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Edge computing: A tractable model for smart agriculture?

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A B S T R A C T

Establishing food security remains a global challenge; it is thus a specific objective of the United Nations Sustainable Development Goals for 2030. Successfully delivering productive and sustainable agricultural systems worldwide will form the foundations for overcoming this challenge. Smart agriculture is often perceived as one key enabler when considering the twin objectives of eliminating world hunger and undernourishment. The practical realization, deployment, and adoption of smart agricultural systems remain distant due to a confluence of technological, social, and economic factors. Edge computing offers a potentially tractable model for mainstreaming smart agriculture. A synergistic relationship exists, which, if harnessed productively, would increase the penetration of smart agricultural technologies across Majority-Minority world boundaries. The paper considers the prevailing context of global food security, smart agriculture and the pervasive issue of internet access. A survey of the state-of-the-art in research utilizing the Edge model of computing in agriculture is reported. Results of the survey confirm that the Edge model is actively explored in a number of agricultural domains. However, research is rooted in the prototype stage, and detailed studies are currently lacking. While potential is demonstrated, several systemic challenges must be addressed to manifest meaningful impact at the farm level.

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1. Introduction

Smart agriculture envisages harnessing a variety of Information and Communication Technologies (ICTs) to increase productivity that is once sustainable, and economically viable. The paradigm is technology-agnostic; it envisages the provision of a suite of technologies that may be utilized as the situation demands. Such technologies could be adopted anywhere within the agricultural value chain from producer to consumer. At the farm level, it is the possibilities offered for minimizing inputs while maximizing productivity that has grasped the attention of the farming community. Adoption of ICTs in the agricultural sector faces many challenges (Archontakis and Anastasiadis, 2019). Sector growth is envisaged. The market for smart agriculture goods was estimated at USD 6.34 billion in 2017; this market is projected to reach USD 13.50 billion by 2023, at a Compound Annual Growth Rate (CAGR) of 12.39% (MarketsandMarkets, 2018).

Benefits that accrue from smart agriculture are well-documented – cost-effectiveness, sustainability, and so forth. One common theme emerges; services provided under the umbrella of smart agriculture are almost invariably dependent on continuous internet access. Such access is first and foremost a societal problem; farmers are particularly vulnerable due to their rural and often remote status. In general, the problem is twofold; some have no internet access while others have access to an intermittent, poor quality connection. Thus, those for whom even relatively simple services would prove most beneficial, cannot take advantage of their availability.

Edge Computing (Shi et al., 2016) offers a means through which the farming community could more effectively access and utilize smart agriculture services. It can help mitigate the internet access problem but not eliminate it. Integrating an Edge model into their designs would provide a challenge for service providers. Indeed, the agriculture domain, specifically at the farm level, provides a compelling test case for the validity of the Edge computing model for smart service delivery. Thus this paper seeks to assess how Edge computing is being harnessed by the research community in the broad agricultural domain.

1.1. Contribution

This paper surveys the research literature and provides a snapshot of the state-of-the-art concerning the adoption of Edge computing in agriculture. A contextual background in terms of global food security and distributed computational architectures as envisaged by Edge/Fog computing is provided. Insights that emerge from the survey are finally presented.

Table 1
Estimates of the prevalence of undernourishment in the world for 2017 (FAO, 2019).

Region	Prevalence of undernourishment (%)
Africa	19.8
Asia	11.4
Latin America & The Caribbean	6.5
Oceania	6.1
North America & Europe	<2.5
World	≈10.8

2. The global food problem

Food poverty presents many challenges globally (FAO, 2019). To elucidate:

- Over 820 million people suffer from hunger; that is, almost one in every nine people in the world.
- Prevalence of undernourishment globally is estimated as being slightly below 11%.
- In high-income countries, there is a lack of regular access to nutritious and sufficient food; it is estimated that 8% of the population in Northern America and Europe is food insecure.
- Food insecurity is slightly higher amongst women than men.

Such figures are a stark illustration and reminder of the problems encountered by a large proportion of the world's population. The situation is exacerbated when it is considered that a large proportion of the world population is also affected by hidden hunger, that is, micronutrient (vitamin and mineral) deficiencies. Critical for physical development and disease prevention, micronutrients can only be obtained from diet. Policies to combat world hunger tend not to differentiate between chronic and hidden hunger; however, there is evidence to suggest that national strategies augmented with additional specific interventions at the micro-level (i.e., the community, household, or individual) could be more effective (Gödecke et al., 2018). Table 1 illustrates the prevalence of undernourishment in the world for 2017. The global population surpassed some seven billion people by 2017; it is expected to exceed 9.7 billion by 2050. This development has ramifications for the supply of food; it is projected that the demand for food may need to increase by between 25% and 70% to meet demand (Hunter et al., 2017).

2.1. Food poverty: an inherent contradiction?

Obesity is an international epidemic; traditionally associated with adults, prevalence in children is increasing rapidly. According to WHO,[1] in 2016, >1.9 billion adults aged 18 years and older were overweight; of these, over 650 million adults were obese. In the case of children, an estimated 41 million children under the age of five years were overweight or obese. Obesity is increasingly present in low- to middle-income countries. The science behind obesity is complex; many factors combine to cause it, including genetics, hormones, and the environment. Surprisingly, obesity may be regarded as a dimension of food poverty; following a healthy diet is often expensive for those on low-incomes in high-income countries, resulting in an obesity-poverty paradox (Żukiewicz-Sobczak et al., 2014).

A second contradiction arises when food waste and loss are considered. An estimated one-third of all food produced for human consumption is lost or wasted across the food supply chain (Fig. 1), from production to consumption (FAO, 2018). Such losses are equivalent to 1.3 billion tons/year; in essence, a quarter of the calories produced for human consumption becomes food waste (Kummu et al., 2012). For 2012, the value of food waste was estimated at USD 936 billion; this was slightly larger than the GDP of Indonesia or the Netherlands for

[1] WHO: Obesity and overweight fact sheet. https://www.who.int/en/news-room/fact-sheets/detail/obesity-and-overweight.

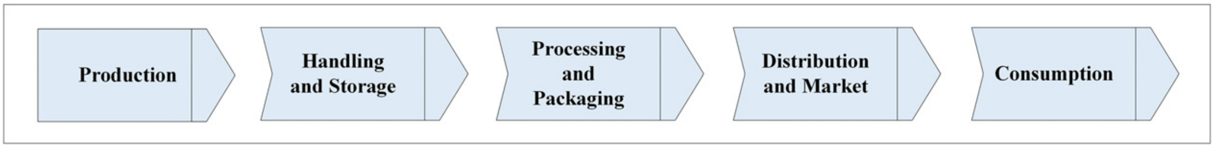

Fig. 1. Phases of the food supply chain.
Adapted from FAO (2018).

that year.[2] Food loss is caused by problems along the supply chain – lack of infrastructure, inadequate technology, and poorly trained personnel, for example.

2.2. Establishing food security

Reasons why the production and supply of food are insecure, are complex and multifactorial. A broad spectrum of issues, including political instability, conflict, poor economic prospects, and natural hazards, all contribute. In the case of natural hazards, floods, droughts, and tropical storms affect food production the most (FAO, 2015); drought, in particular, causes >80% of the total damage and losses in agriculture, with the livestock and crop production subsectors being particularly affected. As there is no single reason why the supply food is problematic, there can be no singular solution to the problem; rather, a *blended portfolio* of strategies should be adopted (Fraser et al., 2016).

One recurring theme that emerges within the context of discussions on food security is that of sustainability. Nevertheless, this concept is problematic and, in a sense, polarizing. As highlighted in Béné et al. (2019), the concept of sustainability is widely adopted by different communities but yet remains poorly defined and applied. Focusing on narrow interpretations will make the invariable trade-offs necessary to reconcile the conflicting demands of aligning nutrition, energy, and water use, as well as greenhouse gas emissions, a more difficult proposition (Global Panel, 2016). Ultimately, recognizing food security as a *wicked problem* (Peters and Pierre, 2014) and thus one worth solving, may help in acknowledging its scale and complexity, and promote the consideration of disruptive approaches for its resolution.

2.3. Towards operational smart agriculture

Historically, adoption of ICT in agriculture has been relatively slow; various reasons are attributed as to why this was the case, but an intrinsic lack of infrastructure is a crucial inhibitor (Trendov et al., 2019). Socio-economic issues obviously contribute (Tamirat et al., 2018); nonetheless, the value proposition is key, and this remains unclear for many farmers in the USA (Thompson et al., 2018). Thus, it beholds policymakers to ensure the value proposition is meaningful, not only for farmers but all actors in the value chain. It is estimated by the World Economic Forum (WEF) that if Internet of Things (IoT) solutions were deployed in 50–75% of the supply chains in developed countries by 2020, savings of 10–50 million tons of food would accrue (WEF, 2018).

Smart agriculture offers one vision of how technology will transform farming practice. The production of food begins on the farm; as such, sustainable solutions to the global problem of food supply must likewise begin on the farm and with the farmer. One global solution will not emerge for the farm level; instead, a diversity of farm systems must be supported by smart agriculture (Walter et al., 2017). Part of the solution may involve farmers adopting an Research & Development (R&D) role, as envisaged by MacMillan and Benton (2014), to increase innovation and validate solutions.

[2] FAO: Food wastage footprint & Climate Change. http://www.fao.org/3/a-bb144e.pdf.

3. Smart agriculture

ICT technologies continue to permeate agriculture, resulting in several paradigms being defined to capture this phenomenon. Smart Agriculture, Digital Agriculture, and e-agriculture are just some terms encountered in the academic literature and popular press. Though often used interchangeably, each paradigm may have nuances depending on the end-user constituency. One of the most common terms is Precision Agriculture (PA), especially when discussing operations at the farm level; the ubiquity of this paradigm has been demonstrated in multiple farm systems - see Table 2. Definitions are multiple; nonetheless, that of Gebbers and Adamchuk (2010) is probably archetypical - "*Precision Agriculture comprises a set of technologies that combines sensors, information systems, enhanced machinery, and informed management to optimize production by accounting for variability and uncertainties within agricultural systems.*" It is important to emphasize that smart agriculture and equivalent paradigms are not coupled to a singular technology; rather, they comprise a spectrum of technologies that must be harnessed according to need and context.

3.1. Constituent technologies

Technologies that are utilized in Smart Agriculture are many and varied; however, the core technologies tend to coalesce around five technologies (Fig. 2).

3.1.1. Positioning systems

Satellite-based positioning utilizing GPS, Galileo, and equivalent systems, provide a basis for many smart services. In practice, the signal must be augmented to deliver the necessary accuracy required on the ground. To deliver centimeter accuracy, it is necessary to use Real-Time Kinematic (RTK); this requires that the receivers on the farmer's machinery be suitably equipped. As the accuracy of RTK is proportional to the distance from the base station, it may be necessary to install an RTK base station on the farm. Position accuracy is fundamental for Automated Guidance and steering, yield monitors, and Variable-Rate Technology (VRT).

3.1.2. Remote & in-situ sensing

Remotely-sensed imagery, captured from satellite or Unmanned Aerial Vehicle (UAV), allows an objective time-series analysis of the farm, enabling the identification of factors stressing crops such as poor soil moisture. In-situ sensing refers to those sensor platforms installed at the farm level; examples include weather stations and soil sensors.

Table 2
Application of precision agriculture in different farming systems.

Farming system	Reference
Apiculture	Henry et al., 2019
Aquaculture	Føre et al., 2018
Cotton	Guo, 2018
Crops	Baylis, 2017
Horticulture	López et al., 2011
Livestock	Berckmans, 2017
Rice	Guan et al., 2019
Viticulture	Santesteban, 2019

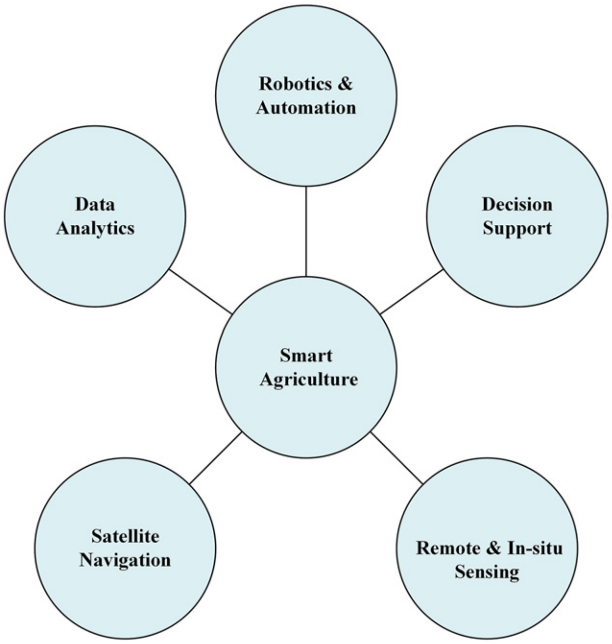

Fig. 2. Technologies fundamental to the delivery of Smart Agriculture services.

3.1.3. Data analytics

For an average farm, significant data volumes may be quickly generated from satellite, UAV, and in-situ sources. Processing this data such that it is easily interpreted demands access to a variety of analysis techniques from image processing to machine learning. Cloud and Edge technologies are attractive solutions for data analyses.

3.1.4. Decision support

Transforming information into knowledge-enabling, evidence-based, decisions constitutes the farmer-centric dimension of Smart Agriculture. Uptake of such decision-support tools by farmers on the ground is considered slow. Why this is the case has been investigated; researchers in the UK identifying 15 characteristics (including cost and trust) that contributed to the effective use of decision support tools (Rose et al., 2016).

3.1.5. Automation & robotics

Very much a nascent technology at present, robots remain at the research phase, although field trials are documented. Spraying, weeding, and harvesting are three activities currently being prioritized. Agricultural robots are invariably lighter than the traditional tractor/machine combination thus reducing the problem of soil compaction in arable farming systems.

3.2. Smart production of wheat in the UK

Wheat is the largest agricultural crop in the world after rice; it grows in a wide variety of climatic conditions, but yields vary considerably depending on the climate and growing conditions. Taking the UK as an example, high yields are achieved on average when compared with the rest of the world; however, there is still considerable variation across regions, farms, and fields. Smart agriculture offers excellent potential to understand the historical and current variation in crop performance; in this way, growing systems may be optimized to deliver performance that is at once economic and sustainable. Adoption of technologies in the UK is rising as farm sizes are increasing thus reducing cost on a per hectare basis. Increasingly, machinery manufacturers are delivering equipment that supports smart agriculture. Standardized technologies such as ISOBUS are crucial here as they ensure greater interoperability between the machines on the ground and the supporting service platforms. GPS steering and soil mapping are the most common PA technologies in use in the UK.

A key technology in understanding crop performance is yield mapping; here, combine harvesters are fitted with yield monitoring equipment that, coupled with a GPS, enable the generation of yield data points across a field. It must be emphasized that yield at a given point is the cumulative result of all the factors (for example, weather) that have impacted the crop throughout the season. Understanding these factors, particularly the processes that go on in the soil, are complex and not well understood at this time. However, this situation is changing, and innovative products are appearing on the market. For example, in 2018, Teralytic Inc. (USA)[3] launched a soil probe with sensors at different depths to measure soil nutrients and other environmental parameters. These are reported in near real-time via a wireless Long-Range Wide Area Network (LoRaWAN) to the farm-based gateway and then uploaded to the Cloud for analysis. There, the farmer and their advisors can access the information and make more informed decisions concerning crop management. Though promising, the effectiveness of these probes is compromised in that they are in-situ and static. In the longer term, the use of mobile, and possibility collaborative robots, such as those being prototyped by the Small Robot Company[4] in the UK, offer more flexible and comprehensive possibilities.

3.3. Internet access: a global problem

A rural-digital divide exists in the case of internet and broadband access; this is a recurring theme across the world. Pragmatically, there will always be a differential in Quality of Service (QoS) between urban and rural areas; nonetheless, bridging this gap and minimizing the divide is essential from a social and economic perspective, and is the subject of many government initiatives. To quantify: in the USA, the FCC reported that 39% of rural Americans do not have broadband access.[5] In the EU, coverage in rural areas was 47%, against an overall average of 80%; in 14 of the member states, the high-speed broadband coverage in rural areas is <50% (European Court of Auditors, 2018). On average, 50% of the world is online; however, the other 50% is likely dominated by those who are poor and live in (relatively) isolated regions. A key objective of UN SDG 9[6] concerns the provision of universal and affordable access to the Internet in the Least Developed Countries (LDCs) by 2020. Disruptive technologies are on the horizon, for example, TV white space (Johnson and Mikeka, 2016). Fig. 3 illustrates how access to the internet various globally at the household level. For the LDCs, it may be surmised that in the case of farmers, access is often non-existent.

3.4. Edge computing: state of play

The value proposition of Edge models is that of pushing computation, networking, and storage to the edge of the mobile network to enable a sufficient QoS for computationally-intensive, latency-sensitive and bandwidth-demanding services (Abbas et al., 2018). For this discussion, Edge Computing and Fog computing are considered interchangeable; Fog computing tends to focus on infrastructure dimension, whereas Edge computing tends to focus on the device dimension (Shi et al., 2016). Fog computing tends to view the world from a Cloud lens, whereas Edge computing is often perceived from a networking perspective (Fig. 4). Standardization initiatives are ongoing. The OpenFog Consortium[7] has defined an open reference architecture for Fog computing; in 2018, this was adopted as an official standard (IEEE

[3] Teralytic Inc. https://teralytic.com/.
[4] Small Robot Company. https://www.smallrobotcompany.com/.
[5] 2016 Broadband Progress Report. https://www.fcc.gov/reports-research/reports/broadband-progress-reports/2016-broadband-progress-report.
[6] SDG – Goal 9: https://unstats.un.org/sdgs/report/2016/goal-09/.
[7] OpenFog Consortium. https://www.openfogconsortium.org/.

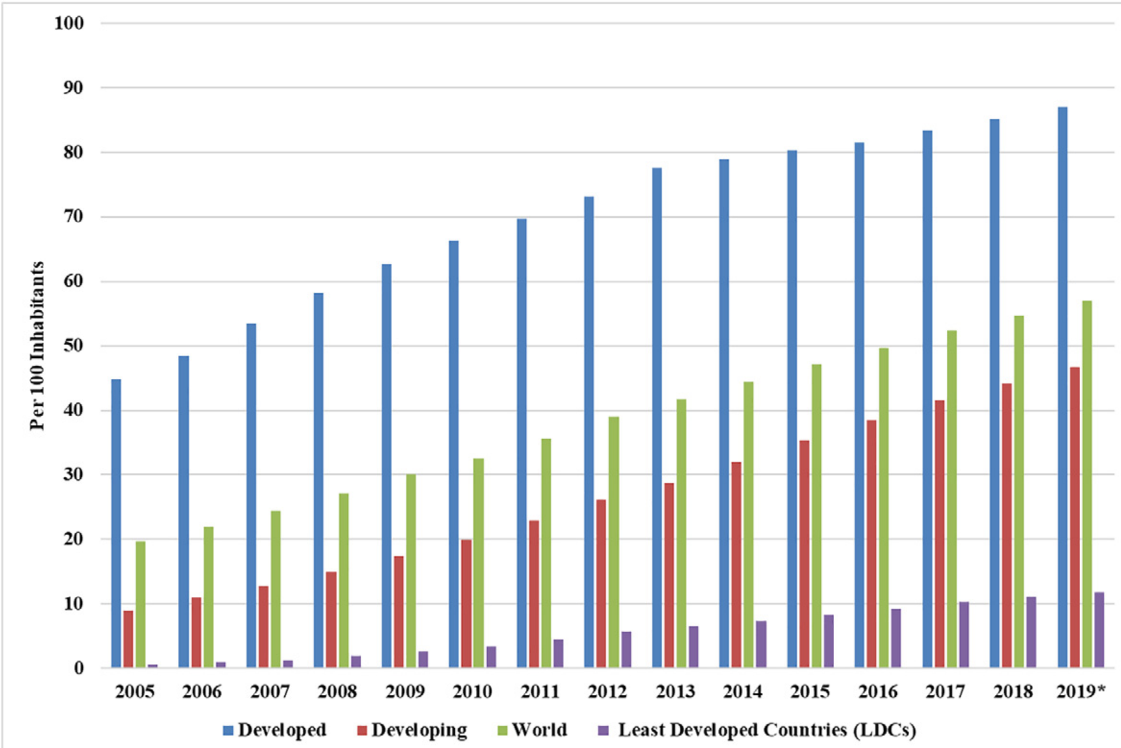

Fig. 3. Households across the world with internet access. * ITU Estimate.
Source: ITU World Telecommunication/ICT Indicators database.https://www.itu.int/en/ITU-D/Statistics/Pages/publications/wtid.aspx.

1934) by the IEEE Standards Association (IEEE-SA). ETSI (European Telecommunications Standards Institute) has developed standards for Edge Computing, or more formally, Multi-Access or Mobile Edge Computing (MEC).[8] ETSI and the OpenFog Consortium actively collaborate; industry engagement is common to both.

Studies have shown that precision agriculture is economically advantageous but site-specific (Griffin et al., 2018). At present, the IoT is seen as a pivotal contributor to modern agriculture going forward. When considering ongoing developments in Edge computing, it may be envisaged that by enabling intelligence at the fringes of the network, Edge computing has the potential to radically transform current practice so as to deliver tractable smart farming services.

4. Edge computing in agriculture

A survey of Edge Computing in agriculture is now presented. The methodology for identifying research for this survey was as follows. Both the Scopus and Web of Science repositories were searched using a combination of search terms. The primary search terms were *Edge computing* or *Fog computing*. These were augmented with wildcard variations of *agriculture* and *farm*. A second level of domain-specific search terms was then added - *horticulture*, *aquaculture*, and *forest*. Finally, an additional level of specific terms was then added to complete the search query; these included *crop*, *animal*, *fruit*, *vegetable*, and *fish*. All search terms were expressed in the final script with wildcards. A total of 135 papers resulted. These were screened to exclude extended abstracts, concept papers and poster abstracts. This exercise resulted in the identification of 46 papers that merited a more detailed study. One limitation of this methodology is that it does not include research published outside the traditional channels – the so-called grey literature. Table 3 summarizes the Edge computing techniques identified in this survey.

4.1. Livestock: health and welfare

Bhargava and Ivanov (2016) illustrate an Edge Mining (EM) (Gaura et al., 2013) approach for predicting heat stress in dairy cattle. Temperature Humidity Index (THI) is calculated using data from a suite of physical in-situ sensors. The collar of each cow serves as the base station for both evaluating the THI and estimating the probability of heat stress. Risk is then communicated to the farmer as needed. Though the case study is that of dairy cows, the methodology may be applied across different farming systems.

A modification of the EM approach has been described in Bhargava et al. (2017). Here, the motion of the dairy cow is classified on the collar device using a classification technique developed by the authors called Interactive Edge Mining (IEM). Two approaches – Bare Necessities and ClassAct are harnessed to deliver a decision-tree classification of the signal. The signal in question is that from an accelerometer from which activity states are deduced. This information is uploaded to the Cloud; here, analysis of the animal's movements will be undertaken prior to communication with the farmer. Uploading occurs only when the cow is at the milking station. A subsequent investigation of the performance of the Linear Spanish Inquisition Protocol (L-SIP) has been undertaken (Bhargava et al., 2016). A more recent iteration of EM research evaluates both a revised IEM algorithm (IEM2.0), augmented with the Cooperative Activity Sequence-based Map Matching (CASMM) – an extension of ASMM (Zhou et al., 2015), to deliver a Fog analytics solution for activity recognition and localization for dairy cows (Bhargava et al., 2019). Initial results are promising, achieving a localization accuracy of up to 99%. Again, the core methodologies are generic and transferable.

Taneja et al. (2018) likewise demonstrate the use of Edge computing for herd health monitoring using a Fog node hosted on a workstation on the farm, and pedometers attached to the feet of the cows in the herd –

[8] Multi-access Edge Computing (MEC). https://www.etsi.org/technologies/multi-access-edge-computing.

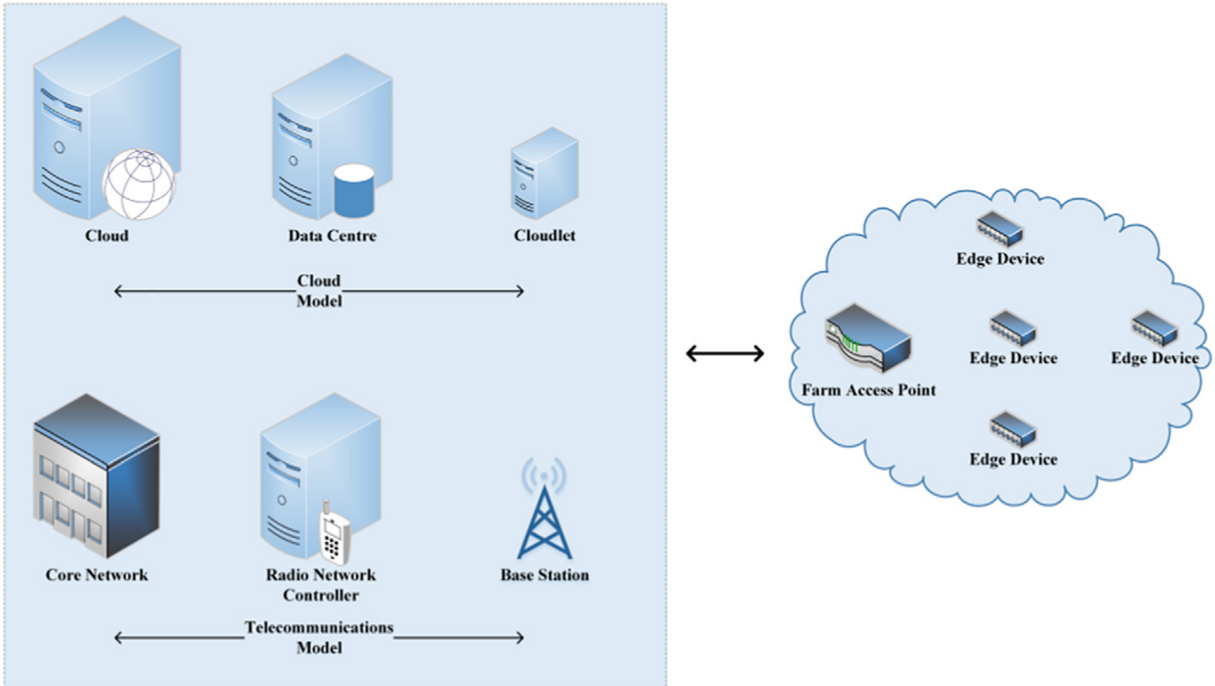

Fig. 4. Edge-enabled agriculture as a Cloud and telecommunications model.

one per cow. On the node, data aggregation, pre-processing, classification, and feature selection occur. Such behavioral analytics allow behavior norms be observed; deviations from these norms may be an indicator of illness for example. Alerts are sent to the farmer when conditions such as lameness are detected (Byabazaire et al., 2019). Generic architectures for utilizing Edge computing for animal welfare monitoring are presented by Caria et al. (2017) and Taneja et al. (2019).

Debauche et al. (2018) explore the potential of CE devices, in this case, a smartphone platform (iPhone), as an Edge node animal behavior. The device was hosted on a halter, and five individual parameters were measured from the device's IMU. After processing these, a net total of 41 parameters resulted. When data are considered in terms of frequency and number of sources (cows), data management challenges quickly arise; a lambda Cloud architecture is harnessed for managing this challenge. The use of Edge Computing on the iPhone reduced the size of the raw data for transmission by 43.5%.

Jukan et al. (2019) describe a low-cost, integrated, cloud-to-fog architecture for smart farming. An interesting feature of this architecture

Table 3
Utilization of Edge computing techniques in agricultural domains.

Theme	Domain	Edge computing techniques	Reference
Animal welfare	Precision dairy	Latency-sensitive analytics.	Bhargava and Ivanov, 2016
Animal welfare	Precision dairy	Edge Mining (L-SIP) for data compression.	Bhargava et al., 2016
Animal welfare	Precision dairy	Computation offloading (learning of behavior models).	Bhargava et al., 2017
Animal welfare	Precision dairy	Computation offloading (context-aware sensing).	Bhargava et al., 2019
Animal welfare	Precision dairy	Reducing data traffic.	Byabazaire et al., 2019
Animal welfare	Precision dairy	Computation offloading (data classification and analyses).	Taneja et al., 2019; Taneja et al., 2018
Animal welfare	Precision livestock	Computation offloading (local data analytics)	Caria et al., 2017
Animal welfare	Precision livestock	Reducing data traffic.	Debauche et al., 2018
Animal welfare	Precision livestock	Reducing latency.	Jukan et al., 2019
Animal welfare	Poultry	Computation offloading (data analytics).	Yang et al., 2019
Aquafarming	Aeroponics	Computation offloading.	Chang et al., 2018
Aquafarming	Hydroponics	Computation offloading (automated control).	Ferrández-Pastor et al., 2016
Aquafarming	Aquaculture	Reducing data traffic; computation offloading.	Romli et al., 2017
Aquafarming	Aquaponics	Computation offloading.	Romli et al., 2018
Crops	Precision Viticulture	Computation offloading (alert generation).	Morais et al., 2019
Crops	Disease modelling (Viticulture)	Computation offloading.	Oliver et al., 2018
Crops	Tomato production	Computation offloading (privacy protection).	Park et al., 2017
Farm environs	Metagenomics	Computation offloading (data analysis).	D'Agostino et al., 2019; Merelli et al., 2018
Farm environs	Water quality	Latency reduction.	Fan and Gao, 2018
Farm environs	Micro-climate (temperature)	Computation offloading (data analysis).	Krintz et al., 2018
Farm environs	Soil Fertility	Computation offloading (data analysis).	Lavanya et al., 2019
Farm environs	Precision irrigation	Computation offloading.	Zyrianoff et al., 2018
Forestry	Fire detection	Computation offloading.	Avgeris et al., 2019
Forestry	Fire detection	Computation offloading (energy-intensive tasks).	Kalatzis et al., 2018
Forestry	Fire detection	Computation offloading; distributed data collection.	Neumann et al., 2018
Forestry	Fire prediction	Computation offloading (predictions).	Rajagopal et al., 2018
Safety	Wildlife surveillance	Computation offloading (animal classification).	(Elias et al., 2017)
Safety	Wildlife surveillance	Latency reduction; computational offloading; data traffic reduction.	(Singh et al., 2018)
Supply chain	Shelf-life prediction	Computation offloading (data analysis and prediction).	Musa and Vidyasankar, 2017

is that it encompasses a heterogenous suite of sensors for both monitoring animals and their physical indoor environs; however, the standard platform is the Raspberry Pi. By harnessing Edge computing, the authors demonstrate decreased latency and increased support for scalability, modularity, and reliability. Looking forward, the use of machine learning is perceived as a viable approach for reducing sensor infrastructure and a basis for more sustainable unobtrusive sensing. Yang et al. (2019) likewise address the issue of indoor environmental monitoring, in this case, of chicken houses. Temperature, humidity and light intensity are monitored, allowing near real-time control. Analysis of data from the sensors takes place on a gateway (Edge) node, thereby driving control of both the fan and the lights.

4.2. Crop production

Oliver et al. (2018) have described a generic monitoring framework based on the IoT paradigm; it has been deployed and validated in a viticulture scenario where a variety of weather and soil parameters are monitored. Strategically, the objective is to proactively anticipate certain diseases synonymous with vineyards, but where meteorological conditions are the critical predictors of outbreaks. Examples of such diseases include downy mildew and black rot. The overall architecture is Cloud-centric, with an Edge computation node being harnessed to collect data from the distributed sensor network.

mySense is a generic platform conceived for the rapid creation and deployment of monitoring applications in precision viticulture scenarios (Morais et al., 2019). It comprises four layers – sensors/actuators, WSN/gateway, Web/Cloud, and applications. Fog computing is utilized at the WSN/Gateway layer for local tasks and real-time alert generation. The platform has been utilized in a vineyard for researching disease dynamics in the context of prevailing micro-climates.

An exemplary case study illustrates how Edge computing can demonstrate scalable data analytics has been described by Park et al. (2017). Here, a Raspberry Pi acts as both a base station for a sensor configuration and, from a network perspective, an Edge node. A prediction of growth state for cherry tomatoes is produced on the Edge node and dispatched to a central server on the Cloud for subsequent conflation, model integration, and analyses, leading to yield predictions. As well as reducing data traffic, this approach enables farmers to protect their data and only share what data they choose.

4.3. Aquafarming

In conventional aquaculture, the use of Recirculating Aquaculture Systems (RAS) offer significant potential to reduce the need for fresh water by harnessing sophisticated biofiltration processes; however, near real-time control and monitoring are essential. Romli et al. (2017) describe a Fog Computing approach for data acquisition and monitoring of the RAS using a Raspberry Pi as a Fog node. A similar model has been demonstrated for controlling the level of water in a growbed tank (Romli et al., 2018). Inlet and outlet water speed are monitored using a NodeMCU; a Raspberry Pi acts as the broker in the configuration. An alternative approach utilizing an ultrasonic sensor for measuring water level was subsequently tested.

Ferrández-Pastor et al. (2016) present a generic low-cost sensor/actuator platform, based on the IoT, for delivering precision agriculture services. Modeled on the IoT, Edge computing is harnessed to enable a multi-protocol approach for process control. The production of hydroponic crops in a greenhouse was used to validate the platform. Chang et al. (2018) describe a fog-enabled controller, for enabling aeroponic-style cultivation in a greenhouse. The application layer is based on the Cloud-based ThingSpeak[9] platform.

[9] https://thingspeak.com/.

4.4. Forestry

Forestry plays a vital role in agriculture, with trees and shrubs cultivated amongst arable and pasture land in combination with other farm enterprises. Many benefits accrue from such an approach; crop yields have been shown to increase in agroforestry enterprises (Barrios et al., 2018) while shelterbelts offer protection to livestock both in winter and summer.

Kalatzis et al. (2018) showed how UAVs, equipped with a Raspberry Pi, can capture image data for detecting fire outbreaks. This case study compares several data processing methods, one involving a UAV with a Raspberry Pi payload as an Edge node. The tradeoffs are interesting. Image processing on a UAV is computationally expensive, while the use of power must be reconciled with an omnipresent need to maximize flying time. When processing images on the Edge node, privacy is respected, and only a calculated risk-index need be transmitted. However, an off-loading approach was demonstrated as being the most sustainable.

A different approach to the problem of fire detection was adopted by Neumann et al. (2018). Here, a participatory data collection paradigm is harnessed via an Edge computing solution. A suite of sensors supporting the capture of temperature and humidity were deployed throughout a forest; these communicate using Bluetooth Low Energy (BLE). Smartphones carried by guards and visitors act as mobile hubs. When passing within range, parameters are uploaded to the smartphones (mobile hubs); these parameters are then transmitted to a host server where they give an indication of fire risks, thereby informing risk assessment and enabling more effective planning and response strategies.

Data mining can predict areas prone to outbreaks of forest fire (Rajagopal et al., 2018). A Support Vector Machine (SVM) prediction model, utilizing wind speed, precipitation, relative humidity, and temperature parameters, is hosted on a local Fog node, from where predictions are communicated to the Cloud. An Edge computing framework for fire detection that incorporates IoT, the Cloud, and participatory sensing elements, is described by Avgeris et al. (2019). The core model is that of a Cyber-Physical-Social System (CPSS) (Wang et al., 2017); offloading to the network edge is seen as essential to ensuring time criticality and rapid decision-making.

4.5. Farm security

Animal habitats are increasingly shrinking, leading to a corresponding increase in the possibilities of encounters between humans (and implicitly domesticated and farmed livestock) with wild animals. While animal-vehicle collisions are one obvious consequence, disease (for example, bovine tuberculosis) and personal safety are also omnipresent risks. Solutions such as fencing and boundary walls will invariably reduce encounters; nonetheless, scale and inhospitable terrain often render such initiatives uneconomic and unfeasible.

Singh et al. (2018) considers the issue of animal-human cohabitation and propose an early warning system based on IoT and Edge technologies. A hybrid Fiber-Wireless (FiWi) network links a suite of Edge nodes (wireless sensors) to the Cloud. A PIR sensor, on detecting movement, activates a camera module to capture an image of the animal. For image processing, a Convolutional Neural Network (CNN) is harnessed. Simulations results demonstrated that dynamic allocation of bandwidth in the access network, as well as processing data at its origin, reduced end-to-end delays; energy consumption was likewise reduced by processing on the Edge devices. Understanding trade-offs between computation and communication are recurring themes in WSN research over many years. However, each scenario is different; thus, an understanding of resources and power constraints is a prerequisite to effective WSN deployment, irrespective of domain. A similar architecture incorporating IoT and an Edge Cloud model has been described by Elias et al. (2017); here, specific instances of wildlife (bears, deer, and coyotes) can be identified. While the objective is automated wildlife monitoring, the model is transferable to security contexts.

4.6. Monitoring farm environs

Productive soils are the foundation of almost any successful farming system. Lavanya et al. (2019) developed a prototype IoT-based sensing platform for determining Nitrogen-Phosphorus-Potassium (NPK) concentrations in soil. The sensor utilizes a colorimetric approach that is enabled via Light Dependent Resistors (LDR) and Light Emitting Diodes (LEDs). Most interestingly, the logic for analyzing the sensed values to determine nutrient deficiency is delivered via a fuzzy rule-based system that is implemented on an Edge device, in this case, a Raspberry Pi. This logic is further augmented with additional rules for identifying concentrations of fertilizer that must be applied to remedy any nutrient deficiencies. Fertilizer requirements are expressed in terms of urea, potash, or ammonium phosphate, and so are immediately comprehensible to the farmer. Such an approach offers a cheap and fast alternative to the lab-based approaches that are often time-consuming and expensive. In helping farmers accurately manage their soil nutrition, soil fertility is optimized, resulting in financial savings sustainable farm management and increased environmental protection through eliminating water contamination by runoff and leaching.

Air temperature is a crucial weather parameter that influences plant productivity; it also influences many operational decisions on farms concerning, for example, greenhouse management and irrigation scheduling. Krintz et al. (2018) have explored how the CPU temperature of inexpensive single board computers and micro-controller may be utilized to predict outdoor temperature. The CPU temperature is first transmitted to an on-farm Edge cloud. A combination of calibration smoothing, via Single Spectrum Analysis (SSA) and linear regression, are then used to generate a prediction for the temperature at the device. Edge computing provides a means of achieving the low latency required. Advantages of the approach lie in the possibility of utilizing pre-existing sensing infrastructures rather than deploying a local weather station or micro-climate monitoring network. Viewed pragmatically, the need for a farmer to establish the baseline for correlation using an additional temperature gauge may prove problematic.

Sustainable water management is an omnipresent issue at the farm level. Fan and Gao (2018) explore task offloading strategies in mobile Edge computing. Delays due to both transmission link characteristics and computation are often not considered when deciding to proceed with an off-loading process. An innovative link data management scheme is proposed, and an initial validation undertaken within the context of agricultural water monitoring.

Scalable, open IoT middleware platforms are necessary for the rapid deployment of IoT services; however, platforms that can at least be partially deployed on Fog nodes are practically non-existent. In response to this observation, Zyrianoff et al. (2018) assessed the potential of the FIWARE[10] platform using precision irrigation as a case study. It was concluded that while FIWARE was suitable for IoT-enabled smart farms, a deeper understanding of the trade-offs is necessary when optimizing performance in a Fog computing context.

Edge computing as a basis for metagenomics analysis has been considered by Merelli et al. (2018); in the case of agriculture, this offers opportunities for remote microbial analyses of soil, air, and water. Conventional approaches demand significant data transfer to the Cloud. Using a combination of System-on-a-Chip (SoC) and Edge computing, remote analyses may be undertaken, and the results sent to the Cloud. Such an Edge/Cloud combination offers a particularly attractive approach to delivering full analyses workflows. Experimental results demonstrated a reduction of 95% for data streaming; it is concluded that this illustrated the viability of metagenomic analysis in remote regions. An Edge approach is viable for singular analyses. However, subsequent work by the authors showed that when the frequency of analyses increases, moving computation to the Cloud results in improved cost and performance (D'Agostino et al., 2019).

[10] FIWARE. https://www.fiware.org/.

4.7. The food supply chain

Traceability starts on the farm and continues along the supply chain; food safety and perceived competitive advantage are key drivers for implementing food supply chains for which traceability from source to retailer is a distinguishing characteristic (Haleem et al., 2019). Key enabling technologies include RFID (Costa et al., 2013), and increasingly, Blockchain (Kamilaris et al., 2019). Musa and Vidyasankar (2017) focus on RFID and illustrate the potential of Fog Computing in the supply of blackberries. The potential of blockchain is widely acknowledged (Zhao et al., 2019); likewise, its potential for use in the IoT (Fernandez-Carames and Fraga-Lamas, 2018) and mobile Edge Computing (Xiong et al., 2018) is acknowledged. However, case studies describing their collective use in food traceability are rare; at the time of writing, only Lin et al. (2018) have explored these possibilities.

5. Discussion

Edge Computing and associated paradigms are at an early stage in their development, gaining traction only in the last five years. Many challenges exist before meaningful services for the actors in the agricultural value chain become mainstream. From a Technology Readiness Level (TRL) perspective, all systems described previously are essentially prototypical, ranging from TRL 4, validated in a laboratory setting, to TRL 5, being validated in a relevant environment. It may be cautiously observed that the prevalence of Edge Computing in agriculture is more widespread than perceived as it is sometimes a sub-component in other research domains, for example, the IoT.

Two models of Edge-enabled services may be considered - Node-centric services that act independently of the Cloud and Cloud-centric services that depend on at least one service from the Cloud for operation. Most systems considered in the previous section may be regarded as Cloud-centric. Key benefits attributed to Edge Computing – reduced latency, more effective bandwidth utilization, and task off-loading were utilized to varying degrees. Initial data processing was undertaken at the local Edge whereas core Cloud services were used for activities such as second-level off-loading, storage, and alert generation. In summary, the status of Edge Computing in agriculture is reflective of that of elsewhere; it is dominated by physical edge servers coupled with local sensors and sensor networks.

Broadband access at the rural level remains an omnipresent problem worldwide. While Edge Computing offers a tractable approach to partially mitigating the effects of limited internet access, access to the Cloud is a prerequisite for complex analytics-driven service provision. The intractability of this problem suggests that for the agricultural domain, a third model based on delay-tolerance should be considered.

Delay-Tolerant Edge Services may be regarded as a model for the design of services that require access to the Cloud, but in situations where intermittent network access availability is the norm. The principle of delay/disruption tolerance is well-established in the networking domain, where it is seen as a viable strategy for unpredictable network availability, high latency, and so forth. However, from a services perspective, delay tolerance must be factored into the design of the service from its initial conception. At first sight, services that do not respond in near real-time may be perceived as unorthodox when conditioned to instantaneous internet access. Yet many agricultural services can tolerate delay; the need for continuous internet access as envisaged by the Internet of IoT is often unnecessary as many environmental parameters change relatively slowly. In cases where an urgent alert should be brought to the farmer's attention, other wireless technologies may be utilized to cover the farm, for example, LoRA, and connect to the Edge node on the farm. In this case, the logic underpinning the service must be hosted on the node itself. Ultimately, how the Edge node connects to the core Cloud will depend on the prevailing situation on the farm in question. In extreme cases, it may involve the farmer carrying a laptop or even USB to their nearest access point to avail of the more sophisticated services on the Cloud.

Given the nascent state of Edge Computing and those precision farm services based on it, service providers run a risk of alienating a potentially large customer base, unless due consideration is given to the practical issue of internet access in rural areas. Rural internet provision will undoubtedly continue to grow; however, claims of equivalence with metropolitan areas should be treated skeptically. Ultimately, 5G services will be dependent on the deployment of fiber-optic backhaul networks. Nonetheless, 5G may well prove transformative. Only through the deployment of such networks will commercial-grade Edge-based platforms become commonplace.

Research on Edge architectures continues; furthermore, initial products from major multinationals in the ICT and telecommunication sectors are available. Opensource frameworks and platforms are increasingly being released; exemplars include EdgeX[11] and OpenEdge,[12] amongst others. Prototypes described in this survey were dominated by the use of cheap, robust, off-the-shelf components; however, the Edge infrastructure was invariably ad-hoc in nature. Looking forward, researchers should increasingly, but not exclusively, seek to harness developments in commercial and open platforms, mainly where focus is directed towards service provision. In this way, industrial-strength services are more likely to emerge for validation and commercialization.

6. Conclusion

Edge Computing offers intriguing possibilities for smart agriculture. Research and applications of Edge concepts in agricultural systems are only in their infancy. Systems are prototypical, demonstrating select aspects of the Edge computing paradigm to address a selection of problems in a variety of agricultural domains. Crucial issues of interoperability and scalability have not received sufficient consideration. The adoption of mature, robust platforms for Edge-enabled services, rather than customised implementations, will help address these deficiencies. Inadequate internet access is a global problem, and the represents a crucial constraint on the potential of edge computing, particularly amongst communities that would benefit significantly even from lightweight smart agricultural services. Acknowledging this situation and identifying suitable remedies are prerequisites for equipping farmers with the necessary tools to deliver sustainability and help meet the global challenge posed by food insecurity.

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References

Abbas, N., Zhang, Y., Taherkordi, A., Skeie, T., 2018. Mobile edge computing: a survey. IEEE Internet Things J. 5 (1), 450–465.
Archontakis, F., Anastasiadis, F., 2019. Technology and innovation in Southern Europe's agri-food sector: a Delphi study. International Journal of Technology Management & Sustainable Development 18 (1), 17–36.
Avgeris, M., Spatharakis, D., Dechouniotis, D., Kalatzis, N., Roussaki, I., Papavassiliou, S., 2019. Where there is fire there is SMOKE: a scalable edge computing framework for early fire detection. Sensors 19 (3), 639.
Barrios, E., Valencia, V., Jonsson, M., Brauman, A., Hairiah, K., Mortimer, P.E., Okubo, S., 2018. Contribution of trees to the conservation of biodiversity and ecosystem services in agricultural landscapes. International Journal of Biodiversity Science, Ecosystem Services & Management 14 (1), 1–16.
Baylis, A., 2017. Advances in precision farming technologies for crop protection. Outlook Pest Man 28 (4), 158–161.
Béné, C., Oosterveer, P., Lamotte, L., Brouwer, I.D., Haan, S. de, Prager, S.D., Talsma, E.F., Khoury, C.K., 2019. When food systems meet sustainability – current narratives and implications for actions. World Dev. 113, 116–130.
Berckmans, D., 2017. General introduction to precision livestock farming. Animal Frontiers 7 (1), 6–11.
Bhargava, K., Ivanov, S., 2016. Collaborative edge mining for predicting heat stress in dairy cattle. 2016 Wireless Days (WD). IEEE, Toulouse, France, pp. 1–6.
Bhargava, K., Ivanov, S., Donnelly, W., Kulatunga, C., 2016. Using edge analytics to improve data collection in precision dairy farming. Proceedings of the 41st Conference on Local Computer Networks Workshops (LCN Workshops). EEE, Dubai, pp. 137–144.
Bhargava, K., Ivanov, S., Kulatunga, C., Donnelly, W., 2017. Fog-enabled WSN system for animal behavior analysis in precision dairy. International Conference on Computing, Networking and Communications (ICNC) Silicon Valley, CA, USA.
Bhargava, K., Ivanov, S., McSweeney, D., Donnelly, W., 2019. Leveraging fog analytics for context-aware sensing in cooperative wireless sensor networks. ACM Transactions on Sensor Networks 15 (2), 23.
Byabazaire, J., Olariu, C., Taneja, M., Davy, A., 2019. Lameness detection as a service: application of machine learning to an internet of cattle. Proceedings of the 16th IEEE Annual Consumer Communications and Networking Conference (CCNC). IEEE, Las Vegas, USA, pp. 1–6.
Caria, M., Schudrowitz, J., Jukan, A., Kemper, N., 2017. Smart farm computing systems for animal welfare monitoring. in: 40th International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO), Opatija, Croatia. pp. 152-157.
Chang, H.-Y., Wang, J.-J., Lin, C.-Y., Chen, C.-H., 2018. An agricultural data gathering platform based on internet of things and big data. Proceedings of the 4th International Symposium on Computer, Consumer and Control (IS3C). IEEE, Taichung, Taiwan, pp. 302–305.
Costa, C., Antonucci, F., Pallottino, F., Aguzzi, J., Sarriá, D., Menesatti, P., 2013. A review on agri-food supply chain traceability by means of RFID technology. Food Bioprocess Technol. 6 (2), 353–366.
D'Agostino, D., Morganti, L., Corni, E., Cesini, D., Merelli, I., 2019. Combining edge and cloud computing for low-power, cost-effective metagenomics analysis. Futur. Gener. Comput. Syst. 90, 79–85.
Debauche, O., Mahmoudi, S., Andriamandroso, A.L.H., Manneback, P., Bindelle, J., Lebeau, F., 2018. Cloud services integration for farm animals' behavior studies based on smartphones as activity sensors. J Ambient Intell Human Comput 20 (S1), 273.
Elias, A.R., Golubovic, N., Krintz, C., Wolski, R., 2017. Where's the bear? - automating wildlife image processing using IoT and edge cloud systems. In: Abdelzaher, T., Kumar, P.R., Buchmann, A., Lu, C. (Eds.), Proceedings of the IEEE/ACM Second International Conference on Internet-of-Things Design and Implementation (IoTDI). IEEE/ACM, pp. 247–258.
European Court of Auditors, 2018. Broadband in the EU Member States: despite progress, not all the Europe 2020 targets will be met. http://publications.europa.eu/webpub/eca/special-reports/broadband-12-2018/en/#chapter3. Accessed 2nd September 2019.
Fan, D.H., Gao, S., 2018. The application of mobile edge computing in agricultural water monitoring system. IOP Conference Series: Earth and Environmental Science. 191. IOP Publishing (1).
FAO (Food and Agriculture Organization), 2015. The impact of disasters on agriculture and food security. http://www.fao.org/resilience/resources/resources-detail/en/c/346258/. Accessed 2nd September 2019.
FAO (Food and Agriculture Organization), 2018. Food loss and waste and the right Food loss and waste and the right to adequate food: making the connection. http://www.fao.org/3/ca1397en/CA1397EN.pdf. Accessed 2nd September 2019.
FAO (Food and Agriculture Organization), 2019. The State of Food Security and Nutrition in the World 2019: safeguarding against economic slowdowns and downturns. http://www.fao.org/3/ca5162en/ca5162en.pdf. Accessed 28th November 2019.
Fernandez-Carames, T.M., Fraga-Lamas, P., 2018. A review on the use of blockchain for the internet of things. IEEE Access 6, 32979–33001.
Ferrández-Pastor, F.J., García-Chamizo, J.M., Nieto-Hidalgo, M., Mora-Pascual, J., Mora-Martínez, J., 2016. Developing ubiquitous sensor network platform using internet of things: application in precision agriculture. Sensors 16 (7), 1141.
Føre, M., Frank, K., Norton, T., Svendsen, E., Alfredsen, J.A., Dempster, T., Eguiraun, H., Watson, W., Stahl, A., Sunde, L.M., Schellewald, C., Skøien, K.R., Alver, M.O., Berckmans, D., 2018. Precision fish farming: a new framework to improve production in aquaculture. Biosyst. Eng. 173, 176–193.
Fraser, E., Legwegoh, A., KC, K., CoDyre, M., Dias, G., Hazen, S., Johnson, R., Martin, R., Ohberg, L., Sethuratnam, S., Sneyd, L., Smithers, J., van Acker, R., Vansteenkiste, J., Wittman, H., Yada, R., 2016. Biotechnology or organic? Extensive or intensive? Global or local? A critical review of potential pathways to resolve the global food crisis. Trends Food Sci. Technol. 48, 78–87.
Gaura, E.I., Brusey, J., Allen, M., Wilkins, R., Goldsmith, D., Rednic, R., 2013. Edge mining the internet of things. IEEE Sensors J. 13 (10), 3816–3825.
Gebbers, R., Adamchuk, V.I., 2010. Precision agriculture and food security. Science 327 (5967), 828–831.
Global Panel, 2016. Food systems and diets: Food systems and diets: Facing the challenges of the 21st century. https://glopan.org/sites/default/files/ForesightReport.pdf. (Accessed 28 November 2019).
Gödecke, T., Stein, A.J., Qaim, M., 2018. The global burden of chronic and hidden hunger: trends and determinants. Global Food Security 17, 21–29.
Griffin, T.W., Shockley, J.M., Mark, T.B., 2018. Economics of precision farming. In: Shannon, D.K., Clay, D.E., Kitchen, N.R. (Eds.), Precision Agriculture Basics. American Society of

[11] EdgeX Foundry - https://www.edgexfoundry.org/.
[12] Open Edge Computing Initiative - https://www.openedgecomputing.org/.

Agronomy, Crop Science Society of America and Soil Science Society of America, Inc., Madison, WI, USA, pp. 221–230.
Guan, S., Fukami, K., Matsunaka, H., Okami, M., Tanaka, R., Nakano, H., Sakai, T., Nakano, K., Ohdan, H., Takahashi, K., 2019. Assessing correlation of high-resolution NDVI with fertilizer application level and yield of rice and wheat crops using small UAVs. Remote Sens. 11 (2), 112.
Guo, W., 2018. Spatial and temporal trends of irrigated cotton yield in the Southern High Plains. Agronomy 8 (12), 298.
Haleem, A., Khan, S., Khan, M.I., 2019. Traceability implementation in food supply chain: a grey-DEMATEL approach. Information Processing in Agriculture 6 (3), 335–348.
Henry, E., Adamchuk, V., Stanhope, T., Buddle, C., Rindlaub, N., 2019. Precision apiculture: development of a wireless sensor network for honeybee hives. Comput. Electron. Agric. 156, 138–144.
Hunter, M.C., Smith, R.G., Schipanski, M.E., Atwood, L.W., Mortensen, D.A., 2017. Agriculture in 2050: recalibrating targets for sustainable intensification. BioScience 67 (4), 386–391.
Johnson, D.L., Mikeka, C., 2016. Bridging Africa's broadband divide. IEEE Spectr. 53 (9), 42–56.
Jukan, A., Carpio, F., Masip, X., Ferrer, A.J., Kemper, N., Stetina, B.U., 2019. Fog-to-cloud computing for farming: low-cost technologies, data exchange, and animal welfare. Computer 52 (10), 41–51.
Kalatzis, N., Avgeris, M., Dechouniotis, D., Papadakis-Vlachopapadopoulos, K., Roussaki, I., Papavassiliou, S., 2018. Edge computing in IoT ecosystems for UAV-enabled early fire detection. Proceedings of the IEEE International Conference on Smart Computing (SMARTCOMP) Taormina, Italy.
Kamilaris, A., Fonts, A., Prenafeta-Boldύ, F.X., 2019. The rise of blockchain technology in agriculture and food supply chains. Trends Food Sci. Technol. 91, 640–652.
Krintz, C., Wolski, R., Golubovic, N., Bakir, F., 2018. Estimating outdoor temperature from CPU temperature for IoT applications in agriculture. Proceedings of the 8th International Conference on the Internet of Things(IOT '18), Santa Barbara, California. ACM, p. 11.
Kummu, M., Moel, H. de, Porkka, M., Siebert, S., Varis, O., Ward, P.J., 2012. Lost food, wasted resources: global food supply chain losses and their impacts on freshwater, cropland, and fertiliser use. Sci. Total Environ. 438, 477–489.
Lavanya, G., Rani, C., Ganeshkumar, P., 2019. An automated low cost iot based fertilizer intimation system for smart agriculture. Sustainable Computing: Informatics and Systems. Elsevier In press.
Lin, J., Shen, Z., Zhang, A., Chai, Y., 2018. Blockchain and IoT based Food traceability for smart agriculture. Proceedings of the 3rd International Conference on Crowd Science and Engineering (ICCSE 2018). ACM, Singapore.
López, J.A., Garcia-Sanchez, A.-J., Soto, F., Iborra, A., Garcia-Sanchez, F., Garcia-Haro, J., 2011. Design and validation of a wireless sensor network architecture for precision horticulture applications. Precision Agric 12 (2), 280–295.
MacMillan, T., Benton, T.G., 2014. Agriculture: engage farmers in research. Nature 509 (7498), 25–27.
MarketsandMarkets, 2018. Smart Agriculture Market by Agriculture Type Precision Farming, Livestock Monitoring, Fish Farming - 2023. https://www.marketsandmarkets.com/Market-Reports/smart-agriculture-market-239736790.html. Accessed 2nd September 2019.
Merelli, I., Morganti, L., Corni, E., Pellegrino, C., Cesini, D., Roverelli, L., Zereik, G., D'Agostino, D., 2018. Low-power portable devices for metagenomics analysis: fog computing makes bioinformatics ready for the internet of things. Futur. Gener. Comput. Syst. 88, 467–478.
Morais, R., Silva, N., Mendes, J., Adao, T., Padua, L., Lopez-Riquelme, J., Pavon-Pulido, N., Sousa, J.J., Peres, E., 2019. mySense: a comprehensive data management environment to improve precision agriculture practices. Comput. Electron. Agric. 162, 882–894.
Musa, Z., Vidyasankar, K., 2017. A fog computing framework for blackberry supply chain management. Procedia Computer Science 113, 178–185.
Neumann, G.B., Almeida, V.P., Endler, M., 2018. Smart forests: fire detection service. Proceedings of the IEEE Symposium on Computers and Communications (ISCC). IEEE, Natal, Brazil, pp. 01276–01279.
Oliver, S.T., González-Pérez, A., Guijarro, J.H., 2018. An IoT proposal for monitoring vineyards called SEnviro for agriculture. Proceedings of the 8th International Conference on the Internet of Things (IOT '18). ACM, Santa Barbara, California, pp. 1–4.
Park, J., Choi, J.-H., Lee, Y.-J., Min, O., 2017. A layered features analysis in smart farm environments. Proceedings of the International Conference on Big Data and Internet of Thing (BDIOT2017). ACM, London, United Kingdom, pp. 169–173.
Peters, B.G., Pierre, J., 2014. Food policy as a wicked problem: contending with multiple demands and actors. World Food Policy 1 (1), 4–11.
Rajagopal, A.S., Nishanth, M., Rajageethan, R., Rao, R., Ezhilarasie, R., 2018. Data mining approach to predict forest fire using fog computing. Proceedings of the 2nd International Conference on Intelligent Computing and Control Systems (ICICCS). IEEE, Madurai, India, pp. 1582–1587.
Romli, M.A., Daud, S., Zainol, S.M., Kan, P.L.E., Ahmad, Z.A., 2017. Automatic RAS data acquisition and processing system using fog computing. Proceedings of the 13th IEEE Malaysia International Conference on Communications (MICC) Johor Bahru, Malaysia.
Romli, M.A., Daud, S., Raof, R.A.A., Ahmad, Z.A., Mahrom, N., 2018. Aquaponic Growbed water level control using fog architecture. J. Phys.: Conf. Ser. 1018, 12014.
Rose, D.C., Sutherland, W.J., Parker, C., Lobley, M., Winter, M., Morris, C., Twining, S., Ffoulkes, C., Amano, T., Dicks, L.V., 2016. Decision support tools for agriculture: towards effective design and delivery. Agric. Syst. 149, 165–174.
Santesteban, L.G., 2019. Precision viticulture and advanced analytics. A short review. Food Chemistry 279, 58–62.
Shi, W., Cao, J., Zhang, Q., Li, Y., Xu, L., 2016. Edge computing: vision and challenges. IEEE Internet Things J. 3 (5), 637–646.
Singh, S., Carpio, F., Jukan, A., 2018. Improving animal-human cohabitation with machine learning in fiber-wireless networks. Journal of Sensor and Actuator Networks 7 (3), 35.
Tamirat, T.W., Pedersen, S.M., Lind, K.M., 2018. Farm and operator characteristics affecting adoption of precision agriculture in Denmark and Germany. Acta Agriculturae Scandinavica, Section B — soil. Plant Sci. 68 (4), 349–357.
Taneja, M., Byabazaire, J., Davy, A., Olariu, C., 2018. Fog assisted application support for animal behaviour analysis and health monitoring in dairy farming. Proceedings of the 4th World Forum on Internet of Things (WF-IoT), pp. 819–824 Singapore.
Taneja, M., Jalodia, N., Byabazaire, J., Davy, A., Olariu, C., 2019. SmartHerd management: a microservices-based fog computing-assisted IoT platform towards data-driven smart dairy farming. Software - Practice & Experience 49 (7), 1055–1078.
Thompson, N., Bir, C., Widmar, D.A., Mintert, J.R., 2018. Farmer perceptions of precision agriculture technology benefits. J. Agric. Appl. Econ. 40, 1–22.
Trendov, N.M., Varas, S., Zeng, M., 2019. Digital technologies in agriculture and rural areas - Briefing paper. http://www.fao.org/3/ca4887en/ca4887en.pdf. Accessed 2nd September 2019.
Walter, A., Finger, R., Huber, R., Buchmann, N., 2017. Opinion: smart farming is key to developing sustainable agriculture. Proc. Natl. Acad. Sci. 114 (24), 6148–6150.
Wang, X., Yang, L.T., Xie, X., Jin, J., Deen, M.J., 2017. A cloud-edge computing framework for cyber-physical-social services. IEEE Commun. Mag. 55 (11), 80–85.
WEF (World Economic Forum), 2018. Innovation with a purpose: the role of technology innovation in accelerating food systems transformation. http://www3.weforum.org/docs/WEF_Innovation_with_a_Purpose_VF-reduced.pdf. Accessed 2nd September 2019.
Xiong, Z., Zhang, Y., Niyato, D., Wang, P., Han, Z., 2018. When mobile blockchain meets edge computing. IEEE Commun. Mag. 56 (8), 33–39.
Yang, X., Zhang, F., Jiang, T., Yang, D., 2019. Environmental monitoring of chicken house based on edge computing in internet of things. Proceedings of the 8th Joint International Information Technology and Artificial Intelligence Conference (ITAIC), Chongqing, China. IEEE, pp. 617–620.
Zhao, G., Liu, S., Lopez, C., Lu, H., Elgueta, S., Chen, H., Boshkoska, B.M., 2019. Blockchain technology in agri-food value chain management: a synthesis of applications, challenges and future research directions. Comput. Ind. 109, 83–99.
Zhou, B., Li, Q., Mao, Q., Tu, W., Zhang, X., 2015. Activity sequence-based indoor pedestrian localization using smartphones. IEEE Trans. Human-Mach. Syst. 45 (5), 562–574.
Żukiewicz-Sobczak, W., Wróblewska, P., Zwoliński, J., Chmielewska-Badora, J., Adamczuk, P., Krasowska, E., Zagórski, J., Oniszczuk, A., Piątek, J., Silny, W., 2014. Obesity and poverty paradox in developed countries. Annals of Agricultural and Environmental Medicine 21 (3), 590–594.
Zyrianoff, I., Heideker, A., Silva, D., Kamienski, C., 2018. Scalability of an internet of things platform for smart water management for agriculture. Proceedings of the 23rd Conference of Open Innovations Association (FRUCT), Bologna, Italy. pp. 432-439. IEEE.