision agriculture (or smart farming) can significantly boost the agriculture production both in terms of productivity and sustainability [6,7]. Although productivity seems to be the driven force of every technological advance in agriculture, the importance of sustainability should not be neglected. Sustainability emerges as a major issue throughout the spectrum of human activity [8,9], thus one of the goals of smart agriculture is the minimization of the environmental impact of the agriculture activities.

The field that is considered as predecessor of smart farming is precision agriculture [10,11]. Although the two terms seem identical, they have differences, as the concept of smart farming goes beyond in-field

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management tasks and expands to a wider ecosystem considering the constant integration of new technologies (cloud computing, Internet of Things (IoT), Geographic Information System (GIS), etc.) to the existing infrastructure and the exploitation of data from multiple sources (descriptive, vector and remote sensing).

To address the challenges of constant integration of new technologies in the area of smart farming, complex systems have to be built where concepts of scalability [12] and interoperability [13] are their foundations. Novel approaches have to be followed in the upcoming agriculture systems in order to fully exploit the emerging digital technologies, able to collect, store and model huge amounts of data coming from various heterogeneous sources. This heterogeneity in data poses the greatest challenge towards the improvement of agriculture productivity through the extensive exploitation of the generated data. The challenge is the constant extraction of knowledge from raw data, thus the agriculture systems should incorporate new methods and techniques such as data mining [14], applied statistics [15] and machine learning [16–19] that would enable the potential of the collected data.

Prerequisite for better understating the concept of big data in agriculture is the exploration of small data, as described in Coble et al. [20]. The remarkable growth in producers ability to collect data from multiple on-site sources and their combination with data collected from Global Navigation Satellite Systems (GNSS) [21,22] or from national authorities have formed complex data warehouses with heterogeneous data and eventually the combination of those fragments of information (small data) have created the area of big data in agriculture. Considering the spectrum of applications of big data in various areas and domains it is difficult to provide a definition to cover every possible scenario, but in the agriculture sector big data is mostly related with the variety of data, rather with volume or velocity.

The remainder of this article is organized as follows. Section 2 provides an overview for the field of smart agriculture and defines the objectives of this literature review paper. Section 3 describes the existing agriculture systems and frameworks, including both early theoretical frameworks and state-of-the-art agriculture system, capable of exploiting different technologies which have been employed and tested in different sites. Section 4 provides an in-depth analysis of big data in agriculture focusing on the variety of sources. The research work presented in this section is classified based on the sources of data that are used, starting from the simplest form of data (textual descriptive data) and ending up to complicated data warehoused capable to combine descriptive, vector and imagery data, exploiting IoT devices, satellite images and archives from national authorities. Section 5 presents challenges and technological trends towards the exploitation of multiple sources in the era of big data in agriculture. Finally, Section 6 concludes this paper and presents future directions.

2. Motivation

Although smart agriculture as a term is recently introduced, there are already numerous commercial solutions and platforms [27,31,23–26,28–30] indicating the market demand. The majority of the commercial solutions are focusing on the collection, integration, and visualization of data collected with the use of IoT sensors, whereas only few offer predictive analytics [24,26].

The technological advances of the recent years have created the need for constant development of the existing commercial systems and solutions in every industry sector, including agriculture. The successful commercial solutions constantly invest in new technologies and consider the progress in research level. This paper offers a complete survey on existing research agriculture systems and an overview of the state-of-the-art techniques for collecting data and it can be used as point of reference for future commercial systems.

Focusing on the capabilities of the existing agriculture systems and in the combination of different kind of data from multiple sources, this literature review provides a useful insight for both the state-of-the-art agriculture systems and the status of big data in the agriculture sector, with a focus on the aspect of data variety. The recent related review papers have different orientations, as the paper of Kamilaris et al. [32] focuses on big data and is equally devoted in the three V's (volume, velocity, variety), offering an in-depth review of tools, algorithms and sources of data. We provide the necessary background knowledge for the topic of big data in agriculture, but through a more tangible approach using existing agriculture systems and focusing on the process of data collection. Both Wolfert et al. [33], and Coble et al. [20] present the wider concept of big data in agriculture including management, legislation, research methods and applications, but they overlook the important connection of agricultural systems with the exploitation of the collected data. The in-depth review of Morota et al. [34] is focused on big data in livestock rather than farm agriculture. On contrary, we focus on farm agriculture and how it can be benefited with the use of big data and other related technological advances.

Apart from the use of big data in agriculture, other approaches in recent reviews in smart agriculture include a climate-oriented approach, stressing the importance of the climate change in the agriculture sector. In Long et al. [35] a conceptual framework is proposed, aiming to tackle the existing barriers in socio-economic level and the successful adoption of the recent technological advances, emphasizing on their analysis and potential to smart farming. We adopt a more data-driven approach compared to [35], reviewing the existing agriculture systems and the current techniques for collecting land data. The review paper of Zougmoré et al. [36] connects climate change with adjustments that should take place in different agriculture sub-sectors, and it is focused on strategies and policies, rather on the existing technologies and approaches that form the current status of smart agriculture.

The contribution of this work lies on four main axes. The first one is the presentation of the agriculture systems' development. The second point of contribution for this review paper is the research of the sources that are used for the step of data collection in different agriculture architectures, schemes and applications. The third objective of the paper is to reveal the connection between big data and agriculture systems. The last contribution of the paper is the identification of the future trends and developments in the field providing a critical view on the potential of the ICT sector in agriculture systems.

The first part of this extensive survey paper illustrates the evolution of agriculture systems that is achieved through the integration of the available technological advances, starting from simple evaluation schemes to integration of state-of-the-art technological concepts such as cloud development and big data. The second part of the paper is dedicated to big data in agriculture, adopting a practical approach and focusing on the methods and techniques that are used for collecting and combining different sources of data.

Overall, the aim of this paper is to present the evolution of agriculture systems and how they adopt the incoming data from various sources and this is attempted through elaborate and critical projection on the following steps:

- Present the advancement of agriculture systems, indicating the differences through time and the trends.
- Stress the importance of new technologies in agriculture systems.
- Present the different sources of data and their usability in the agriculture domain.
- Explain how big data and the evolution of IoT enablers are exploited within a computational intelligence platform in the agriculture sector.

3. Agriculture systems and frameworks

The recent advances in ICT have significantly progressed the agriculture sector through services offered from computer-based agriculture systems in problems that were previously faced only through empirical knowledge of few people. The ongoing land degradation [37,38] in combination with a potential food security crisis [39,40] and the need for adoption of a more sustainable agriculture approach (productive, profitable, environmentally-friendly) [41,42], require the exploitation of the recent technological advantages.

In order to fully utilize the latest technological advances, novel schemes, products and applications should be developed that will be able to handle heterogeneous data, perform data analysis and offer personalized interfaces [43,44]. In this section we present the evolution of agriculture systems through time, starting from simple rules and ending up to data-driven approaches.

3.1. The early steps

Probably the most influential framework that has been proposed is from the Food and Agriculture Organization (FAO) [45–47] receiving many updates, as many research works have been relied on it in order to expand its capabilities. The fundamental concept of the methodology is based on two objectives: (i) provide suitable land classifications and (ii) evaluate the land procedures. The FAO framework has been built based on those two objectives and has developed the concept of matching tables (known as transfer functions) that are designed to calculate the suitability of the land for specific purposes.

In 1983 one of the first modifications of the initial FAO framework developed and published, the Land Evaluation Computer System (LECS) methodology [48]. The LECS methodology is a pragmatic approach that was adopted for a regional study in Sumatra (Indonesia) with the data then available. It is considered as a simple model in relation to more complex land systems that have been proposed later, but it illustrates in a great extent the capabilities that a computerized evaluation offers. LECS uses both physical and economic data in order to provide individual crop recommendations for each land unit on an economic basis. Two stages of analysis take place before the final output, the evaluation of each land unit (considering a soil degradation model) and the potential productivity at three management levels.

In accordance with the FAO's framework, the Automated Land Evaluation System (ALES) [49–51] was proposed in 1990, a computer program that allows land evaluators to build their own knowledge-based system. The proposed model predicts the economic suitability of a land area taking into account different parameters, without having a fixed list for land characteristics or land use requirements. ALES is not considered a user-friendly system, but rather a system designed for experts which does not offer either GIS functions or display the map of the geographical area that is researched.

The development of Geographic Information Systems (GIS) has revolutionized the way people gather, manage, depict, and therefore, interpret data. A GIS has the capability to combine spatial location with different kind of information, as it organizes them into layers and visualizes them using maps and 3D scenes. Maps are used as geographic containers for incorporation of data layers and analytics, such as imagery data, features, and basemaps linked to spreadsheets and tables. As a result, GIS reveals deeper insights into data, patterns, relationships, and eventually provides a more intuitive depiction of data.

GIS technology is applied in different scientific fields, including the agriculture sector, and materializes complicated systems that can communicate, perform analysis, share information, and solve complex problems. Adoption of GIS technologies in the agriculture sector took place in [52] where a MultiCriteria Evaluation (MCE) framework was proposed aiming at the ease of the decision-making process through a finite number of alternatives for the problem of land suitability for agriculture. Eventually a spatial decision support system is created through the integration of MultiCriteria Decision Analysis Approaches (MCDAs) in a GIS environment, which produces land suitability maps using the ELimitation Et Choix Traduisant la REalitÃ©(ELECTRE Tri) [53,54] method.

Based on the concept of automatic methods' inefficiency for any kind of problem if they are not combined with analytical methods, Sys et al. [55][56] modified the FAO methodology through the assignment of the correct severity level for the suitability of the land providing given data values for each land characteristic. The FAO-SYS methodology presents a variance of the method of matching tables which assigns the correct severity level of the land suitability, given data values for each land characteristic. Five different descriptive classes are defined, indicating different levels of the land competency. There are three different sub-categories indicating the suitability of the land, suitable, moderately suitable and marginally suitable, whereas two sub-categories indicate the unsuitability: unsuitable for economic reasons but otherwise marginally suitable, and unsuitable for physical reasons.

Based on the FAO-SYS methodology, Tsoumakas and Vlahavas [57] presented the Intelligent System for Land Evaluation (ISLE), a knowledge-based model with GIS functionality and map interaction capabilities. The system receives the digital map of an area alongside with its geographical database, displays the generated map, evaluates the land units selected by the user according to FAO-SYS methodology and finally visualizes the results of the land units in color. A similar approach based on FAO SYS frameworks exploiting GIS capabilities was also followed in ALSE [58], where a realistic, practicable and functional system was introduced. The necessary modifications realized in order the system to determine the quality of land for different types of crops in tropical and subtropical regions (Malaysia).

A similar approach for the land evaluation is followed by Kalogirou [59], who presented the Intelligent Geographical Information System (LEIGIS), where a land suitability evaluation model is introduced through the combination of expert systems and GIS technologies. The model is based on the FAO land classification for crops and both physical and economic parameters are considered. The novelty of this work lies on the model's ability to alter its rules based on different performance observed in local areas while the map interaction capabilities offer a user-friendly environment that allows the evaluation of spatial datasets without requiring special computer skill.

Focusing on the specific features of the Mediterranean land, De la Rosa et al. [60] introduced the software Mediterranean Land Evaluation Information System (MicroLEIS). MicroLEIS was developed through time receiving significant updates, as it has been originally developed in 1992 for Disk Operating System (DOS) and it has been integrated with many software tools such as databases, statistics, expert systems, neural networks, Web and GIS applications [61], and it has been used for different case studies [62–64]. The software has evolved towards an agro-ecological decision support system following a toolkit approach containing two major components, land evaluation using spatial characteristics and units; data and knowledge engineering through the use of software tools.

One more research work focusing on the Mediterranean area was held by Yialouris et al. [65], where an expert system developed for the diagnosis and treatment of pests, diseases and nutrient disorders of certain vegetable species. The software is offered in more than one language, similar to MicroLEIS, but instead of offering the options of English/Spanish, VEGES is available on Greek/English/French. Concerning the implementation of the system, it is developed through the definition of a series of rules in both natural language and forms of Object-Attribute-Value (OAV). A similar approach to VEGES was followed in LIMEX [66], but with a focus on the assist of the lime cultivation was held by Mahmoud et al. LIMEX is an expert system adopting the KADS methodology [67] for knowledge representation.

3.2. From theoretical frameworks to web and mobile technologies

The growth of the Internet in early '00s has affected the agriculture sector, as web technologies provide significant capabilities to both farmers and agriculture systems. The advances in the agriculture domain through the exploitation of the Internet accomplished in two stages, the first one included general-purpose web technologies aiming at the better collaboration of the involved stakeholders for effective farm management and the second stage concerns the exploitation that IoT offers.

Table 1
Existing agriculture systems. FAO: if the system adopts the FAO framework and directions, GIS: if GIS capabilities are supported, Web: if the system offers a web-interface, Mobile: if the system offers a dedicated mobile interface, Big Data: if big-data architecture was designed, Cloud: if a cloud-based approach was adopted, Area - the area where the test case was applied. *In [71] is explicitly mentioned mobile application as future work.

System	Year	FAO	GIS	Web	Mobile	Big Data	Cloud	Area
LIMEX [66]	1995	No	No	No	No	No	No	Egypt
VEGES [65]	1997	No	No	No	No	No	No	Southern Greece
ISLE [57]	1999	Yes	Yes	No	No	No	No	Greece
LEIGIS [59]	2002	No	Yes	No	No	No	No	Greece
WASS [68]	2004	No	No	Yes	No	No	No	Not Applied
Micro-LEIS [61]	2004	No	Yes	Yes	No	No	No	Andalusia, Spain
Web-GIS [69]	2008	Yes	Yes	Yes	No	No	No	Sri Lanka
Nikilla [70]	2010	No	Yes	Yes	Yes	No	No	Not Applied
MCDA [52]	2012	Yes	Yes	No	No	No	No	Mleta, Algeria
MCC [52]	2012	No	No	Yes	Yes	No	Yes	Not Applied
ALSE [58]	2013	No	Yes	No	No	No	No	Malaysia
RemoteAgri [71]	2014	No	Yes	Yes	No*	No	No	Greece
Reznik [72]	2017	No	Yes	Yes	Yes	Yes	Yes	Czech Republic
AaaS [73]	2017	No	No	Yes	Yes	Yes	Yes	India

The integration of IoT capabilities to the agriculture domain has established Agriculture 2.0, where sensor networks have a prominent role in data collection and in the automation of the agriculture procedures.

In 2004, Hu et al. [68] proposed a Web-based agricultural support system with the acronym WASS, focusing on the organizational structure of a complete agriculture system. The proposed system exploits the capabilities that Web offers for collaboration (chat rooms, video conferencing, etc.) creating a meta-laboratory that spans in multiple geographical areas. Following the same principles of collaboration that Web can offer a Web-based GIS consulting system was introduced in Jayasinghe and Machida [69], providing information for tomato and cabbage cultivation in areas of Sri Lanka. Both research works apply already known and widely-used Web technologies applied in the agriculture sector, addressing mostly problems of communication between farmers and experts. The importance of the different roles that stakeholders may have in the Web-based farm management systems is stressed in [70]. An architecture is detailed illustrated and partially realized as a proof of concept implementation presenting the technologies and protocols that are used in each layer of it, from the format of the input files to the user entities engaged in the provided services.

Other concepts such as IoT, big data, image processing and cloud computing are applied in the field offering new unexplored capabilities in the field of agriculture. Cloud computing implements the concept of on-demand delivery of compute power, database storage and application, instead of using a local server or a personal computer with predefined capabilities. The cloud providers typically use the “pay-as-you-go” model, providing the opportunity for business to grow without demanding a big initial capital. Cloud computing is classified based on the level of abstraction that offers to the users, and there are three main approaches Infrastructure as a Service (IaaS), Platform as a Service (PaaS) and Software as a Service (SaaS). IaaS offers only basic resources such as virtual-machines and different categories of block storage, PaaS provides the capability to the consumers to deploy and configure their application onto the provided cloud infrastructure, without having to control the underlying infrastructure components (servers, OS, network, etc.), and SaaS is the ultimate level of abstraction, where the consumer has access only to limited user-specific application configuration and settings the application is accessible from different client devices.

Prasad et al. [74] introduced the term of Mobile Cloud Computing in the field of agriculture, which is a combination of the technologies of the mobile and cloud computing. A simple conceptual architecture for agriculture is consisting of three basic components i) farmers education and awareness, i) weather forecasting, and iii) crop advice and analysis. The proposed model is characterized by its authors as ‘a very simple model’ as it targets to the wider acceptance from the farmer’s community, who receive the technology either as SaaS either as IaaS, but without knowing details concerning its implementation.

Influenced from the trend of cloud technologies Gill et al. [73] introduced the concept of Agriculture as a Service (AaaS), where a complete architecture is provided integrating other cloud-related technologies such as SaaS, PaaS and IaaS. The concept for the creation of the architecture is the continuous interaction between different stakeholders in a holistic approach including i) selection, ii) preprocessing, iii) transformation, iv) classification and v) interpretation of the gathered data.

In Table 1 a summarization of the aforementioned agriculture systems with the features of each system take place. The first column depicts the name of the proposed system, the second one indicates the alignment of the system with the FAO methodology, the third column demonstrates if the system includes GIS capabilities, the next two columns exhibit the available interfaces of the application (web-based and mobile), the sixth column indicates the exploitation or not of big data from the proposed agriculture system, the seventh column declares existence or not of a cloud infrastructure, and the last column indicates the area where the system was tested.

From the agriculture systems that are presented in the table, only three systems follow the FAO methodology, and the most recent system adopting the proposed methodology implemented in 2012. The use of GIS is wide-spread in agriculture systems, however it seems that the functionalities provided from GIS are overlooked in some cases where web technologies are enabled. As the use of mobile phones is prominent regardless the geographic location or even the technological background of the users, mobile interfaces are offered to the most recent agriculture systems offering an instant interaction with the users of the system. The latest technological advances (big data and cloud-enabled technologies) that are presented in the paper are applied in three agriculture systems, and the combination of both technologies applied only in two systems.

The constant development of the agriculture system can be easily noticed from the addition of features through time, starting from the inclusion of GIS capabilities and ending up to development of application in cloud infrastructure. Although the FAO framework was a point of reference for both researches and farmers, the recent approaches do not take it into consideration, revealing needs that are beyond a simple land evaluation. The focus of the researches has moved towards the tailoring of the system to specific needs and to the ease of access, thus web-based and mobile applications have gained the interest of both industry and research society. Another point that should be stressed is the lack of GIS capabilities in some of the state-of-the-art systems revealing the need for easily readable information from the users, instead of a process-demanding map interaction. From the evolution of agriculture systems, it becomes evident that the use of diverse information from multiple sources becomes more than a necessity. These aspects are considered in the next section, with the aim of revealing the potential of information extracted from multiple data in smart agriculture.

4. Big data and sources of data in smart agriculture systems

With the emerge of Internet of Things (IoT) the generated data are increasing rapidly and a significant part of them are generated from sensors, actuators and software, providing a useful insight for a number of different topics and problems. The concept of big data is becoming a prominent trend in many and different fields including agriculture, although not every aspect (or dimension) of the concept is covered. A recent review on big data and agriculture [32] considered that only two research work used all of the three basic dimensions of the big data concept. In the aforementioned literature review a number of different areas are included under the term of agriculture, from weather and climate change to supply chain and biodiversity. The term of big data is used often and some times abusively, as only few researchers have the know-how to exploit the capabilities that are offered from the massive amount of data.

This section presents the existing agriculture systems exploiting different sources of information, focusing on the attribute of variety in big data. The initial step towards the exploitation of big data is the combination of data from different sources that would eventually lead to sophisticated data and software architectures in agriculture capable to utilize big data.

4.1. Descriptive data

In this paper we use the term descriptive data in order to classify the data describing the features and the characteristics of the situation or problem that is being studied. Descriptive data are numerical data that have been collected and stored without using any kind of automation, such as analysis of the chemical attributes of the soil in an independent lab. They are the most popular type of data in the agriculture sector and they are widely used for different research questions. The majority of research projects exploit them, since they are easily accessible, often publicly available and relatively reliable as they offered either from publicly services or research organizations. Table 2 illustrates a typical format of descriptive data, where in the first column the years of observation are depicted and the features of the object are represented in the rest of the columns. The table portrays the weather index insurance of specific counties in Mexico, the data are derived from the Secretary of Agriculture, Livestock, Rural Development, Fisheries and Food (SAGARPA) and they have been elaborated from [75].

The impact of precipitation is the main topic both in Tripathi et al. [83] and Fuchs et al. [75], however the two research works have different objectives as the former focuses on downscaling the precipitation index at monthly time scale using a SVM approach and the latter adopts a holistic approach concerning farmer's rainfall insurance problems. Both works use three different databases, applied in specific sites (Mexico, Kamataka-India), use similar features (Table 3) and their methodology can easily be adopted for different case studies.

Table 2
Example of descriptive data as presented in Fuchs et al. [75] describing the weather index insurance's coverage for maize. In the first column the years are depicted, and on the rest of the columns the code of the county, the production value, the premium and the indemnity payments are described.

	Counties	Extension	Value	Premium	Indemnity
2003	5	69,010	24,912,610	2,389,119	0
2004	39	189,742	142,306,500	17,803,054	0
2005	162	756,806	431,086,720	59,951,795	75,726,560
2006	552	1,069,670	625,505,760	68,524,501	11,596,080
2007	507	1,117,200	658,377,600	77,109,615	38,441,200
2008	633	1,532,239	1,197,676,908	192,455,049	73,061,820

The work of Frelat et al. [76] belongs in the wider area of agriculture, as it is focused on food availability, but for sake of completeness we include in our taxonomy. Their methodology uses different databases and their test case covers 93 sites in 17 countries, but it is not clear which features are used from which database.

Table 3 summarizes research work exploiting descriptive data from databases and their included features. Because descriptive data are often freely available from national authorities and research centres, we present the owners of the data that are used in each research work. This approach is also followed in the upcoming tables, in order to guide the reader in the demanding task of data detection and retrieval, where million of data sources exist providing any kind of data. Two of the research works presented in the table [75,76] are related only in national or regional authorities for the collection of datasets, and on research work [83] exploits data from an agency abroad. As agriculture is a sector which is closely connected to the geographical locations where the experiments take place, the databases often contain data that cannot be used in other experiments in different areas.

Considering the features that are used in the reviewed research work of this subsection, there is a wide range of different types of data from air temperature and specific humidity, to country poverty index and family size. The combination of data retrieved from meteorological stations (air temperature, humidity, wind, etc.) and demographic statistics (household information, family size, poverty index) show a great diversity in the used data types, revealing the wide spectrum of application of the agriculture domain and the different goals each research work has. It is notable that none of the three research papers presented in the Table 3 exploits data related to the soil's condition.

4.2. Exploration of vector data

Apart from descriptive data, another source that is widely used is vector data. Vector data represent real world features (parcels, pastures, forest, etc.) within the GIS environment and each vector feature have attributes, which consist of text or numerical information that describe them. In this literature review article we distinguish vector data from remote sensing data, mostly because we emphasize in the collection of data, where vector data is mostly used as a common database integrated in maps, whereas data collected with remote sensing techniques are often collected for specific purpose and they cannot be shared easily amongst research organizations.

In this subsection we explore datasets and features used in modern research work that exploit descriptive and vector data, whereas research studies that also use other forms of data are presented in the next subsections. The majority of the systems that are presented in this subsection are agriculture systems that were analyzed in the first section of the paper where the emphasis was given in the technologies that they support, whereas in this subsection the focus is given in the datasets and the features that are used.

Every research work grouped in this category uses soil maps as vector data and the descriptive data provide additional information for the soil's composition. The descriptive data are composed from different databases characterizing the physical (slope, soil texture, etc.) and chemical attributes (soil pH, organic C(%), etc.) of the soil in the area where the case-study took place. An example of combining vector and descriptive data is the Fig. 1, where the available farmland of Malaysia is evaluated based on the suitability for Mango cultivation. The image offers both geographical points of reference, but also illustrates the results of the analysis that took place in Elsheikh et al. [58].

Meteorological data (rainfall and temperature) have been used to enrich the databases both in Jayasinghe and Machida [69], and Elsheikh et al. [58]. Concerning the source of the data, Elsheikh et al. [58] use

Table 3
Indicative existing research work in the (wider) area of agriculture. Owner: the organization that the used dataset is in its possession, Database: the name of the used database, Features: the characteristics of the databases that have been used in each research work. The research work presented in this table have been limited in the use of only descriptive data.

Authors:	Owner	Database:	Features:
Frelat et al. [76]	Lund University [77]	AFRINT	livestock products, Off farm income, cash crops products, food crop products, cash available, food available, food need, household size crop land used by the farm household (in ha), the livestock herd size (expressed in TLU), the family size (in MAE)
	CCAFS-CGIAR [78]	CGIAR Research Program on Climate Change, Agriculture and FoodSecurity (CCAFS)	
	Cialca [79]	Consortium for Improving Agriculture- based Livelihoods in Central Africa (CIALCA)	
	DFAT - CORAF [80]	Conference des Responsables de Recherche Agronomique Africains Australian Aid (CORAF-AUSAID)	
	n2africa [81]	N2Africa	
	SIMLESA [82]	Sustainable Intensification of Maize and Legume Systems for Food Security in Eastern and Southern Africa (SIMLESA)	
Tripathi et al. [83]	National Oceanic and Atmospheric Administration and Cooperative Institute for Research in Environmental Sciences Climate Diagnostics Center [84]	NCEP/NCAR [85]	air temperature, relative humidity, specific humidity, geo-potential height, zonal, vertical and meridional wind velocities at various pressure levels and sea level pressure.
	Indian Institute of Meteorological Department [86]	Parthasarathy et al. [87]	monthly area weighted rainfall data
	Canadian Center for Climate Modelling and Analysis (CCCma) [88]	Coupled General Circulation Model (CGCM2)	air temperature, specific humidity, geopotential height, zonal and meridional wind velocities at various pressure levels and sea level pressure.
Fuchs et al. [75]	Mexican Ministry of Agriculture [89]	rain-fed dataset	number of hectares sowed and harvested per year, tons of production at the county level
	Mexican Ministry of Agriculture.	Weather index insurance coverage	weather stations used, insured crops (maize, beans, sorghum and barley), number of hectares insured, value of insured production, value of the premiums paid, and indemnity payments (in case a drought occurred).
	Not provided	Program for Direct Assistance in Agriculture (PROCAMPO) [90]	producer level information of the total number of hectares used for production, total assistance amount, received, whether the beneficiary produces in private or communal land and total land size (in hectares)
	National Water Commission	daily rainfall	daily rainfall
	National Population Council (CONAPO) [91]	Poverty Index	County Level Poverty Index
	National Institute of Statistics and Geography (INEGI) [92]	National Household Expenditure and Income Survey (ENIGH) [93]	household level information

the data from the responsible national authority (Department of Irrigation and Drainage / Department of Irrigation and Drainage, Kuala Lampur) whereas Jayasinghe and Machida [69] combines multiple sources of data, such as previously held research work, national authorities and international databases.

The work of Tsoumakas and Vlahavas [57] can be characterized as software-oriented research, as their contribution lies on development of an expert system (ISLE), which is based on previously established expert systems (LEVAL [99], LEVAL 2 [98]). Apart from the established rules, a digital map of the area (owned by the university) is also provided as an input for the system.

The combination of five different sources took place in the work of Mendas and Delali [52], including national authority (ANRH) [94], studies from private-held company (SCET-Tunisia) [95] and open GIS databases (diva, ASTER-GDEM) [96,97]. Although the GIS databases are created through the use of remote sensing techniques, we do not categorize the specific research as remote-sensing-based, as the authors do not provide information for the use and exploitation of the available sources.

Table 4 presents the aforementioned research work, displaying the authors of the research paper in the first column, the owners of the databases that are used in the second column, the names of the databases in columns three and four categorized based on the type of data (descriptive, vector), and the features offered from the entire database in the last column. Research projects that desire to perform combination of different sources of data, must exploit more than one dataset as agriculture datasets rarely mx different types of data. From the 4 research papers in the table, half of them combine databases with vector data in order to get unique features (soil/flood map, terrain, land-use map, etc.) from each database. More than half of the papers combine databases with descriptive data gaining information for the weather (rainfall and temperature) and the soil condition (chemical and physical values). It has to be mentioned that in Jayasinghe and Machida [69] the collected information are named regional experience, as they have been created from measurements and assessments of local experts.

The great advantage that vector data provide is the explicitly definition of boundaries in the tested area, leading to a more precise installation of the available meteorological stations for a future research. On the other hand, as vector data are not used for general-purpose tasks, they are combined with technical descriptive data which include numerical features such as temperature, average rainfall and soil characteristics, creating a database which cannot be re-used easily in other research, because it is case-study oriented.

4.3. Satellite exploitation and remote sensing

The term of remote sensing is mostly used to contrast with the on-site observation and on this paper refers to the use of satellite-based sensors capable to detect and monitor the physical characteristics of an area by measuring the reflected and emitted radiation from the targeted area. Remote sensing techniques are mostly used in earth science disciplines (geology, ecology, meteorology, etc.), but they can also provide

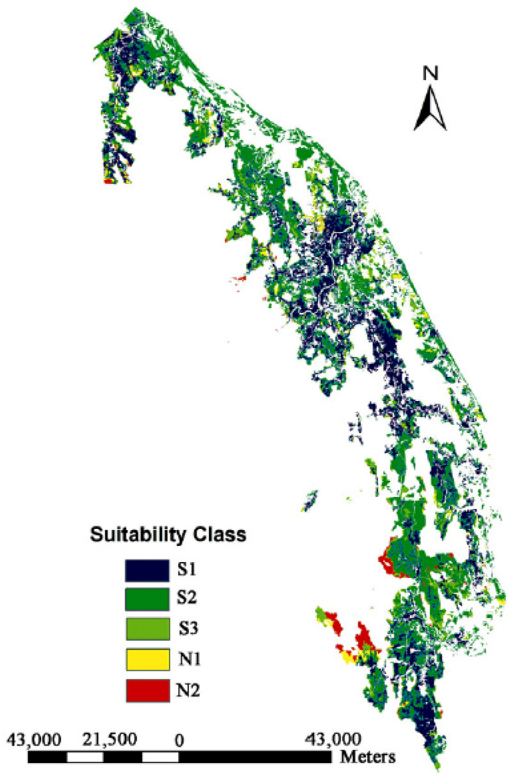

Fig. 1. Suitability map of Malaysia for mango cultivation, according to FAO-SYS classification, as it has been presented in Elsheikh et al. [58].

useful information for the field of agriculture, such as Vegetation Indices (VIs). A VI is a spectral transformation of two or more spectral bands of the electromagnetic spectrum that are measured as reflectance from the Earth's surface designed to enhance the contribution of vegetation properties.

The construction of smoothed VI [112] time series of land-use and land-management through the exploitation of MODIS data [113] takes place in Galford et al. [114], aiming at the detection of changes in land-cover and land-use. Concerning the technical details, the authors have focused on the transformation of the wavelet and the optimal use of its power, rather on the aggregation with different sources of data. The use of a second database took place only as reference data (known cropping patterns) in order to calculate omission and commission errors of the proposed wavelet transformation.

An example of image taken from satellite is depicted in Fig. 2 originated from [114], where a pseudo-color infrared MODIS image is illustrated. The different colors of the image express different types of vegetation, with the bright red areas representing cerradÃ£o savanna native vegetation, the dark greens areas suggest cerrado native vegetation, the bright turquoise blues show row-crop agriculture, and the white areas of the map indicate bare agricultural fields.

A similar approach was also followed in Sakamoto et al. [115], proposing a new method for monitoring remotely the phenological stages of paddy rice. Apart from MODIS/Terra database, statistical data and digital land information was provided from the national authorities in charge and used as descriptive and vectorized data accordingly.

The research project entitled CRC/TR 32, as presented in Waldhoff et al. [116] is one of the few research projects where the adoption of a multi-data approach is the main objective. Remote sensing databases are incorporated with additional official spatial land-use information. Five different remote sensing databases were registered to the official unified spatial database of ATKIS [118], offered from the official national authority of the test-area. Apart from the ATKIS database, the field blocks database [119] was used to enrich the unified spatial database.

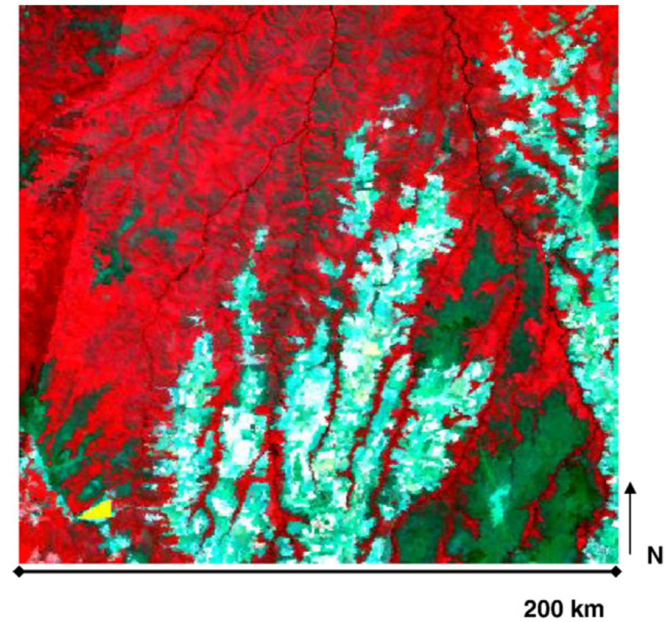

Fig. 2. A pseudo-color infrared MODIS image, illustrating different degrees of VI of the test area, as it has been presented in Galford et al. [114].

Multi-temporal, multi-sensor radar and ancillary spatial data were combined in Barrett et al. [123] in an effort for grassland monitoring. Three different satellites were used to create the synthetic aperture radar (ENVISAT [130], ERS-2 [131], ALOS PALSAR [132]) and four different sources generated both descriptive and vector data.

Research work combining remote sensing, descriptive and vector data are summarized in Table 5. The prominent position of NASA in RS databases is evident, as three out of the four research papers presented in the table exploit a database that is its property. There are alternatives to NASA, as databases from three more space agencies (ISRO, DLR, ESA) are exploited in the research papers presented in this section. Descriptive data are not included either in the work of [114] or in [116], whereas in [115] and [123], they are utilized. Considering the work of Barrett et al. [123], it exploits technical reports which include both maps and descriptive data, therefore these sources belong in both descriptive and GIS data.

As it has been previously stated, in this review paper we classify as remote sensing databases the data that have been created exploiting remote sensing methods and the methods are adequately described, and as vector data we defined databases, which their creating methods are not provided and there are probably manually digitized. With the proper use of remote sensing data useful information can be extracted such as the VI and its products that are used to describe soil's characteristics. Although remote sensing and vector data seem partially to overlap, this rarely happens, because usually vector data are preferred when both types are available and intend to provide the same information. Therefore, remote sensing data are mostly used for extracting advanced information for the VI and other derived products for the test area.

4.4. *Data acquired from IoT and drone sources*

On this review paper we distinguish airborne images from remote sensing due to the different way those two sources are collected. The satellites databases are well-known, reliable with fixed frequency, which may does not fit the requirements of research study. On the other hand, a UAV can be employed when asked and stay focused on a specific area. Considering their use, UAVs have been used either for extraction of

Table 4
Existing research work in the area of agriculture, combining descriptive and vector data. Owner: the organization that the used dataset is in its possession, Database: the name of the used database, which are classified in descriptive and vector database depending on their content, Features/Details: the characteristics of the databases that have been used in each research work.

Authors:	Owner:	Database:		Features / Details:
		Descriptive:	Vector:	
Mendas and Delali [52]	ANRH-Algeria + SCET Tunisa [94,95]	ANRH-Algeria + SCET Tunisa		Water reserve, drainage, permeability, pH, Electrical conductivity, Active limestone, cation exchange capacity, soil texture, soil useful depth
	METI+NASA		ASTER GDEM [96]	Slope
	DIVA-GIS [97]		World population map	Availability of labour
	Not provided		Proximity (roads)	Topographical map in 1/25,000
	Not provided		Nord Sahara 1959	Geographical data
Tsoumakas and Vlahavas [57]	Tsioumberi [98]	LEVAL		Expert system with rules
	Sakellariou and Vlachavas [99]	LEVAL 2		
	Lab of Remote Sensing and GIS, Department of Agriculture, Aristotle University of Thessaloniki [100]		Research map of the area	Digital map
Elsheikh et al. [58]	Department of Agriculture (DOA) [101]	Soil chemical and physical values		Profile data for each type of soil
	DOA		Soil map	Soil semi detail map, scale 1:25,000
	DOA		Terrain	Terrain value extracted from topographic map
	DOA		Land-use map	Scale 1:50,000
	Department of Irrigation and Drainage (DID) [102]	Rainfall precipitation		Monthly rainfall from 34 stations during 10 years
	DOA		Length of dry season map	Scale 1:50:000
	DOA		Drainage network	Scale 1:25:000
	DID		Flood map	Scale 1:30:000
Jayasinghe and Machida [69]	Not provided	Average annual rainfall		
	Not provided	Average annual temperature		
	International Research Institute for Climate and Society (IRI) [103]	Topography		
	Panabokke [104]	Soil properties		
	Urbuan Development Authority [105]	Land use		
	Not provided		District maps	
	DOA	Regional experience		Soil pH Texture drainage organic C (%) CEC (cmolckg-1) Available P (ppm) Elevation (m) Temperature (C) Rainfall (mm)
	Senarath and Dassanayake [106], Senarath and Dassanayake [107], Dassanayake and Hettiarachchi [108], Dassanayake et al. [109], De Silva and Dassanayake [110], Dassanayake and De Silva [111], Panabokke [104]		Soil maps	

various VIs either for identification of cropping patterns, whereas satellite images can only identify the photosynthetic activity of an area.

The evaluation of applicability of MODIS time-series for the task of land-use land-cover, rather the aggregation of multiple sources of data drove the research of Wardlow et al. [133]. The followed approach for MODIS exploitation is quite similar to Galford et al. [114], but the work of Wardlow et al. [133] combines four databases and three different sources of data, whereas Galford et al. [114] used only already known cropping patterns of the area. Apart from the remote sensing sources (MODIS, Landsat ETM), aerial images and a geo-referenced public land survey system were also used.

The remote sensing-based grass growth analysis that took place in the context of TO2 project [134] combines four different sources of data: the vectorized parcels of the test area, satellite data from DMC [135] and SPOT satellites [136], eBee images [137] and descriptive field measurements. TO2 project is a good example of a research which integrates IoT-generated data in a previously available descriptive dataset, a technique that can improve and keep up-to-date existing descriptive datasets.

The reduction of the environmental impact of the agriculture sector through the exploitation of the big data from different sources is the research topic in Řezník et al. [72]. A complete architecture is proposed combining three different kind of data sources (farm machinery telemetry, agrometeorological observation, remote spatial sensors), while big data related technologies are applied, such as array-based databases and parallelizing storages. It is important to be stressed that the authors express their skepticism concerning the term big, both in the title of their work and on the main body of their research.

The definition of management zones through clustering techniques (k-means) is the objective of Schuster et al. [138]. The originality in their work lies on the use of airborne sensors using multi-spectral images for the collection of geo-referenced field, instead of satellite databases. Furthermore, physical characteristics of the soil were collected from both a descriptive dataset and a sensor-based system, combined with a sub-meter accurate Global Positioning System (GPS) receiver. The “Helena fertility trial” database that was used is one exceptional example of a multi-source database, as it incorporates descriptive, vector, image and sensor-based data.

The data collection process is not the main research question of the papers presented in Table 6, therefore in some cases the type of data is not clearly defined. For instance, in Kempenaar et al. [134] one of the datasets has been created with the use of field measurements, that were not collected systematically and different means were used in each time, so that the specific dataset was classified as both IoT-collected and descriptive. The features that are described in Table 6 are more

Table 5
Existing research work in the area of agriculture, combining data derived from remote sensing techniques, descriptive and vector data. Owner: the organization that the used dataset is in its possession, Database: the name of the used database, which are classified in descriptive and vector database depending on their content, Features: the characteristics of the databases that have been used in each research work.

Author:	Owner:	Database:			Features:
		RS:	Historic:	Vector:	
Galford et al. [114]	NASA	MODIS EVI data MOD09 (V004)			8-day, 500 m wavelet-smoothed time series, EVI, band 3
	Not provided			Cropping patterns	Referenced data for Fazenda Santa Lorders
Waldhoff et al. [116]	Chamber of Agriculture of North Rhine-Westphalia [117]			ATKIS [118]	road network, prominent landscape features, residential, industrial and impervious surface areas, forest areas arable land grassland
				Field blocks [119]	coherent parcels (arable land or pasture)
	NASA	ASTER (VNIR only)			
	Indian Space Research Organization (ISRO) [117]	IRS-P6 (LISS III)			
	NASA	Landsat ETM+ (L7)			
	NASA	Landsat TM (L5)			
	German Aerospace Center (DLR) [120]	Rapid Eye			
Sakamoto et al. [115]	NASA	MODIS/Terra data			Smoothed EVI time profile land 3 8d frequency
	Ministry of Agriculture, Forestry and Fisheries (MAFF) of Japan [121]		Statistical data		150 cropping zones
	Ministry of Land, Infrastructure and Transportation of Japan [122]			Digital national land information	paddy fields, upland fields, forest, wasteland, buildings, roads and rail roads, rivers and lakes, seaside, sea, golf courses, and other types
Barrett et al. [123]	European Space Agency (ESA)[124]	ERS			C-band single mode, both asc and desc orbit
		ENVISAT-ASAR			C-band, asc orbit
		ALOS PALSAR			L-band, asc orbits
	Irish Department of Agriculture, Food & the Marine [125]			Irish LPIS	area, crop type, stocking densities
	O'Neill et al. [126], O'Neill et al. [127]		NPWS semi-natural grasslands field survey		515 2m*2m releves
	Forest Service (Ireland) [128]		Forest Inventory & Planning System (FIPS)		
	Fealy et al. [129]		Teagasc-EPA Soils and Subsoils dataset		10m spatial resolution DEM and OSI orthophotagraphy

limited compared to those that have been presented in Table 3, as there is greater focus and some features provided from descriptive databases are not included.

From the four research papers presented in Table 6, only in Schuster et al. [138] RS data are not included in the expanded data collection, revealing the need for combination of different data sources. Considering the features that have been collected from the IoT devices and the UAV, they are limited to meteorological and topographic data (humidity, temperature, wind speed, geodetic information, etc.). Although IoT devices and UAV have been used for the data collection process, they currently cannot offer drastically advanced features, as the existing agriculture systems are not designed to handle and combine efficiently different sources.

5. Discussion & trends

The recent technological advances have created an environment where agriculture systems are thriving and have the potential to have an even greater impact to the society. The presence of commercial systems presented as complete technological solutions and the integration of new technologies in the recent research works indicate the high market and a prosperous research field. New technologies are integrated into existing agriculture systems, creating products capable to cover the requirements of the modern agriculture, and as the demands of the market are growing, improved services are offered. State-of-the-art technologies such as IoT and UAVs have the capability to reform the field of smart farming, if successfully exploited, offering an automatic collection of the data and information generated from aerial photos.

Agriculture systems have been evolved from simple guidelines for land evaluation to complicated systems able to collect and exploit data from different sources, optimize the chain production and ensure its quality. The high standards that have been posed from the development in the field of human-machine interaction, have also posed standards to agriculture systems, where the usability of the system should be the highest possible aiming at the highest possible user experience.

Technological concepts such as cloud computing and big data are no longer vague ideas, but they can enhance the already existing approaches. Cloud computing can boost the growth of agriculture business, without the need for investment in devoted infrastructure, whereas processing and storing techniques under the wider term of big data enable the exploitation of data with great volume and heterogeneity. The heterogeneity of data is the most important aspect of big data in agriculture, as neither the velocity or the volume are of major importance, since none of them can really offer useful information to farmers or agriculture experts. The introduction of UAV's and other image collecting devices will eventually create the big volume of data, and therefore efficient exploitation of data with great volume will become a challenge. Future proposed agriculture system should prioritize on designing systems capable to combine data from different sources and should exploit further IoT and UAV technologies, which are not utilized enough in the existing agriculture systems.

Table 6
Existing research work in the area of agriculture, combining data derived from remote sensing techniques and IoT devices, descriptive and vector data, and aerial images. The databases that are used are classified in remote sensing (RS), Descriptive, IoT, Vector and Image depending on their content. Features: the characteristics of the databases that have been used in each research work.

Authors	RS	Descriptive	IoT	Vector	Image	Features
Kempenaar et al. [134]				Dairy Campus parcels		Area mowed in ha, Total weight (kg), Percentage dry matter, Weight dry matter (kgds), Weight dry matter per ha (kgds/ha)
	DMC SPOT					NIR and red spectral bands
					eBee emages	amount of light
		field measurements				grass height, dry matter measurementes
Wardlow et al. [133]	MODIS					Time-series, 250 m, Vegetation Index, 16d frequency
					aerial images	
	Landsat					Landsat ETM
				PLSS coverage		
Řezník et al. [72]		MapLogAgri System				humidity, air temperature, vapor pressure Soil moisture, dielectric permittivity, volumetric water content moisture relative humidity, barometric pressure, wind speed, wind direction, rainfall precipitation, and rain and hail intensity temperature
	Landsat 8 Sentinel 2 MODIS					All multispectral bands, EVI, NDVI
Schuster et al. [138]		Helena fertility trial				geodetic information bales of cotton per acre, biomass flow, geo-referenced field topographical characteristic, NDVI
			Sensor cart dataset			soil electrical conductivity, shallow and deep soil resistivities
			RTK GPS			elevation data
		physical characteristics dataset				slope, soil series type, type of irrigation, seed variety, chemical treatments

On research level, smart farming is often connected with image processing for problems such as weed detection and fruit grading, which are tasks that are completed independently without engaging other problems either in pro-harvest or post-harvest cycle. An approach that does not fit the modern needs of an agriculture system, as it is focused on a stand-alone task. Modern agriculture systems should adopt a more holistic approach and be capable to combine different technologies for a series of problems throughout the entire farming cycle, where data from different sources should be appropriately combined in order to maximize the production. The successful and efficient combination of data and technologies is the main research question that should be answered from future research and commercial systems, capitalizing the latest technological advances.

6. Conclusion

6.1. A wide concept

The agriculture sector covers a variety of different areas from soil cultivation and water management to food availability and business modeling, thus instead of trying to cover every possible aspect of big data in agriculture, this literature review is focused on the evolution of agriculture systems and the variety of sources of data in the era of big data. Combining and aggregating data from multiple sources is not an easy task, as it requires technical skills for each stage of the data lifecycle (extract, transform, load) and deeper knowledge for both data mining techniques and agriculture processes. Technical details for the implementation of the agriculture systems that are presented in previous sections are not in the scope of this paper, as well as the used techniques and algorithms for exploiting the different sources of data.

Another choice regarding the focus of the paper is the exception of animal agriculture, as the subject has covered sufficiently from Morota et al. [34]. Other related fields to agriculture such as earth observation [139,140], farm management [141–143] and weather/climate observation [144,145] have used only as tools which serve the final objective; the efficient exploitation of different sources of data.

It becomes clear that directions for future work is not that easy to be provided, as the recent technological achievements have started being integrated in the agriculture sector and establish the era of smart farming. Smart farming combines concepts (precision agriculture, land management), scientific fields (earth observation, climate science) and cutting-edge technologies (image processing, GIS, UAV, multispectral/

hyperspectral imaging) that could improve the agricultural production. Each one of the aforementioned subfields involves different techniques and methods that offer the capability of being explored in depth. The fundamental feature of every system materializing the concept of big data in agriculture is the collection and integration of data from multiple sources in an asynchronous way.

The different areas that smart farming covers have as consequence research projects with different objectives and ambitions. Some of these research projects are not focused on the stage of data collection, but rather on technical details for the implementation of the system or the description of a conceptual framework capable to capitalize the existing technologies, thus leading either to exclusion of the data collection stage either a simple reference of the used datasets. Therefore, it is often the exact latitude and longitude that a digital map covers to be unknown, or the specific features of a descriptive dateset not to be given.

Apart from the lack of description of the used datasets, there has been also noticed a lack of available data from national authorities. If we exclude the remote sensing datasets that are accessible but not easy to use, many descriptive datasets are either university property either belong to a national authority and have been provided explicitly for the implementation of a project. Although descriptive data for a specific site cannot significantly contribute to a research to another area, it would be beneficial to have a knowledge of the structure of databases and data warehouses.

The plethora and heterogeneity of agricultural data poses also the problem of an efficient taxonomy of the existing sources. Although FAO freely offers numerous datasets [146,147], the existing data taxonomy aims at researchers that are fully aware of their goals, objects and the research area, instead of focusing on data scientists that want to experiment and wrangle the existing datasets. Apart from FAO and various national authorities, Kaggle also offers agricultural datasets [148], accompanied with description and a user-voted score.

6.2. Future work

Through the years agriculture was boosted with the use of different technological advances, starting from the integration of GIS to complete cloud deployment of commercial solutions. The next technological advancement that should be incorporated in agriculture is the UAV, as they can be deployed in different tasks of smart farming, since they can acquire, process, analyze and manage data. The body of the UAV can host a wide range of hardware such as sensors and actuators providing the capability to collect valuable data which can be used for further analysis either real time either on demand. Although the integration of UAVs in everyday agriculture activities might seems a futuristic idea, the recent advances on low-power wide-area network (LPWAN) technologies such as LoRaWAN [149,150] provide the potential for their integration to existing agriculture architectures.

The combination of UAVs into existing smart farming processes can provide data that can be used to build precision models for individual crops and plants, indicating the needs (water, fertilizer, pesticide, etc.) each crop requires. The incoming data from UAVs can be used independently from other sources, but they can also be combined with data derived from IoT devices or satellite images enriching the current data warehouses. Armed with this information, agriculture systems can enhance their prediction models and estimate the yield optimizing the production chain downstream.

Agriculture is a prosperous field not only for deploying UAVs, but also for evolving the existing techniques and approaches, realizing the transition from a single UAV system to a multi-UAV system. Collaboration and coordination of multiple UAVs has the potential to build agriculture systems that overcome the capabilities of the existing methods and procedures. An agriculture system designed to handle multi-UAV sub-systems would have significant advantages compared to existing commercial or research solutions as reduction of cost [151], scalability, survivability [152] and heterogeneity [153].

Taking into consideration the existing agriculture systems (commercial and research-oriented), the recent technological advances and the high demand for efficient exploitation of data, we stress the importance of building agriculture systems focusing on the expandability and the integration of new technologies. The primary goal of the agriculture systems should not be the instant knowledge, as it cannot be expressed into action, but the construction of personalized prediction models, built from the combination of data.

Declaration of Competing Interest

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

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Supplementary material

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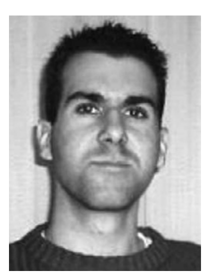

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