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Applications of IoT for optimized greenhouse environment and resources management

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ABSTRACT

The role of Internet-of-Things (IoT) in precision agriculture and smart greenhouses has been reinforced by recent R&D projects, growing commercialization of IoT infrastructure, and related technologies such as satellites, artificial intellige nce, sensors, actuators, uncrewed aerial vehicles, big data analytics, intelligent machines, and radio-frequency identification devices. Even though the integration of intelligent technologies offers unlimited potential in precision commercial agriculture, optimal resource management remains a challenge considering that IoT infrastructure is unevenly distributed across the world and concentrated in high-income countries. The utilization of IoT technologies in smart greenhouses often involves a tradeoff between the cost of agricultural production, environmental conservation, ecological degradation, and sustainability. The installation of IoT infrastructure is capital-intensive and often translates to higher energy demand, that elevates the risk for climate change. The widespread use of IoT sensors and networks also increases new challenges in the management of electronic waste, depletion of finite resources, and destruction of fragile ecosystems, resulting in climate change. the integration of IoT systems in greenhouses would be augmented by the global deployment of advanced 5G technology and Low-Earth Orbit (LEO) constellation broadband internet with low latency and high speeds. Intelligent application of agrochemicals could yield significant savings ($500/acre or more), while need-based irrigation and fertilizer application would help improve crop yields. Globally, the deployment of IoT infrastructure would yield about $500 billion of added value to the GDP by 2030. The forecasted economic benefits affirm that the applications of IoT for optimized greenhouse environment and resources management were sustainable, and any potential risks are incomparable to the long-term benefits in commercial agriculture. The review article contributes new insights on the role of IoT in agriculture 4.0, the challenges, and future prospects for developing nations, which lacked the resources to invest in precision agriculture technologies.

Abbreviations: AChE, Acetylcholinesterase enzyme; AI, Artificial Inteligence; ANN, Artificial Neural Networks; BEMS, Building Energy Management System; BLE, Bluetooth low energy; CNTS, Carbon nanotubes; CPS, Cyber-physical systems; CRAM, crop-residues and animal-manure composting; CSA, climate-smart agriculture; CVM, Collection Vendor Machines; DDRMPC, data-driven robust model predictive control; DDS, Data Distribution Service; ETSI, European Telecommunications Standards Institute; FAM, fuzzy associative memory; GA, Genetic Algorith; GPS, Global Positioning System; GSHP, ground source heat pump; H2M, Human to Machine; HPS, High Pressure Sodium; ICT, Information and Communication Technology; IEEE, Institute of Electrical and Electronics Engineers; ITU, International Telecommunication Union; IOT, Internet of Things; IPR, Intellectual Propoerty Rights; LEO, low-earth orbit; LoRaWAN, LoRa Protocol; LPWAN, Low-Power Wide-Area Network; LSTM, Long Short-Term Memory; M2M, Machine-to-Machine; MQTT, Messaging Queuing Telemetry Transport; NB-IoT, Narrowband Internet of Things; PET, Polyethylene terephthalate; QoS, Quality of Service; RES, Renewable Energy Sources; RFID, Radio Frequency Identification; R&D, Researcd and Development; SHM, Structual Health Monitoring; SiNWs, Silicon-based Nanowires; SVM, Support Vector Machines; TSN, Time-Sensitive Networking; TSFA, Time Series Forecasting Algorithm; XMPP, Extensible Messaging and Presence Protocol; WSN, Wireless Sensor Networks.

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1. Introduction

1.1. Definition of optimized environment and optimized greenhouse environments

An optimized environment is defined by the availability of smart systems for autonomous analysis of water, temperature, humidity, and soil pH among other parameters. The replacement of human labor with computers is justified, given it translated to tangible cost-savings for commercial farms and better yields (Rojas, 2015). The following are the primary options for achieving higher cost savings. One, historical predictive analytics data about markets and weather can be sourced from resesarch institutions (Ferkoun, 2015). However, modern IoT systems have context-specific applications, which require careful identification of sensors and settings, timely data acquisition and optimization, and rule-based control (Popović et al., 2017, Khudoyberdiev, Ullah et al., 2021). A key challenge was the transition from the traditional mechanical modes of farming to intelligent farming, given the resources required to achieve AI optimization.

IoT infrastructure and data-driven decision support systems offer a practical means to reduce the extra pesticide costs, given plants grown under greenhouses are less susceptible to pests compared to those grown in the open field (European Parliament, 2021). In addition, the regulation of the internal microclimate eliminates the risk of frost infestation and blight attributed to temperature and humidity fluctuations. The net effect is optimal production and better yields (Khavalko, Baranovska, and Geliznyak, 2019). The weather and demographic-related disruptions of agricultural systems provide compelling grounds for the sustainable use of IoT systems.

Pilot studies on the use of IoT in agriculture are promising. Zamora-Izquierdo et al. (2018) developed an IoT system based on edge and cloud computing that could regulate the greenhouse microclimate using overhead motorized windows for better ventilation. A thermal-shade screen system was installed on the roof for better energy saving. The system was operated autonomously using an electro-mechanical traction system. Excess heat was removed from the greenhouse structures using air fog and air cooling systems that cool the greenhouse structures through water evaporation, air compression, and humification (Zamora-Izquierdo et al., 2018). The state of the art literature presented by Mavrakis, Papavasileiou, and Salvati (2015), Liu et al. (2017), Pack and Mehta (2012), and Zamora-Izquierdo et al. (2018) affirmed there were various iterations of IoT systems in modern greenhouses and open field agriculture. The present discourse focused on the four priority areas of application for IoT, namely green hardware such as sensors, ultra low-power microcontrollers (Piromalis and Arvanitis (2016)) green software (event prediction, data classification, data delivery, and big data analytics), green communication infrastructure (future internet −5G/LEO constellation; Bluetooth, RFID, Ad hoc and ZigBee), and green architecture in the cloud (Friha et al., 2021). The four-point focus was validated by the immense benefits that would accrue from the adoption of IoT infrastructure in greenhouses (Varjovi and Babaie, 2020). The integration of IoT in other domains apart from agriculture offers unique opportunities for value creation (Bilbao-Osorio et al., 2014). A key constraint is the low pace of IoT technology commercialization and future uncertainties about technology growth returns on investments and hype surrounding new innovations (Government Office for Science, 2014). Despite the concerns, emerging research shows there were satisfactory economic returns associated with intelligent technologies.

Intelligent design for precision farming resulted in 25% savings in irrigation costs in wheat farms (Antony et al., 2020). In addition, judicious use of fertilizers resulted in better yields (Khudoyberdiev, Ullah and Kim, 2021). Other reports presented by Rayhana, Xiao, and Liu (2020) showed that agricultural production improved by 12%. A key constraint moving forward was the inadequate adaptability of precision and IoT agriculture systems to semi-arid regions and hot climatic conditions (Zamora-Izquierdo et al., 2018; Ghoulem et al., 2020). Nonetheless, the long-term benefits validated the need for smart and intelligent agriculture.

1.2. Definition of resource management

In farm environments, optimal resource management is characterized by better irrigation supervision, pesticide control, water quality analysis, and fertilizer control (Jawad et al., 2017). Past scholarly research has desmonstrated that better resource management translated to significant cost savings. IoT connectivity with LoRaWAN and other suitable networks in the open field and greenhouse farming would result to significant cost savings, better resource use and optimization, reduced cost of production by eliminating unnecessary human interventions (Madushanki et al., 2019; Villa-Henriksen et al., 2020), which would translate to lower prices for consumers. The focus on cost savings was reinforced by climate change and global warming-related farming losses, desertification (Lal, 2001; Sivakumar, 2007), and depletion of agricultural land as a result of rapid urbanization (Mavrakis, Papavasileiou, and Salvati, 2015; Liu et al., 2017). The Environmental Protection (2020) noted that US farmers would spend $11 billion more on pesticides due to climate. The global costs are unquantifiable in light of emerging issues concerning eco-toxicity, adverse effects on human health, and long-term efficacy (European Parliament, 2021). The projected increase in the cost of production would strain the already existing fragile agricultural infrastructure, given the global population was projected to surpass 11 billion by 2100 (Friha et al., 2021). The precision agriculture market is projected to record 15% annual growth in the short-term and exceed $12 billion in valuation by 2025 and increase (Bersani et al., 2020); this might translate to higher energy demand and climate change, given commercial power production has a higher carbon footprint.

The widespread growth of IoT systems in agriculture has been augmented by emerging technologies such as fiber-optics, 4G/5G, low-earth orbit (LEO) constellation, and sensors (Tzounis et al., 2017) (multi-wavelength laser-diode photodiode, graphene-based sensors, Bragg, piezoelectric, electrochemical, electromagnetic sensors and RNA sensors), RFID, Al, and machine learning (Symeonaki, Arvanitis and Piromalis, 2019). RFID and Bluetooth connectivity are ideal for short-range device-to-device connectivity, while LEO constellations offer global coverage with reduced latency (Starlink, 2020; OneWeb, 2021); this eliminates the constraints associated with unequal global internet connectivity. Additional benefits would be provided by the global rollout of WiFi 6 and 5G connectivity, which will help improve internet speed and device density while overlaying on the existing 4G infrastructure (Goedde et al., 2020). The potential benefits linked to these technologies would provide massive IoT, characterized by the scaling up of IoT and application of precision agriculture in field crops, tracking of machinery, and the performance of remote structures (Achour, Ouammi and Zejli, 2021; Jamil et al., 2022). The massive IoT would facilitate the use of technology in mission-critical services such as the operation of machinery and drones, among other applications that would require stable real-time connections and improved stability (Goedde et al., 2020). Beyond the connectivity requirements, massive IoT deployment requires the availability of low-cost sensors with higher functionality for monitoring light/imaging, acoustics, vibrations, weather and temperature, water flow, capacitance, and gases (Cisco and the International Telecommunication Union (ITU), 2015). Apart from the temperature monitoring systems (Peña, Peralta and Mar 2020), illuminance, ground, multimedia, climate, radiationand tag sensors, and decision support systems were needed. Presently, there are no low-cost sensors that offer higher functionalities.

At present, the adoption of IoT systems in agriculture is primarily driven by the need to reduce the cost of agricultural production; however, there has been a lesser emphasis on environmental conservation, ecological degradation, and sustainability (Food and Agricultural Organization of the United Nations, 2017; Goedde et al., 2020). From a resource use perspective, LEO constellation, WiFi 6, 5G would facilitate the rollout of massive IoT and data-driven decision support systems to support autonomous functions and precision agriculture (Food and Agricultural Organization of the United Nations, 2017; Goedde et al., 2020; Lehr, Queder and Haucap, 2021). However, market data suggests that WiFi connectivity would be less suitable for IoT infrastructure in outdoor environments. Spitfire Technology Group – an industry leader in the provision of IoT connectivity infrastructure in the UK, established that the technology was less appropriate for extreme environment scenarios, places with intermittent power/insufficient power infrastructure, and real-time communication with mobile devices (Spitfire, 2021); this means that IoT connectivity should be confined to selected low-bandwidth networks such as LoRaWAN, with long-range, low power, low-maintenance requirements. Selected resources for smart/intelligent greenhouses were presented under Table 1.

1.3. Industry 4.0 aims and objectives

The transition to agriculture 4.0 and 5.0 was augmented by the adoption of smart agriculture, AI, big data, UAVs, and IoT in farming (Saiz-rubio, 2020). Additionally, agriculture 4.0 is indispensable to closed-loop control of precision farming (Katamreddy *et al.*, 2019), and efficient use of farming resources (Madushanki et al., 2019). The efficient utilization of energy and water resources in optimized greenhouse environments is vital to the sustainability of smart farming (Popović et al., 2017; Syafarinda et al., 2018; Raviteja and Supriya, 2020; Ruan et al., 2020; Friha et al., 2021; Placidi et al., 2021) and the actualization of global sustainable development goals (Cisco and the International Telecommunication Union (ITU), 2015). The transition from Agriculture 3.0 to Agriculture 4.0 commenced in 2017 and represents one of the most ambitious technological innovations in the agricultural sector, given that it encompasses the integration of big data analytics, uncrewed aerial surveillance vehicles (Jumaah et al., 2021), the internet of things, and artificial intelligence and machine learning (Friha et al., 2021) (see Fig. 1).

The transition has been catalyzed by severe weather events linked to global warming and climate change (Environmental Protection, 2020) and the need for better efficiency and sustainable practices in agriculture to optimize the food supply chains (Sinha, Shrivastava, and Kumar, 2019), and improve traceability. The role of IoT in facilitating agricultural traceability was demonstrated following the outbreak of the African swine flu in China (He and Shi, 2021). However, the unlocking of the maximum benefits would be dependent on the extent to which advanced technologies are integrated into the agricultural sector. The review purposed to build upon existing research by critiquing different narratives on energy, water, and e-waste resource management, optimized environmental challenges, IoT protocols, and digital transformation.

Table 1
Selected resources for smart greenhouses (Singh et al., 2020).

Resource	Purpose
Temperature control system	Regulation of heating, cooling, and ventilation to prevent frost, fungi, and bacteria growth and ensure optimal crop growth.
Illuminance, ground, multimedia, climate, radiationand tag sensors	Remote identification, remote image capture, light monitoring for plant growth, analytic and reasoning functionality, information mining and equipment control, as well as early climate warning
Decision support system (DSS)	Farm-specific semantic annotation and interoperability

2. Challenges of optimized environment and resources management

2.1. Optimized environment challenges

2.1.1. Standardization of IoT platforms

Despite the adoption of IoT platforms (O'Grady et al., 2019), growth and ownership remained a challenge. Considering that different regions and countries have different technological competencies and challenges, global agriculture 4.0 has been characterized by various iterations. For example, 84% of Canadian farmers have integrated at least one type of precision agriculture technology such as GPS. Most farmers intend to adopt IoT technologies in the future (Sinha, Shrivastava, and Kumar, 2019). In contrast, the most common IoT technologies in Europe were GPS-based area measurement and soil sampling, GPS-enabled tractor steering, intelligent pesticide and fertilizer application, yield mapping (predictive models) (Sinha, Shrivastava, and Kumar, 2019). A fundamental concern is that the global south has been lagging behind in the adoption of advanced technologies and precision agriculture, also referred to as climate-smart agriculture (CSA). Such concerns are further validated by the fact that progress made in creating industry awareness about IoT infrastructure did not meet expectations (Gassner et al., 2013); this is an issue that should be resolved given the extensive outreach campaigns by agro-industry partners, and the scientific community did not translate to higher market acceptance. Standards for IoT technologies include 3GPP Standards NB-IoT standard and non-3GPP standards (Elijah et al., 2018). Despite the adoption of industry standards, there were criticla future uncertainties as noted under section 2.1.2. The link between policies, laws, regulations, and success of advanced IT systems was demonstrated in Fig. 2.

2.1.2. Future uncertainties

Even though there is broad consensus that IoT infrastructure such as LoRa network, Low Power Wide Area Network (LPWAN) technology, MAC algorithms, time synchronization would translate to significant energy savings through the automation and intelligent operation of renewable photovoltaic panels and ground source heat pump (GSHP), and heat exchangers, (Awani et al., 2017) mass technology acceptance might be impaired by the following uncertainties. First, a national-wide study on the state of IoT technologies in the UK noted there was limited uptake of IoT technologies in modern farming (Government Office for Science, 2014). The phenomenon is paradoxical considering the immense benefits that accrue from the adoption of IoT infrastructure, such as precision-based irrigation, intelligent application of pesticides and fertilizers, and intelligent regulation of the microclimate and data-driven decision support systems (Antony et al., 2020), and cost-savings of up to $500 per acre (Goedde et al., 2020). The limited utilization of IoT networks was confirmed by Madushanki et al. (2019) during the investigation of the pace of IoT adoption in agriculture and smart farming. According to the report, the pace of Bluetooth connectivity was below 5%. A similar pattern was evident in the utilization of LoRAWAN, RFID, LAN, and GPRS, compared to WiFi (Madushanki et al., 2019). The selective focus on certain communication infrastructure could translate to sub-optimal IoT outcomes (Gassner et al., 2013), which consequently impact public attitudes towards IoT.

Second, despite the promising application of IoT in various facets of everyday life, government reports suggest it would be misleading to presume that the future of IoT technologies was certain (Government Office for Science, 2014). The conservative outlook is premised on the hype surrounding revolutionary and emerging technologies and assumptions, which partly explain why IoT remains at the "peak of inflated expectations." Such expectations might not be actualized over time. In light of the conservative projections, the hypothesized benefits that would accrue from the global rollout of LEO constellation broadband internet services by OneWeb and Starlink (Starlink, 2020; OneWeb, 2021) might not be significant. Alternatively, the benefits could be

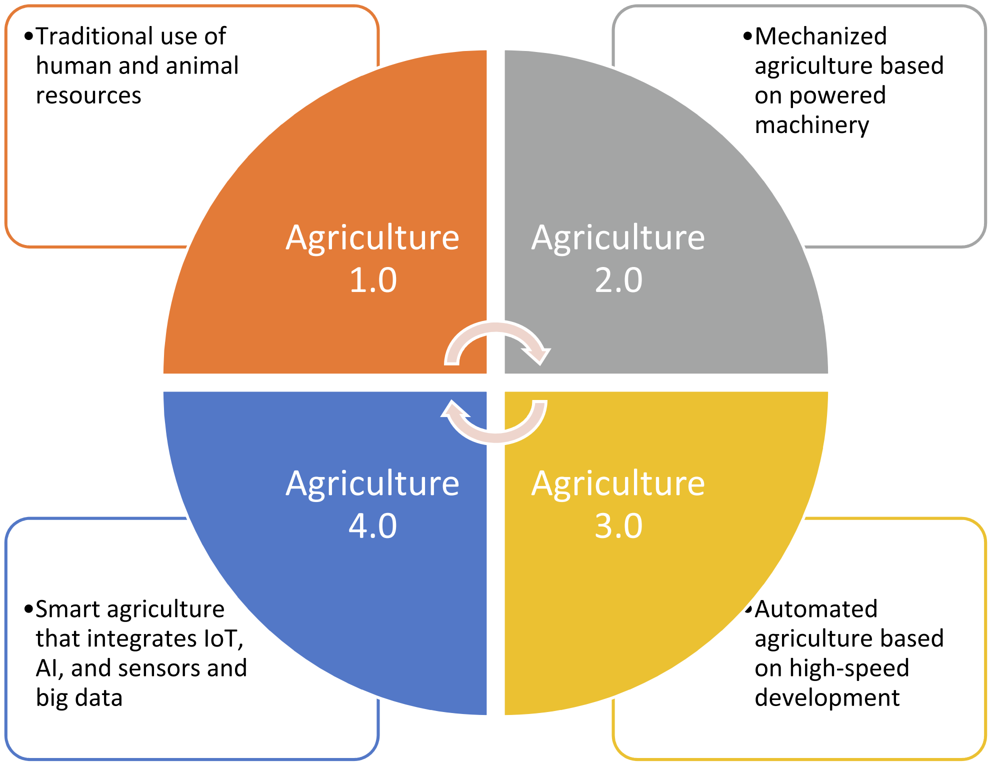

Fig. 1. Increase in agricultural complexity with advances made from Agriculture 1.0 to Agriculture 4.0 (Friha et al., 2021).

Fig. 2. Link between policies, laws, standards, regulations and success of advanced IT systems (Piromalis & Arvanitis, 2016).

localized in advanced economies with better infrastructure, such as the UK, Canada, Japan, and Germany (Bersani et al., 2020). The appraisal of the future uncertainties would enable engineers and researchers to address the barriers to market entry and consumer acceptance.

Third, there are inadequate business models for commercializing IoT technologies in greenhouses and agriculture profitably (Government Office for Science, 2014). The gaps between R&D and the commercialization of new technologies might partly explain the inadequate demand for GPRS, LoRa, Bluetooth (Varjovi and Babaie, 2020) and the agricultural industry in general (Madushanki et al., 2019). The sector has one of the lowest percentages of entities using IoT infrastructure in the automation of operations. Until these issues are resolved, it would become increasingly challenging for businesses to invest significant resources in IoT in light of the concerns about the return on investment (Government Office for Science, 2014). Moving forward, the commercialization of IoT innovations could emerge from leading technology companies that enjoy economies of scale in the production of IoT infrastructure. With this approach, it would be practical to achieve incremental benefits in greenhouses. A major drawback of this approach was that large corporations and government entities were less capable of harnessing the data generated by IoT systems (Government Office for Science, 2014). The inability to interpret the data would limit the synergistic benefits associated with investments in technology and the adoption of energy-efficient IoT predictive models. The challenges documented by Government Office for Science (2014) could be linked to the newness and complexity of agriculture 4.0 (Friha et al., 2021). Considering that the global transition from agriculture 3.0 to agriculture 4.0 officially commenced in 2017, it would take time to resolve the technical constraints associated with the integration of different Al, machine learning, IoT, and big data analytics.

2.2. Resources management challenges

Energy, water, and fertilizer conservation, electronic waste management, using IoT infrastructure translated to better resource management through the intelligent application of pesticides, N and P fertilizers, and irrigation, resulting in lower production costs. In addition, communication between different IoT systems and optimization of agricultural structures through continous monitoring was reviewed under sections 2.2.4 and 2.2.5. The need for practical energy solutions is validated by higher energy expenditure traditional greenhouses. Thermal heating demand in traditional greenhouses accounts for 80% of the energy used, and non-IoT modifications made over time (such as the replacement of high-pressure sodium (HPS) lamps with LED lamps) did not translate to significant energy savings (Bersani et al., 2020). The views advanced by Bersani et al. (2020) were corroborated by Canakci et al. (2013), who estimated the average energy expenditure was 10,459,688 MJ/ha, which translated to 65,891.5– 151,220.6$ per year. The high cost of artificial heating help to explain why it was impractical for smallholder farmers to invest in greenhouses. The observations made by Bersani et al. (2020) and Canakci et al. (2013) contrast with Ahamed et al. (2018), who argued that despite the high cost of artificial heating, the net returns from the production of greenhouse crops were significant. For example, the net returns per m^2 for pepper, cucumber, and tomato were $44, $41, and $69, respectively. In reality, even though Ahamed et al. (2018) reported net benefits, the net returns were case-specific and dependent on the market prices. If the market prices were low, the net returns would be inadequate to sustain thermal heating operations in traditional greenhouses. The energy-related constraints validated the need to use IoT technologies for better energy efficiency.

2.2.1. Energy management

Emerging innovations for optimal energy savings include smart sensors for energy load shaping, smart sensors for the optimization of renewable energy systems, and autonomous energy management (Motlagh and Mohammadrezaei, 2020). Temperature sensors have proven useful in resolving fluctuations in heating and cooling a system by triggering an automated response through the IoT infrastructure. On the downside, despite the immense potential of IoT in energy saving in precision agriculture (Motlagh and Mohammadrezaei, 2020), there is inadequate information in the public domain concerning the long-term cost benefits of energy-saving IoT sensors in commercial agriculture. A large body of knowledge on sensors is grounded in computer simulations and pilot studies. For example, there is a paucity of literature on the actual benefits that accrued from the adoption of the GSM network-based dual communication system, which provided users with real-time updates for better tracing, evaluation, and control of energy flows (Karthikeyan et al., 2021). Singh, Berkvens, and Weyn (2020) and Yaïci et al. (2021)'s research observed that integrating a critical mass of low-cost sensors and providing constant power to the electronic equipment remains one of the critical challenges to the commercialization of IoT in smallholder and large scale farms.

Energy conservation remains a challenge using the existing IoT infrastructure; this informed Singh, Berkvens, and Weyn (2020) on energy-efficient IoT systems for greenhouse structures using WSN technology (Tzounis et al., 2017; Maraveas and Bartnazas, 2021b), crop prediction models, agricultural-IoT solutions to manage the network gap between the gateway/base station and farms. The study confirmed that there were various constraints in connecting wireless technology with hardware such as sensors. High sensor performance involves a tradeoff with power consumption; "the more power optimized the sensor node, the better will be the Quality of Service (QoS) features such as reliability and lifetime of the network." In Singh, Berkvens, and Weyn's (2020) case study, the challenge was partially offset through the deployment of the LoRa network, Low Power Wide Area Network (LPWAN) technology, coupled with novel design techniques for efficient wireless systems, implementation of MAC algorithms, time synchronization, edge computing, and Machine Learning (ML) (Khavalko, Baranovska, and Geliznyak, 2019). The approach employed by Singh, Berkvens, and Weyn's (2020) was comparable to Motlagh and Mohammadrezaei (2020), who noted that optimal performance in sensors could be achieved using low power communication networks such as Bluetooth low energy (BLE) technologies, ZigBee, narrowband IoT (NB-IoT), LTE-M, LoRa, and Sigfox. The road map for energy efficiency is visualized in Fig. 3.

The commercial viability of LoRa was demonstrated by Spitfire (2021). The company adopted the network infrastructure to provide connectivity between different IoT components embedded into renewable energy systems (solar, geothermal, underground water, and wind) and sensors to track wild animals in farms (Arabkoohsar et al., 2016; Chiriboga et al., 2021). From an engineering perspective, the LoRa network offers better capabilities compared to WiFi and broadband internet, which are less suited for communicating with mobile devices, extreme environment scenarios, and insufficient power infrastructure (Spitfire, 2021). The potential benefits that would accrue from the adoption of the low-cost models are reviewed to provide better insights on the sustainability of near-zero energy expenditure in greenhouses. Tangible energy savings were recorded by (Yaïci et al., 2021a) with the integration of IoT in thermoelectric air conditioning systems (see Fig. 4) (Yaïci et al., 2021a). The data recorded over 100 h showed that higher power consumption in the building energy systems was specific to the air conditioning system without IoT.

The use of artificial lighting in greenhouses is key, given that optimal ambient light control translates to better photosynthesis. The energy-saving-related benefits associated with the optimal location of LED lamps for better photosynthesis were reinforced with a parallel particle swarm algorithm for better energy savings (Bersani et al., 2020). The energy savings achieved from lighting had a domino effect on the cost of greenhouse operations, considering that smart greenhouses require artificial lighting at night for optimal photosynthesis. Further energy savings were achieved using Model Predictive Control algorithms such as data-driven robust model predictive control (DDRMPC) for better

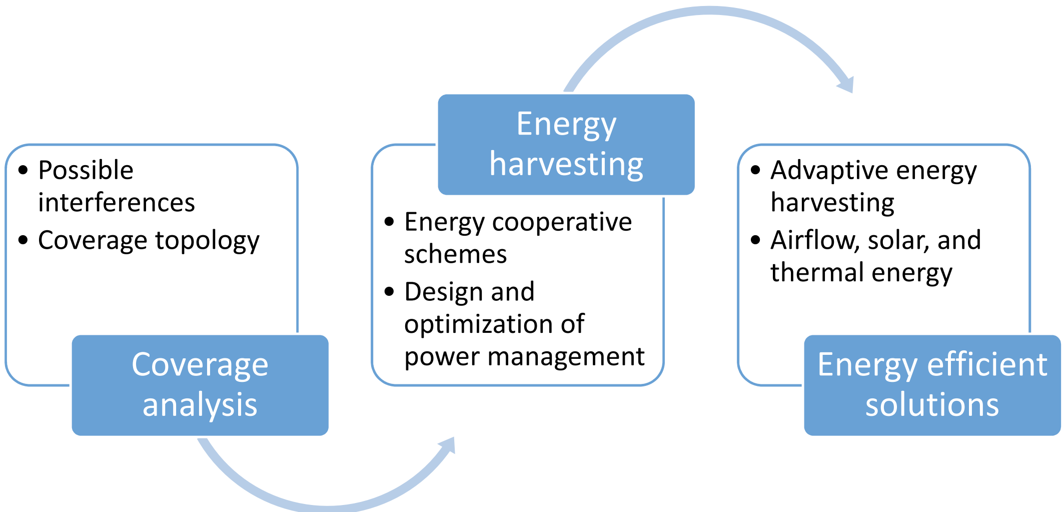

Fig. 3. Technical roadmap for energy efficiency (Singh, Berkvens and Weyn, 2020a).

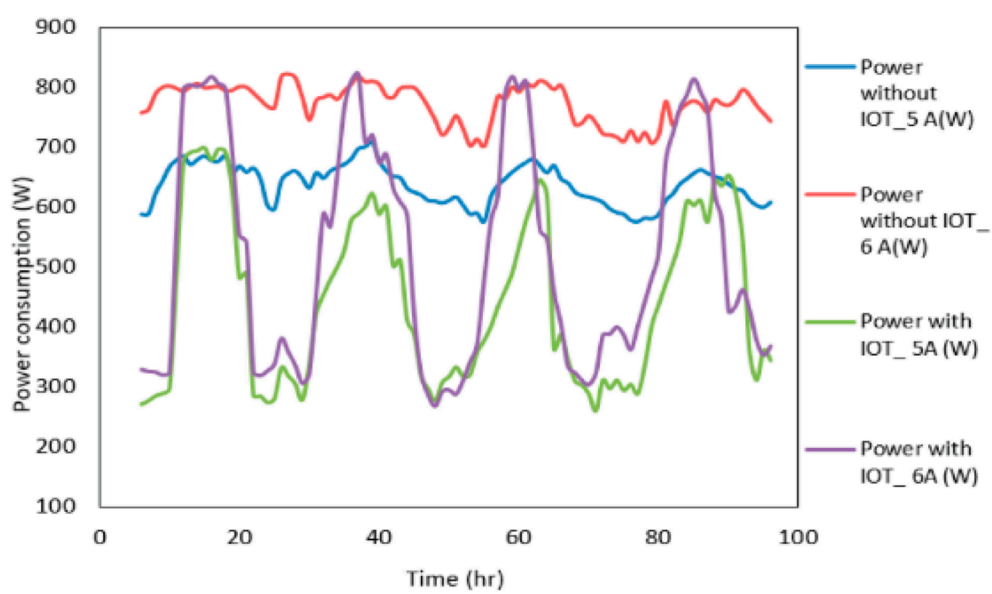

Fig. 4. Power consumption of a thermoelectric air conditioning system with and without IoT infrastructure (Yaïci et al., 2021a).

temperature prediction and regulation. Alternatively, automated temperature regulation could be achieved using sequential quadratic programming and particle swarm optimization algorithms (Bersani et al., 2020). In brief, the use of predictive model control offers the potential to achieve near-zero energy consumption in smart horgreenhouses (Chen, Sivaparthipan and Muthu, 2022). The optimization of light control has been augmented by new evidence - preliminary case studies conducted using Raspberry Pi show that the platform provides advanced capabilities given it facilitated the simultaneous connection of eight channels in a parallel configuration. The channels had different interconnecting backplanes and spreading factors (Placidi et al., 2021). On the downside, market data is limited to IoT platforms such as Industrial Arduino Controller, Open Mote, Raspberry Pi. Such platforms are not ubiquitous in the commercial agricultural sector (Industrial Shields, 2020). The lack of sufficient market data creates a disconnect between innovations and consumer acceptance and adoption in farms. The challenge could be partly offset by adopting emerging innovations including Piromalis 's (2018) smart precision lighting approach.

2.2.2. *Water management*

The role of IoT infrastructure in environmental protection is not confined to energy saving associated with the integration of PV panels and optimal utilization of agricultural resources through data-driven decision support systems for agrochemical applications, and real-time monitoring of physical parameters (Antony et al., 2020; Hernández-morales, Luna-rivera and Perez-jimenez, 2022; Jamil et al., 2022). However, it remains unknown if IoT systems would address historical challenges in agriculture. The need for practical solutions is justified, given excessive use of pesticides results in soil and groundwater toxicity and human toxicity if the contaminated farm produce is consumed. Song et al. (2015) noted that the pesticides inhibit the cellular function of the acetylcholinesterase (AChE) enzyme, which is involved in the regulation of neurotransmitters such as acetylcholine for CNS function. The need to mitigate the risk of groundwater contamination is reinforced by the high cost of cleaning up contaminated groundwater sources (Aktar, Sengupta, and Chowdhury, 2009). A majority of the traditional pesticides have been proven to possess endocrine growth factors, which impair the function of the endocrine system (Pérez-Lucas et al., 2018). The pesticide overuse challenge identified by (Pérez-Lucas et al., 2018) was not localized in the west. (Zhang et al., 2015) noted that excessive pesticide use was a common challenge in China where it was correlated with negative health and environmental externalities. The growing awareness of the adverse effects of pesticides persist over the long term, have led to the exploration of various strategies, including applying lesser pesticides and smart pesticides using robotics and IoT or pest detection using AIoT Based Smart Agricultural System (Chen et al., 2020; Bamini and Shanmugadevi, 2021). A fundamental concern is that each of the proposed solutions has its benefits and drawbacks. The drawbacks were reviewed under section 2.2.3 from the context of e-waste management, while the communication and structural benefits were reviewed under section 2.2.4.

2.2.3. E-Waste management

Despite the clear-cut benefits associated with the integration of IoT systems in commercial agriculture, there are critical drawbacks that should be addressed in the future. For example, it has been demonstrated that widespread deployment of 5G technologies would translate to higher use of computing devices and an increase in energy demand to power the computing devices, which would exacerbate climate change (Curran, 2020). Other reports have raised concerns about radiation exposure (Kelsh et al., 2011). Beyond higher energy demands and radiation, electrochemical sensors contain harmful chemicals that are toxic to soils, crops, and stored grains (Maraveas and Bartzanas, 2021a). Other ecological concerns relate to the long-term generation of electronic waste from higher consumer demand for IoT computing devices. Electronic waste has detrimental effects on the environment (Akram et al., 2019). The potential adverse effects on the environment documented by Akram et al. (2019) and Curran (2020) could be resolved through the use of advanced technologies. Singh et al. (2021) and Kang et al. (2020) argued that the IoT systems would be beneficial in the management of electronic waste. Preliminary case studies of IoT-mediated waste collection systems in Malaysia (Kang et al., 2020) and IoT-based collection vendor machines (CVM) (Singh et al., 2021) for safe disposal of toxic electronic waste components such as cathode ray tubes, mercury-laden switches, printed circuit boards with rare earth and heavy metals. The IoT-mediated electronic waste management help to offset any potential drawbacks associated with the technology. In addition to the IoT-guided waste management, nanomaterials (such as graphene–metal oxide nanohybrids) drawn from electrochemical sensors have potential broad areas of application in precision agriculture such as degradation of organic pesticides and industrial pollutants (Baruah and Dutta, 2009) and detection of microbes, toxic pollutants at the microscopic level (Baruah and Dutta, 2009; Gupta Chatterjee et al., 2015). On a positive note, the listed benefits help to offset the adverse effects on the environment.

2.2.4. Communication services management

Optimal communication service management is dependent on the identification of the most suitable communication system for long-range and short-range machine-to-machine communication. At present, BLE is among the widely preferred short-range wireless communication technologies for exchanging data using radio wavelengths over short distances – 0–30 m (Motlagh and Mohammadrezaei, 2020). Other studies estimate that the communication range could be expanded to 100 m (Villa-Henriksen et al., 2020) or exceed 200 m with BLE (Yaïci et al., 2021b). A key benefit of BLE is the cost of installation and widespread availability across different classes of computing devices and IoT infrastructure. Other key benefits include low power consumption (Yaïci et al., 2021b) and the high data-rate speeds 125 kb/s – 2 Mb/s–500 kb/s (long-range) (Yaïci et al., 2021b). In contrast to Yaïci et al. (2021b), Villa-Henriksen et al. (2020) noted that Bluetooth connectivity in IoT infrastructure could attain data rates of up to 24 Mb/s, which is significantly higher than LoRaWAN's 0–50 Kb/s (Villa-Henriksen et al., 2020). However, the data rates of Bluetooth are considerably lower than 4G/5G technologies, which offer ultra-fast connectivity. The variable data rates could translate to lags in the transmission of data, which might, in turn, impair autonomous decision-making and initiation of a response in the event of an emergency.

Beyond variable data rates, IoT systems had other shortcomings, such as the limited utility of IoT in end-to-end communication owing to a poor technical understanding of its cost benefits. The phenomena had translated to strained usage of the technology (Symeonaki, Arvanitis, and Piromalis, 2019). The problem might have a long-term effect given Bluetooth and LoRaWAN connectivity have been used to facilitate communication with agricultural robots that autonomously apply agricultural pesticides (Bamini and Shanmugadevi, 2021). In other cases, Bluetooth was integrated with other forms of IoT connectivity, such as ZigBee and LAN, to reduce unnecessary human interventions, improve efficiency, and mitigate pollution (Madushanki et al., 2019); this was achieved by integrating temperature and humidity sensors into smart greenhouses for better production.

The autonomous application of pesticides using robots is critical to the viability of data-driven decision support systems for fungicide and pesticide application, intelligent irrigation of crops, regulation of the greenhouse microclimate, and fertilizer application (Antony et al., 2020). The robot plays a vital role within the paper. It contains pesticides to eliminate the pests in the land. When it identifies the pests starts sprinkling within the land through the Bluetooth module.

Even though the low cost of BLE makes it appropriate for smart greenhouses, its application is restricted to small-scale IoT applications and low volume of data; this explains why BLE is widely preferred in commercial and residential building structures relative to smart farm structures. The drawbacks of BLE underscored the need for complementary techniques for machine-to-human and machine-to-machine communication devices in farms. The shortcomings associated with BLE can be offset by LoRaWAN, which has a communication range of 5–20 km (this is particularly ideal for open field commercial agriculture). In addition to the extensive communication range, LoRaWAN shares other benefits with BLE, such as the low cost of operation and installation, low power consumption, security, and availability. The issue of availabiliy was indicated by Antony et al. (2020), who noted that agricultural human–machine interface systems had been "designed for use on smartphones; however, smartphone penetration is low among rural populations in GFSS countries" (p. 13). The influence of mobile computing on green IoT agriculture was also affirmed by Nandyala and Kim (2016). The growth of future IoT systems would be contingent on smartphone penetration. In theory, the challenge could be offset by the transition to ultra-narrow band wireless cellular network such as Sigfox networks, which have been proven useful in agriculture IoT and machine-type communications systems (Jawad et al., 2017). Alternatively, agricultural companies could leverage on the LoRaWAN technology (Sendra et al., 2020; Singh et al., 2020; Placidi et al., 2021). On the downside, there was no adequate market data on longterm efficiency of LoRaWAN and Sigfox in commercial farms.

The road map for achieving optimal efficiency is represented in Fig. 3. A fundamental question moving forward was whether Singh, Berkvens, and Weyn's (2020) model were scalable in real-life agricultural applications. Such concerns are legitimized by the fact that control packets in the IoT infrastructure have a considerable impact on the power loss, especially given there was significant dissipation of energy in the transmission and reception process. Other concerns relate to the cost of the new technology. The cost aspects were critiqued in detail under sections 2.3 and 3.1.

2.2.5. Structural integrity and materials

The structural health of construction materials has a significant impact on resource management in farms, because construction materials predict heating and cooling requirements (energy expenditure). Traditionally, glass, plastic, and steel-reinforced concrete are the material of choice in agricultural construction (Abosrra, Ashour, and Youseffi, 2011; Kotsovos, 2017; Maier, 2020; Maraveas, 2020; Fowler *et al.*, 2008; Lee, Lee and Woo, 2014). Nonetheless, the risk of corrosion (Huang et al., 2015; Chen et al., 2019; Gai et al., 2020; Mukherjee et al., 2021), environmental degradation caused by rain, humidity and sunlight remains high because the traditional materials are susceptible to acids, moisture, bacteria, and other corrosion-inducing agents common in farms (Maraveas, 2020; Maraveas and Bartzanas, 2021b; Seitllari and Naser, 2018). Traditional concrete is susceptible to brittle failure despite the advances in shear design methods (Kotsovos, 2017). The steel reinforcements in concrete undergo environmental degradation/corrosion with constant exposure to humid conditions, marine environments, and chloride-containing aggregates (Abosrra, Ashour, and Youseffi, 2011); this impacts the load-bearing capacity of the building, the flexural strength of the concrete, and structural integrity.

The integration of nanomaterials such as carbon nanotubes (CNTs), IoT, and graphene offers practical benefits over traditional materials. Laboratory-scale studies have demonstrated that the incorporation of 0.15 and 0.25 wt (Mohsen et al., 2019) of CNTs increased the flexural strength of the concrete structures by 100% compared to concrete samples without CNTs. Beyond the flexural strength, the CNTs improved the ductility of the concrete beams by about 150% while suppressing the permeability of the concrete (Portland cement, Class 42.5 R) (Mohsen et al., 2019). Material characterization of the specimens confirmed that the CNTs structures acted as bridges across the micro-cracks (Hassan, Elkady, and Shaaban, 2019); this explains the tangible improvement in the mechanical properties. Similar benefits were observed with nano-engineered graphene composites for ultrahigh performance.

Graphene additives in concrete improved the flexural and compressive strength of concrete by 80 and 46%, respectively (Dimov et al., 2018). The improvements make the material to be ideal for concrete structures in areas prone to flooding. Beyond better strength, advances in technology would facilitate monitoring the impact of temperature and humidity on concrete structures using temperature and humidity sensors for structural health monitoring.

The Stuctural Healtn Monitorinfg (SHM) system can be customized to send periodic updates about the structural health of the concrete structure in line with the client's requirements. Other unique advantages of IoT in structural health monitoring include the ease of integration with external developments (such as smart devices, satellite, and 4G/5Gconnectivity, cloud, or user applications). The commercially available IoT systems for structural health monitoring include Envira DS LOG, Envira DS WEB, and NanoEnvi MOTE (Envira, 2021). The IoT infrastructure and smart sensors can be customized to monitor energy use with the integration of building information modeling (Bottaccioli et al., 2017). Considering new materials and methods are under development and testing, the SHM via IoT becomes critical for the development of new solutions. The case for agrovoltaics should be considered in future studies. Various communication infrastructures have been developed to facilitate communication between the sensors and computing devices, including M2M standard communication protocols such as REST and MQTT (Syafarinda et al., 2018; Park et al., 2019; Mishra and Kertesz, 2020). The prevailing problems, solutions and challenges were reviewed under Section 2.3.

2.3. Problems, solutions, and challenges

Various IoT innovations have been developed recently including IBM Watson IoT Platform Analytics, Azure Stream Analytics, HPV Vitrica, SAP HANA's Smart Data Streaming (IoTEDU Innovation Lab, 2021). However, broad commercialization of IoT systems has been the cost of IoT infrastructure. As of 2020, the distribution of 4G/5G and GPS positioning for navigation of unmanned aerial systems was unevenly distributed across North America, South Asia, the Middle East, and Africa, Latin America, and East Asia (Cisco and the International Telecommunication Union (ITU), 2015). The uneven distribution of IoT infrastructure predicted the rate of smart agriculture assimilation. Bersani et al. (2020) noted that Germany, the US, China, Canada, South Korea, and Japan were leading in the adoption of precision agriculture and smart greenhouses. In particular, Japan was among the leading nations in the adoption of UAVs for open-field spraying in rice fields (Sinha, Shrivastava, and Kumar, 2019). As of 2019, 36% of the rice field spraying was conducted using UAVs (Sinha, Shrivastava, and Kumar, 2019). Beyond precision agriculture, UAVs had potential application in next-generation wireless communication, crop surveying, and humanitarian assistance (Lemayian and Hamamreh, 2020; Ullah, Al-Turjman and Mostarda, 2020; Aggarwal, Kumar and Tanwar, 2021; Chaurasia and Mohindru, 2021; Said Mohamed et al., 2021). The global divide in the adoption of new technologies has practical consequences on global agricultural sustainability. Traditional methods of agricultural production are less sustainable due to climate change.

A key challenge moving forward has been limited access to new technologies. Even in cases where the technology was available, farmers and commercial producers must overcome barriers associated with spectrum and bandwidth, interoperability, and standards. The challenges partly explain why the widespread use of emerging IoT technologies for smart greenhouses is limited (Zamora-Izquierdo et al., 2018) due to a combination of policy and technological barriers (see Fig. 5).

The policy issues encompass data localization, access to data, legacy regulatory models, Intellectual Property Rights (IPR), cross-border traffic, and governance while the technical transcends sensor and technology reliability, scaling, power, cost, capacity, and IPv6) (Cisco and the International Telecommunication Union (ITU), 2015). The intersection of the two domains introduced a third dimension specific to the spectrum and bandwidth constraints, privacy (Symeonaki, Arvanitis and Piromalis, 2019), security, interoperability, and standards (Villa-Henriksen et al., 2020). The operational frequency of IoT infrastructure documented by Villa-Henriksen et al. (2020) is comparable to other surveys on the performance of different infrastructures.

The exclusion of remote areas where most agricultural activities are concentrated remained a critical impediment in the short term. In the long-term, the challenge could be offset by LEO constellation broadband internet services provided by private companies such as OneWeb and Starlink (Starlink, 2020; OneWeb, 2021). Considering that the internet market penetration by Starlink and OneWeb could help resolve the connectivity, related challenges, the review helped to demonstrate that it was feasible to achieve sustainability and environmental protection through the judicious use of IoT systems. However, the LEO constellation does not address other constraints, including the cost of reliable sensors.

2.3.1. Network interoperability solutions

The interoperability of different networks and infrastructure would reduce dependence on specific networks and sensors. The optimism is premised on the global share of IoT projects in Europe and the Americas. Smart agriculture accounts for 31 and 48% of the new projects in these regions (see Fig. 6) (Symeonaki, Arvanitis, and Piromalis, 2019). The uptake of IoT in these regions is significantly higher relative to South Asia and Africa where the level of adoption of advanced technologies such as 5G remains low (Said Mohamed et al., 2021). The global distribution of IoT projects presented by Symeonaki, Arvanitis, and Piromalis (2019) reinforces earlier observations made concerning the uneven distribution of IoT infrastructure. A joint study conducted by Cisco and the International Telecommunication Union (ITU) (2015) confirmed that IoT infrastructure was concentrated in advanced economies. Similarly, Bersani et al. (2020) and Sinha, Shrivastava, and Kumar (2019) observed that Germany, the US, China, Canada, South Korea, and Japan had made significant progress in the adoption of IoT compared to developing nations, that we're still relying on traditional methods of farming. The concerns raised about the limited progress made by developing nations were also acknowledged by Gassner et al. (2013), who attributed the issues to the lack of comprehensive research on the rate of precision agriculture adoption in developing nations.

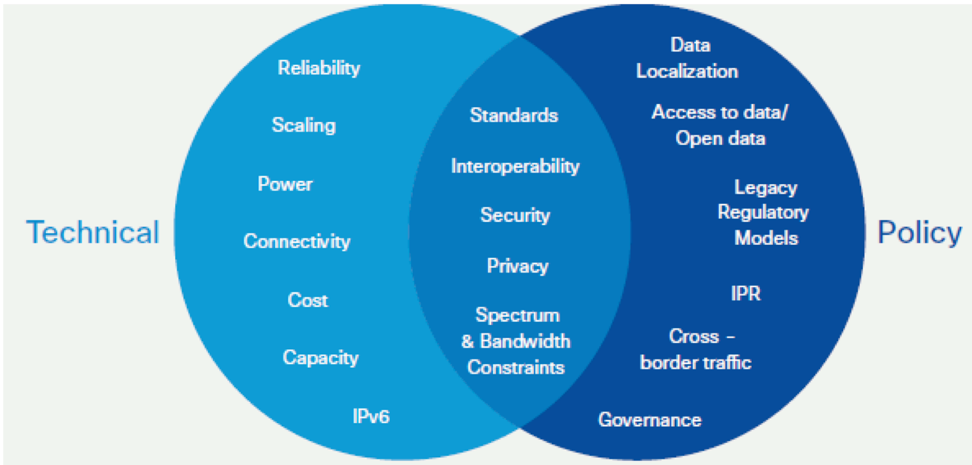

Fig. 5. Policy and technological barriers to the global adoption of IoT systems in agriculture and beyond (Cisco and the International Telecommunication Union (ITU), 2015).

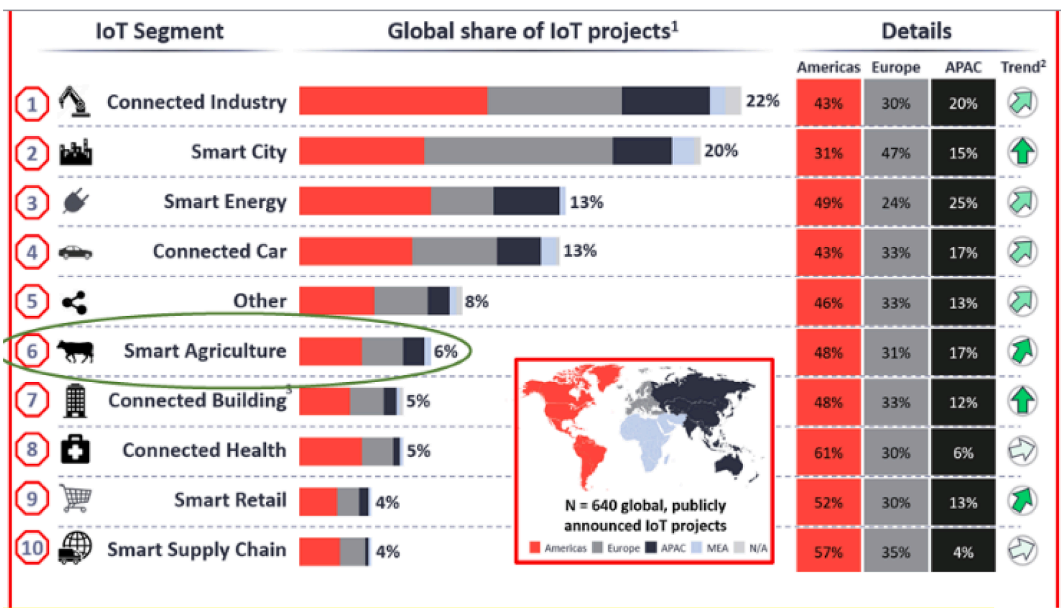

Fig. 6. State of global IoT integration across different industries (Symeonaki, Arvanitis and Piromalis, 2019).

The Government Office for Science (2014) report hypothesized that the place of leading technology companies with economies of scale in the commercialization of IoT infrastructure would be taken by disruptive companies that counter the current status quo (Government Office for Science, 2014). However, the technologically disruptive companies would face similar challenges in attempting to gain entry into existing markets or create new niches. Since the current IoT market is poorly defined, and there is no clear-cut data on the actual demand for IoT systems, forecasting the returns on investments in IoT remains a challenge. In the event that technologically disruptive companies and leading technology entities are unable to penetrate the market, industry coalitions of companies might be created to diversify the risks and exploit the competencies of the different stakeholders. Following the review of the various practical options available for market entry, it was deduced that large investors had better leverage compared to smallholders, given they can easily access state financial support, direct capital investments such as bonds (Khavalko, Baranovska, and Geliznyak, 2019). Despite the constraints, there are immense business opportunities in the analysis of data collected by IoT infrastructure in farms and using the data to develop predictive models. However, there is a need for anti-competition standards to provide a fair platform for competition and industry growth (Government Office for Science, 2014). Such standards would facilitate the security, interoperability, and openness of different IoT infrastructures.

Symeonaki, Arvanitis, and Piromalis (2019) notes that some progress had been made towards the standardization of IoT infrastructure under the Cluster of European R&D Projects on the IoT (CERP-IoT), which is an alliance of key stakeholders such as the European Telecommunications Standards Institute (ETSI), Institute of Electrical and Electronics Engineers (IEEE), International Telecommunication Union (ITU), Internet Engineering Task Force (IETF), ZigBee Alliance, and protocol for Smart Objects Alliance (IPSO) (Symeonaki, Arvanitis and Piromalis, 2019). The alliance offers mixed benefits. On a negative note, the alliance is new, and it would take time to unlock the benefits of interoperable infrastructure. On a positive note, collaboration would help unlock innovations and the standardization of best practices (Friha et al., 2021). Even though standardization was identified as a practical solution, other context-specific constraints abound, including reliance on traditional approaches of farming, size of the farms, and extent of mechanization (Gassner et al., 2013). The latter challenges underscore the need for multistakeholder collaboration and extensive investments in IoT-based solutions for greenhouses.

3. IoT protocols and architectures for greenhouses

3.1. IoT protocols

New advances in technology have led to the development of multiple IoT protocols, including ZigBee, REST, MQTT, LPWAN, LoRaWAN, Data-Distribution Service (DDS) (Zu, Bai, and Yao, 2016; Murugesan et al., 2017), Extensible Messaging and Presence Protocol (XMPP), Z-wave, and IPv6 (Badenhop et al., 2017; Tournier et al., 2021). Each protocol has context-specific applications. For example, highly efficient σcommunication protocols such as MQTT Protocol (Message Queuing Telemetry Transport) (da Cruz et al., 2018; Al-Masri et al., 2020; Sanjuan et al., 2020) have gradually phased out HTTP (Hypertext Transfer Protocol)(Syafarinda et al., 2018). MQTT is capable of running on lower bandwidth, which translates to lower overhead protocols. Similarly, DDS offers practical benefits given it facilitates the seamless transmission of low-latency messages, which is vital for inter-agent communication within smart grids (Saxena et al., 2018); this explains why the framework has been deployed in diverse contexts, including smart and microgrids, defense, finance, and automotive industries (Hakiri et al., 2015; Tekinerdogan, Köksal, and Çelik, 2017; Saxena, Farag and El-Taweel, 2021). The proponents of DDS frameworks argue that they can be easily customized to support interoperability with RIOT-OS, FreeRTOS, and self-contained ZigBee stacks (Beckmann and Dedi, 2015). The benefits attributed to DDS indicate that the specific IoT protocol could be coupled with variois WSNs for better interoperability and support for heterogeneous target platforms. In contrast to Beckmann and Dedi (2015) and Saxena et al.(2018), Köksal and Tekinerdogan (2017) postulated that the commercial viability of DDS as an IoT protocol was constrained by the following challenges scalability, security, reliability, data consistency, integration with WAN, measurement, optimization and performance prediction. The mixed observations made by Beckmann and Dedi (2015), and Saxena et al.(2018), Köksal and Tekinerdogan (2017), raise fundamental questions about future applications in farms and smart greenhouses. The preliminary data is promising – DDS coupled with Multi-Level Time-Sensitive Networking (TSN) has been proven useful in wind farm monitoring, data transfer, and smart farming systems.

The drawbacks of DDS informed the need to invest in other protocols such as ZigBee, MGTT, and Extensible Messaging and Presence Protocol (XMPP). A unique benefit of XMPP was the ability to function optimally in resource-constrained IoT devices and bridge the gap between sensors, actuators, and other systems by eliminating application protocol gateways and protocol translators (Kirsche and Klauck, 2012; Wang et al., 2017). Despite the unique benefits, XMPP is only appropriate in selected applications.

ZigBee is ranked among the best IoT technologies for farming and agriculture (particularly irrigation supervision, pesticide control, water quality analysis, and fertilizer control) due to its low duty cycle (Jawad et al., 2017). ZigBee could be augmented by cloud computing, which has been proven useful in smart greenhouses and precision agriculture (Bo and Wang, 2011; Patil et al., 2012; Rojas, 2015; Choudhary, Jadoun, and Mandoriya, 2016). Similar to DDS, ZigBee has been proven useful in selected farm applications including automated monitoring of a fish farm environment, and physical characteristics of dairy cattle (behavioral characteristics and body temperature) (Li et al., 2010; Chen et al., 2016; Elijah et al., 2018). On the downside, challenges in data acquisition and control in farms have practical effects on the reliability of ZigBee technology in commercial agriculture (Hebel, 2006). However, this view was contested by Verma et al. (2020, p. 400) who claimed that ZigBee technology has a "monopoly over other communication technologies because of its unique characteristics like low cost, unified standard, less power consumption and versatility." The contrasting evidence show that IoT protocols would have an immense value in agriculture 4.0 (Khujamatov and Toshtemirov, 2020). The challenges would be resolved over time.

Cloud computing stands out given it is a low-cost and energy-efficient system (Tzounis et al., 2017; Maraveas and Bartnazas, 2021b). Energy consumption remains a critical issue in IoT systems, as noted by Singh, Berkvens, and Weyn (2020), who documented multiple benefits following the deployment of the Low Power Wide Area Network (LPWAN), but the high power consumption using sensor materials was a major constraint; this informed the exploration of alternative and feasible methods such as predictive temperature control using Al and IoT (Yaïci et al., 2021b), Reinforcement learning-based BEMS architecture, and energy-aware spatial–temporal correlation mechanisms for energy management among others (Yaïci et al., 2021b). On the downside, the alternative energy options are either expensive or less scalable. In an attempt to address the issue, predictive and analytical models have been deployed in pilot phases.

Predictive models rely on historical occupancy and weather data to forecast future scenarios that might require intelligent and autonomous intervention. The Time Series Forecasting Algorithm (TSFA) is a case in point (Suradhaniwar et al., 2021). Even though TSFA has been widely recommended in agricultural environments (Ali and Hassanein, 2020), there are multiple constraints, which hinder its widespread application. A key constraint is that the reliability of the model data is influenced by multiple externalities, such as the stochasticity of historical data, structural vs. empirical risk minimization, and the relevance of the algorithmic assumptions (Suradhaniwar et al., 2021). Additionally, the TSFA is dependent on WSN-based Long Short-Term Memory (LSTM) models. The challenges associated with TSFA can be resolved using the adaptive models (Salerno et al., 2021; Wang et al., 2021; Yaïci et al., 2021b), which rely on real-time monitoring. However, the recommended process which is intrusive and energy-intensive. The lack of reliable historical data has made it challenging for automated systems to regulate and predict changes in temperature, moisture, pH, pesticides, humidity, UV radiation, rain, CO_2, and pressure (Navarro, Costa, and Pereira, 2020; Miller and Cappuccio, 2021). The constraints associated with historical data can be addressed through the collection of data and R&D.

New IoT infrastructure integrates predictive and adaptive methods to exploit the synergistic benefits associated with either technique. Other alternatives that have been explored to attain greater energy saving include window shading with intelligent shade systems, smart glass, and switchable films, which reduce the energy demand by up to 43% (Yaïci et al., 2021b). Further cost benefits can be achieved with the installation of IoT-based photovoltaic panels and ground source heat pump (GSHP) systems. The transition from the grid to renewable energy sources (RESs) is supported by the adverse ecological effects and CO_2 emissions attributed to higher energy demand.

Other notable applications of new IoT systems include using LoRa and NB-IoT to enhance device connnectivity and QoS, latency, reliability, and range (Sinha, Wei, and Hwang, 2017); fusion of air quality sensors and LPWANs for CoVID-19 monitoring (Peladarinos *et al.*, 2021); IoT communication protocols (Al-Sarawi *et al.*, 2017); and RFID, smart sensors for machine-to-machine communication (Al-Fuqaha *et al.*, 2015). Nonetheless, the existing barriers to new technology adoption in the agriculture sector must be addressed; these include the disproportional link between speed, distance, and power (see Fig. 7).

3.2. Existing approaches in IoT architectures

In the recent past, the deployment of Cyberr-Physical Systems (CPS) depended on progress made with IoT and big data. The view is consistent with Ruan et al. (2019), who observed that CPS systems based on genetic algorithm (GA) and support vector machines (SVM) were dependent on big data. The core arguments made by Ruan et al. (2019) partly align with An et al.'s (2017) study, which noted that agricultural cyber-

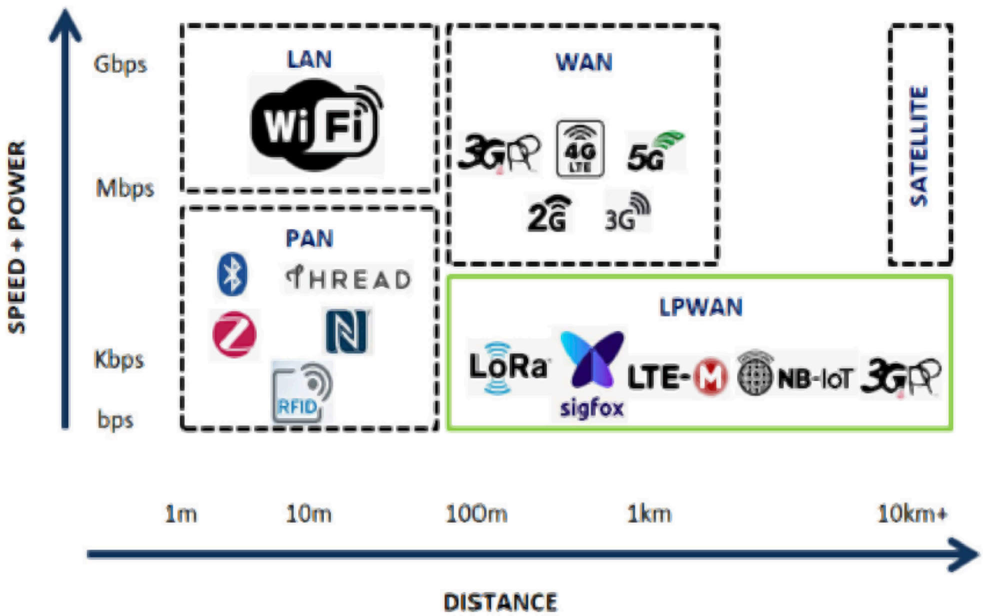

Fig. 7. Impact of speed, power, distance and choice of WAN and LAN (Peladarinos et al., 2021).

physical systems could achieve optimal function using data drawn from GIS, UAV, and sensors. The link between CPS, UAV, GIS, and sensors underscores the practical benefits of machine-to-machine networks for agricultural applications. The elimination of human interventions has been proven to mitigate human errors. Other benefits include the exploitation of the synergistic benefits such as intelligent and autonomous applications associated with networked machines compared to isolated components (Chen, Wan, and Li, 2012; Wan et al., 2013). On the downside, the benefits associated with machine-to-machine systems must be considered from the broader context of the costs involved in setting up and maintaining the systems.

The need to integrate complementary technologies in agricultural production is grounded on the 2016 USDA Agricultural Resource Management Survey, which affirmed that the efficiency gains linked to precision agriculture were contingent on the inclusion of complementary tools (DeLay, Thompson, and Mintert, 2021). The worldview was also shared by the Precision Agriculture Alliance (PrecisionAg Alliance, 2020). The only drawback is the high initial costs and payback period. The preservation of sensor data in the cloud and utilization of feedback to determine nutrition status, water levels, temperature, and humidity was economically favorable (Rojas, 2015). For example, the historical predictive analytics data could help producers predict supply and demand trends across different product markets. However, constraints associated with insufficient network coverage and low internet speeds could be addressed using WSN technology and satellite systems (see Fig. 8).

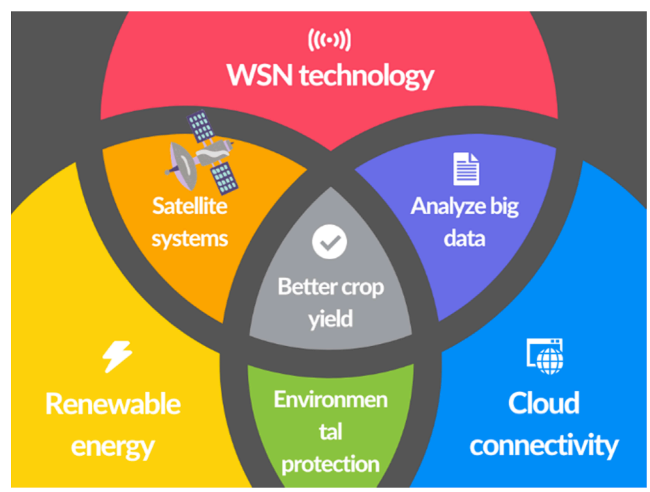

Fig. 8. The intersection of cloud computing, WSN, geo-location, satellites, and computer to human interfaces (Maraveas and Bartzanas, 2021a).

The positive assessment of the role of edge computing by Zhang et al., 2020 is consistent with O'Grady et al. (2019) and Akhtar et al. (2021). Both studies concurred that edge computing would have a positive impact on the agricultural industry. In contrast to cloud computing in agriculture, which is well-grounded, edge computing is an emerging application and a nascent field. In 2021, the first prototypes of edge computing were still under development. In addition, there has been no reliable and widespread validation of edge-driven services in farms. At present, interoperability remains a key issue (see Fig. 9).

3.3. Market maturity challenges

The sustainable use of IoT systems introduces new challenges and dimensions in terms of ecological conservation and resource utilization. On a positive note, it was possible to achieve significant cost savings by using IoT systems and sensors to regulate the internal greenhouse temperatures, shading, automated irrigation, autonomous monitoring of plants, assess pest and disease infestation, and improve security (Agrawal et al., 2016; Chiesa et al., 2020; Singh, Berkvens and Weyn, 2020b). The use of data-driven decision support systems for fungicide application, regulation of soil water content translated to cost savings of about $500/acre (Antony et al., 2020). The transition from transitional systems to precision agriculture would translate to $500 billion of added value to the global GDP by 2030 (Goedde et al., 2020) (see Fig. 10). The actual cost savings from the automation of agricultural processes would reach $2-$3 trillion in the long term. On the downside, unlocking these benefits has often remained a challenge for smallholder farmers and commercial companies. One of the primary barriers to technology assimilation has been the concentration of 4G/5G and GPS positioning in urban areas rather than rural areas in North America, South Asia, the Middle East, and Africa, Latin America. The uneven distribution of key infrastructure helps to explain why the US was among the leading nations in the adoption of GPS-enabled spraying of crops (Sinha, Shrivastava, and Kumar, 2019). The technology eliminates the need for

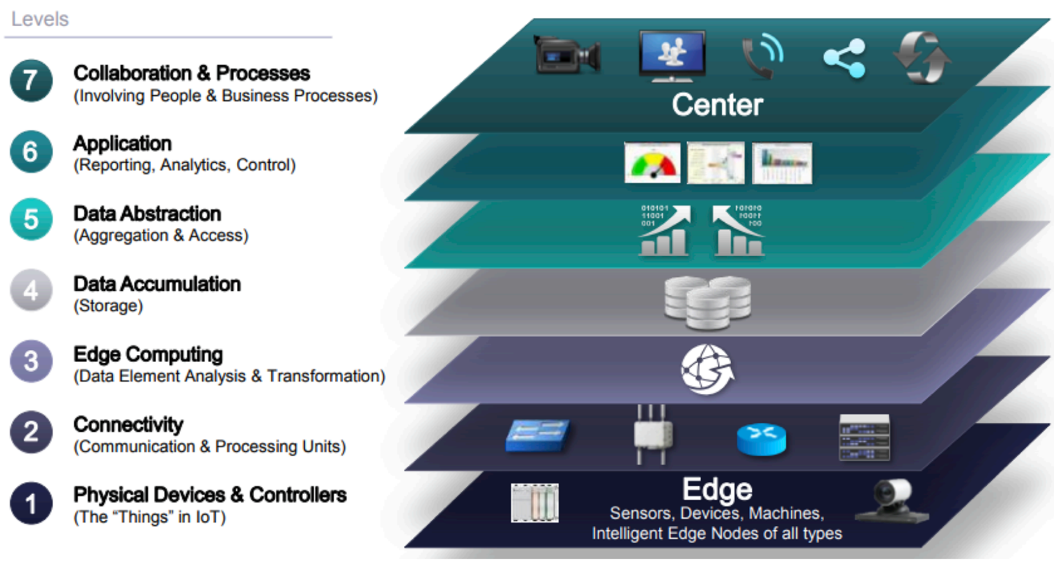

Fig. 9. Interoperability of Applications from Different Vendors (Cisco and the International Telecommunication Union (ITU), 2015).

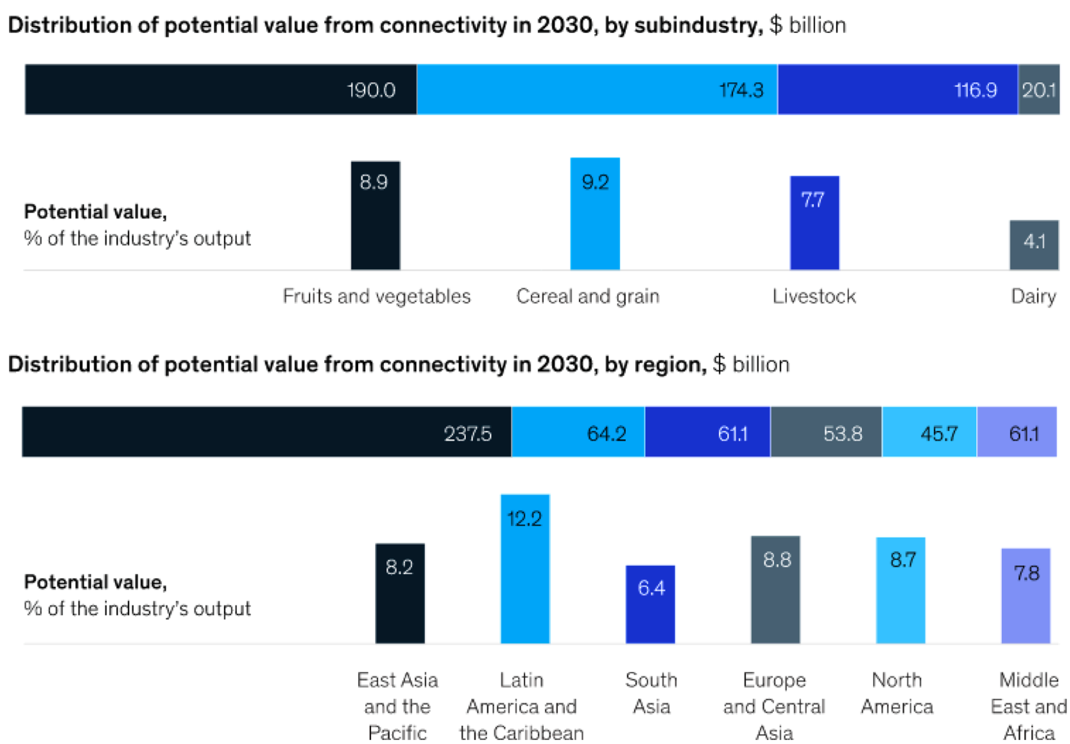

Fig. 10. The distribution of potential value from IoT connectivity across different regions (North America, South Asia, Middle East, and Africa, Latin America, and East Asia) and agricultural subsectors (fruits and vegetables, dairy, livestock, cereals, and grains) (Goedde et al., 2020).

human labor, which, in turn, translates to better efficiencies in the production process.

3.4. Challenges in the context of industry 4.0

The realization of the benefits reported by Goedde et al. (2020) remains a challenge due to the cost of IoT infrastructure (Cisco and the International Telecommunication Union (ITU), 2015). Modern technologies have made it a challenge to provide sensors with high functionality at a lower cost. Sensors that are extremely accurate/precise and capable of industrial-scale deployment in large enterprises are expensive – the cost ranges between $150 and $1,000+ per sensor (Cisco and the International Telecommunication Union (ITU), 2015). Considering that smart greenhouses require multiple sensors for water, soil pH, and nutrition monitoring, and microclimate regulation (Moretti and Marucci, 2019; Sagheer et al., 2020), the sensors are out of reach of smallholder farmers.

Investment in low-cost sensors is not a viable option considering that such sensors have limited capabilities in terms of single functionality, limited compatibility with other hardware, amateur applications, and basic function. The issue concerning the cost of sensors was also highlighted by Placidi et al. (2021), who estimated that reliable soil water content sensors cost $150-$5,000. The costs were higher if the sensors had greater functionalities. Based on the high cost of sensors for agriculture and non-agriculture applications, the following observations can be made. First, sensor technology is not market-ready considering that cost is a critical barrier that impedes market entry. Two, further research and development are necessary to ensure the widespread availability of accurate sensors with higher functionality (extreme accuracy/precision, and industrial-scale deployment, solution interoperability) (Kishore, 2020; Villa-Henriksen et al., 2020; Sagheer *et al.*, 2021). Third, large commercial producers (early adopters of technology) would immensely benefit from the early adoption of expensive IoT infrastructure compared to smallholder farmers (late adopters of technology) (see Fig. 11).

The benefits would have practical consequences on agricultural sustainability. From another dimension, the limited uptake of IoT technology among smallholder farmers could be attributed to other externalities beyond cost and the distribution of network infrastructure. The view is supported by Varjovi and Babaie (2020), who noted that the attitudes of farmers towards risk and uncertainty, human capital characteristics (demographics, gender, and education), labor availability land, access to credit and extension services, size of the farm and land tenure contracts. The multidimensional view advanced by Varjovi and Babaie (2020) complements prior arguments made concerning the barriers to IoT technology integration in agriculture.

Despite the high cost associated with IoT sensors, current R&D offers promising prospects for the reduction of the cost of installation and maintenance of IoT infrastructure. Recently, Changqing, Hui, and Wenjun (2018) successfully developed a low-cost communication system for greenhouses using the LoRa wireless network construction and a single chipset STM32F103 for master control. In line with Changqing, Hui, and Wenjun (2018), Zeed, Ali, and Baghdadi (2019) highlighted the recent progress made in the deployment of low-cost IoT systems for greenhouses. For example, the cost of power consumption associated with the deployment of intelligent infrastructure and agriculture/industry 4.0 could be offset by the interaction of solar panels.

4. Disgital transformation: towards greenhouse 4.0

4.1. Industry 4.0 core technologies

Research and development have contributed to emerging innovations in ICTs, which would have direct positive benefits on commercial production and the future of precision agriculture (Dachyar, Zagloel, and Saragih, 2019; Singh, Berkvens and Weyn, 2020; Friha et al., 2021). The technologies that would have the most notable impact include CPS, WSN (Bravo-arrabal et al., 2021), big data, Machine to Machine (M2M) (Chen, Wan, and Li, 2012; Wan et al., 2013), Human to Machine (H2M), LoRa Protocol (LoRaWAN) (Compte, 2019; Sendra et al., 2020), multi-agent-IoT systems (Wang et al., 2020a), ZigBee/Z-Wave (Mainetti, Patrono and Vilei, 2011; Kazeem, Akintade, and Kehinde, 2017), Radio Frequency Identification (RFID) systems for tracing and tracking of vegetables (Yang et al., 2008; Mainetti et al., 2013), GPRS, Application Programming Interface (API), Advanced Encryption Standard (AES), and Digital Twins, among others.

The cost-related savings were demonstrated through the deployment of OLI and WorldView-2 satellites to map greenhouses. The technology proved effective in mono-temporal greenhouse mapping (Ou et al., 2019), which guides data-driven decisions on precision agriculture, improving crop yields. Similarly, digital twins have potential broad areas of application in vertical farming. Monteiro et al. (2018) claimed that the deployment of digital twins in agriculture would help improve productivity through self-optimized learning using various data sources, structural monitoring and self-protection, energy-saving, and continuous assessment of ecological changes. The unique benefits associated with digital twins documented by Monteiro et al. (2018) were in line with Howard et al. (2020). However, in the latter case, it was deduced that the digital twin benefits transcended basic monitoring to encompass the seamless integration of big data and IoT for optimal communication and relay of energy and climate data and estimation of future greenhouse states.

4.2. Artificial intelligence and edge computing

AI and edge computing offer diverse benefits in IoT-based agriculture (Liao et al., 2017), especially where there is an imminent risk of fire hazard triggered by flammable liquids, machine moving parts (such as worn or misaligned moving parts, frayed drive belts, and broken or exposed electrical wiring), and open burning of agricultural waste. For example, multifunctional AI frameworks were vital for fire safety and general hazard mitigation in farms and system automation (Naser, 2019;

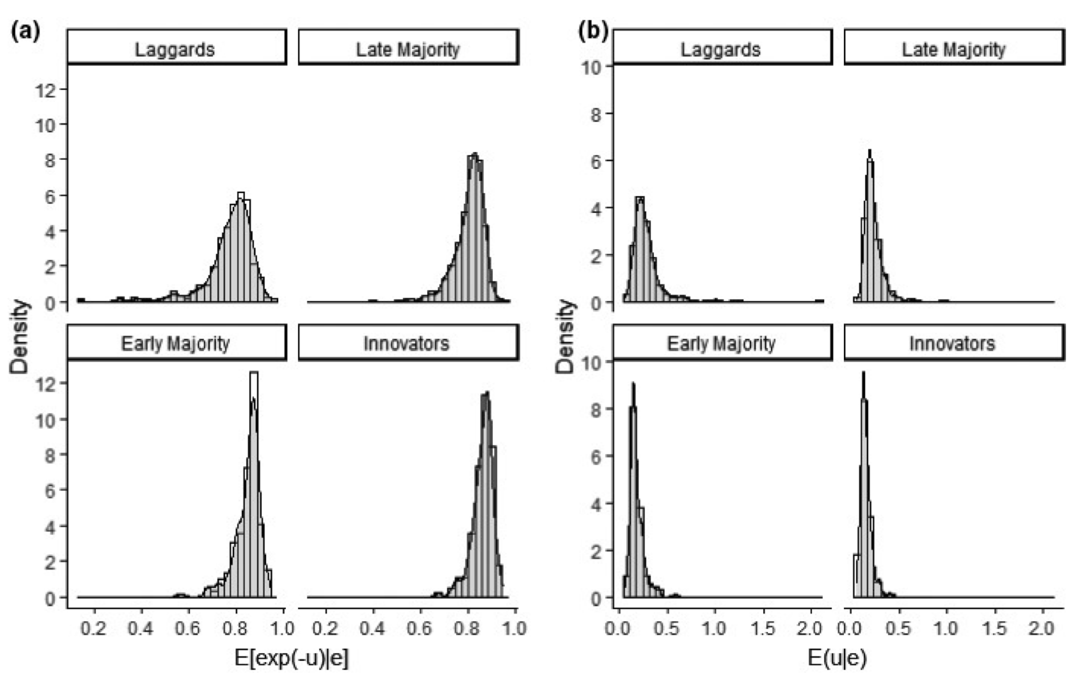

Fig. 11. Technical efficiency benefits associated with the early adoption of precision agriculture (DeLay, Thompson, and Mintert, 2021).

Park et al., 2019; Shamshiri et al., 2020). The claims made by Naser (2019), Park et al. (2019), and Shamshiri et al. (2020) linking AI and better safety management were in agreement with Ayhan and Tokdemir (2019), Zhang et al. (2021), and Zhang et al. (2021) who documented similar benefits in farm and non-farm-based environments. Based on available evidence, the researcher posits that greater benefits would be achieved using AI-guided fire fighting robots and risk warning systems (Ramasubramanian et al., 2020; Zhang et al., 2021); the recommendation was validated by the enormous costs associated with fire damage.

Beyond better safety and management, AI and edge computing would be instrumental to the management of smart infrastructure in smart cities, smart grid operation (Raza and Khosravi, 2015; Foresti et al., 2020), distributed smart systems (Molinara et al., 2021), and construction engineering management, thermal comfort, and energy efficiency in buildings (Ben Slama, 2021; Halhoul Merabet et al., 2021; Pan and Zhang, 2021). Even though AI and edge computing offered unlimited potential in farms and beyond, it was challenging to achieve and sustain most of the promising applications highlighted by Naser (2019), Park et al. (2019), and Shamshiri et al. (2020) without addressing the challenges associated with hierarchical systems to attain security and stability. The key challenges include the need for smart modular, interoperable, reliable, scalable, and efficient meters and edge sensors for communication between appliances and the database (Ben Slama, 2021). Considering such systems are highly susceptible to cyberattacks, significant resources must be invested in architectures and tools, data transmission rate, and cybersecurity (Bilbao-Osorio et al., 2014; Risius and Spohrer, 2017; Dachyar, Zagloel and Saragih, 2019; Zhao, Askari, and Chen, 2021), which is expensive in the long-term. The need to protect agricultural systems from cyberattacks is justified, given the resources involved.

4.3. IoT-enabled digital twins

Section 4.3 deleted because it was similar to Section 4.1.

4.4. The overall merit for commercial greenhouses

The role of IoT infrastructure in environmental protection is not confined to energy saving associated with the integration of PV panels and optimal utilization of agricultural resources through data-driven decision support systems for fungicide and pesticide application, analysis of soil water balance and soil water content, and demand-driven and intelligent irrigation of crops, and fertilizer application (Antony et al., 2020). Li et al. (2018) believed that IoT was indispensable in carbon dioxide enrichment within a greenhouse. The enrichment of CO_2 had long-term benefits, such as improvement in crop yields through better photosynthesis (Hydrate, 2017; Bao et al., 2018; Li et al., 2018b; Rodríguez-Mosqueda, Bramer and Brem, 2018; Oreggioni, Luberti and Tassou, 2019). Under normal conditions, the volume of CO_2 in greenhouses is suboptimal (Jin et al., 2009), a factor that impacts agricultural production due to the photosynthesis/CO_2 link. A key challenge is the autonomous regulation of the CO_2 level, which is influenced by other factors such as the greenhouse temperature, humidity, and light intensity (Runkle, 2015; Pan et al., 2019; Chowdhury et al., 2021). The interdependent nature of these parameters makes it challenging to regulate such parameters using traditional labor-intensive methods such as crop-residues and animal-manure composting (CRAM) (Jin et al., 2009). In line with Jin et al. (2009), Li et al. (2018) noted that carbon dioxide enrichment strategies offered mixed benefits. On the one hand, the compost helps to regulate the phosphorous, nitrogen, and carbon emissions from commercial agriculture and improves the yield of selected crops such as stem and leaf lettuce and celery (Li et al., 2018a). On the other hand, it generates significant amounts of compost products that are often expensive to dispose of. The drawbacks underscore the need for smart solutions in intelligent greenhouses.

The IoT-mediated CO_2 enrichment process in smart greenhouses entails the use of computers to predict weather patterns, and control the environmental variables and modify the key parameters (Li et al., 2018a). However, the automation process must overcome multiple barriers. One, it is challenging to determine with precision the parameters that influence crop growth (the preferred setpoint tracking is often offset by actuators for other parameters and control loops). Two, effective regulation of CO_2 requires the integration of humidity, light intensity, and temperature sensors, which are expensive to install and operate. Chaudhary et al. (2019) reported successful CO reported successful CO_2 enrichment in a greenhouse using PID-based controllers are used for temperature and humidity, MATLAB Simulink models, and Fuzzy inference systems. On the downside, the technology was expensive and outreach for most smallholder farmers. The cost-related barriers and lack of technical expertise clearly demonstrate that optimal resource utilization in greenhouses through CO_2 enrichment would not be ubiquitous. Since capital significantly predicted the rate of CO2 enrichment and better yields, commercial agricultural producers with access to capital had better leverage compared to smallholder farmers with limited resources. The concerns raised about the capital-intensive IoT infrastructure for greenhouses and precision agriculture were also documented by Villa-Henriksen et al. (2020) were corroborated by Madushanki et al. (2020), who noted that the lower production margins recorded by smallholder farmers limited the need for experimentation. From a cost perspective, farmers had inadequate income to invest in new IoT connectivity or sensors for data-driven decision support systems.

The effective use of agrochemicals for optimal production remains a critical challenge from the following dimensions. On the one hand, pesticides are indispensable to modern agriculture (Aktar, Sengupta, and Chowdhury, 2009; Hossard et al., 2013; Chao et al., 2015; Zhang et al., 2015; Bamini and Shanmugadevi, 2021). The ubiquity of plant pathogens, insect pests, and weeds necessitate the use of pesticides to improve crop yields (Pérez-Lucas et al., 2018). The improvements in crop yield vary between 37 and 79% depending on the crop under cultivation and the agrochemical applied (Chao et al., 2015). The estimated improvements in crop yields associated with the application of agrochemicals were region and methodology-specific. Studies conducted in China argued that the improvements in yield could be lower after taking into account the damage control agent (Zhang et al., 2015). The findings documented by (Zhang et al., 2015) and (Chao et al., 2015) show that there was no consensus among scholars on the yield-related benefits associated with continued use of pesticides. The lack of consensus has a domino effect on resource management in commercial agriculture and environmental conservation by extension, given that excessive pesticide application has a deleterious impact on groundwater systems. In theory, the adverse effects could be offset through a combination of different interventions such as precision agriculture and precise application to minimize waste.

On the other hand, the excessive use of pesticides results in soil and groundwater toxicity and human toxicity if the contaminated farm produce is consumed. Song et al. (2015) noted that the pesticides inhibit the cellular function of the acetylcholinesterase (AChE) enzyme, which is involved in the regulation of neurotransmitters such as acetylcholine for CNS function. The need to mitigate the risk of groundwater contamination is reinforced by the high cost of cleaning up contaminated groundwater sources (Aktar, Sengupta, and Chowdhury, 2009). A majority of the traditional pesticides have been proven to possess endocrine growth factors, which impair the function of the endocrine system (Pérez-Lucas et al., 2018). The pesticide overuse challenge identified by (Pérez-Lucas et al., 2018) was not localized in the west. (Zhang et al., 2015) noted that excessive pesticide use was a common challenge in China where it was correlated with negative health and environmental externalities. The growing awareness of the adverse effects of pesticides persist over the long term, have led to the exploration of various strategies, including applying lesser pesticides and smart pesticides using robotics and IoT or pest detection using AIoT Based Smart Agricultural System (Chen et al., 2020; Bamini and

Shanmugadevi, 2021). A fundamental concern is that each of the proposed solutions has its benefits and drawbacks.

Based on the preliminary data, halving the pesticide used in greenhouses and other applications is not a sustainable or feasible alternative considering that lesser pesticide application translates to lower yields (Hossard et al., 2013). Field trials conducted in 2018 showed that a 50% reduction in pesticide application translated to lower crop yields – 20% for french beans and wheat (Hossard et al., 2013). The yield-related losses could be higher after taking into account the growing risk of global warming and its domino effect on commercial agriculture. From an economic perspective, a decline in crop yield was unsustainable in light of the climate change-related losses. As indicated in the introduction, \$220 million was lost due to climate change-related disruptions in production in the cherry-growing areas of America. The additional costs associated with pest management were estimated to exceed \$11 billion nationally (Environmental Protection, 2020). Since higher crop yields have a direct influence on smallholder farmer revenues, reducing pesticide applications was unfeasible. In light of these challenges, the accurate and real-time monitoring of the pesticide levels was a practical alternative. Traditional methods of pesticide analysis such as mass spectrometry (MS), gas chromatography (GC), infra-red spectroscopy (IR), UV–Visible spectroscopy, and high-performance liquid chromatography (HPLC) are unsuitable for real-time monitoring of pesticides considering the samples must be transported to the laboratory for analysis (Mazzei et al., 2004). In addition to the cumbersome transportation methods, the HPLC, MS, GC, IR, and UV/Vis instruments are expensive and require skilled technicians for maintenance and operation (Wong et al., 2017). The complexity of lab-scale analytical methods reinforces the need for sensors that are capable of autonomously monitoring the concentration of N-methyl carbamates, organochlorines, organophosphates, neonicotinoids, and pyrethroids (Wong et al., 2017). The detection of pesticides in farmlands using smart sensors is integral to the conservation of the environment and the protection of fragile ecosystems. A key concern is that the choice of sensors in isolation does not suffice given that accurate assessment must be coupled with the control and understanding of other parameters such as the solubility, organic matter, geological conditions, the depth of the groundwater, solubility, degradation, and absorption (United States Geological Survey, 2021; University of Massachusetts Amherst, 2021). The potential influence of the geological parameters is compounded by the distinct performance of different classes of sensors depending on the testing mechanism and electrode sensor materials; this impacts the limit of detection and reliability of electrochemical, piezoelectric, optical, fluorescence, chemiluminescence, and nano colorimetric sensors used to measure the pesticide levels in soils.

Electrochemical sensors for the optimization of the greenhouse microclimate and sustainable farming have proven useful in the accurate monitoring of humidity, light intensity, soil nutritional content, water and temperature, and plant physiology (Wang et al., 2020a, 2020c). However, the accuracy of the sensors (Zamora-Sequeira et al., 2019) depends on the sensor electrode material's/transducer potential and redox behavior, and electroanalytical environment. Modern sensors are made of CNTs, poly(3,4-ethylene dioxythiophene) (PEDOT), alkaline phosphatase (ALP)-based biosensors (inhibition-based), among other materials (Mazzei et al., 2004; Wong et al., 2017; Zamora-Sequeira et al., 2019). Out of the listed materials, carbon-based offers among the best limits of detection and accuracy.

Electrochemical sensors made of Polyethylene terephthalate (PET)-derived activated carbon electrode materials, molecularly imprinted polymer-reduced graphene oxide and gold nanoparticles, and citrate-capped gold nanoparticles (AuNPs)/(3-mercaptopropyl)-trimethoxysilane (MPS)/gold electrode (Au), O_2-plasma oxidized multi-walled carbon nanotubes (SWCNTs) (Wong et al., 2017), gold nanoparticles-coated silicon nanowires (Su et al., 2008), were useful in the detection of pesticides in soil (Zamora-Sequeira et al., 2019). In other cases, porous materials, nanoparticle rods, conducting polymers, metal nanoparticles, CNTs, and graphene rods offered better accuracy and reproducibility (Wang et al., 2020b). Wong et al. (2017) noted that the reliability of the sensors could be optimized through the surface modification of the sensor materials; various mechanisms were explored, including the surface oxidation of the CNTs; this contributed to surface defects and the incorporation of oxygen moieties, and the fourfold increase in the detection of Cd^{2+} and Pb^{2+} ions. However, the carbon-based sensors are less suitable for the detection of organophosphorus and organochlorinated agents in soils (Mazzei et al., 2004). Mazzei et al. (2014) noted that certain classes of pesticides could be best detected using inhibition-based ALP biosensors that inhibit enzymatic activity.

One of the fundamental benefits of these sensors was the recovery of the biocatalytic membrane without the need for reactivation (Mazzei et al., 2004). In addition to the observations made by Mazzei et al. (2004) were corroborated by Song et al. (2015, p. 104) study on bio-based enzyme inhibition sensors ability to offer "alternative to traditional methods for carbamate pesticide detection due to their high sensitivity, rapid response, and easy operation." On the downside, the performance of the ALP and other enzyme inhibition biosensors is incomparable to silicon-based nanowires (SiNWs). SiNWs have better mechanical, electronic, and optical properties, including piezoresistance coefficient, thermal conductivity, quantum size effects. The unique properties translated to a significantly higher binding affinity for acetylcholinesterase. The unique performance of the different classes of sensors was also documented using gold nanoparticle electrodes synthesized using molecular polymer printing technology.

The Au nanoparticles were surface-functionalized with citrate (AuNPs)/(3-mercaptopropyl) trimethoxysilane (MPS) (Song et al., 2015; Tan et al., 2015). The regulation of the greenhouse microclimate (humidity, light intensity, soil nutritional content, water, and temperature, and plant physiology) influences crop yields (Placidi et al., 2021). Excess humidity (>95%) and temperature (35 °C) elevate the risk of plant damage, suboptimal growth, limited pollination, leaf growth, and photosynthesis (Chauhan and Ratan, 2019). Even though there is an adequate understanding of the challenges associated with poor regulation of the microclimate, achieving the desired temperature has often been a challenge owing to the dynamics of smallholder and large-scale agricultural production. Even though each form of production was subjected to diverse challenges associated with climate change, smallholder farmers were faced with unique challenges in agrarian communities (Hall, Scoones, and Tsikata, 2017). Smallholder farmers across the world lack adequate resources to invest in capital-intensive IoT infrastructure compared to large commercial producers.

The unequal distribution of resources has long-term effects on the sustainability of agriculture, considering the adverse effects of climate change on global production systems. In the short-term and medium, it is anticipated that precision and IoT-mediated agriculture would largely benefit commercial producers with access to resources that were necessary for commercial agricultural production. The large capital outlay required in commercial agricultural production translates to significant capital savings. Under a hypothetical scenario, if producers save a minimum of \$500/acre per crop cycle following the adoption of data-driven decision support systems (Antony et al., 2020), it could translate to \$150,000 annually – assuming the area under greenhouse cultivation is 100 acres and producers are capable of maintaining three active crop cycles. The projected cost savings would help to offset the initial capital expenditure. The contrary was true for smallholder farmers, whose production margins made it impractical to invest in new smart farming technologies.

The widespread adoption of IoT systems and infrastructure might increase energy efficiency in commercial agriculture, thereby reducing greenhouse gas emissions; this could be achieved through the integration of PV panels on greenhouses and solar farms on large open-field commercial farming (Dahlqvist and Nilsson-Hedman, 2015; Tiwari et al., 2016; Mazzaro and Vomiero, 2018; Zisis et al., 2019; Behzadi and Arabkoohsar, 2020). Smart sensors would help guide data-driven decision support systems and consequently improve the level of understanding about resource efficiency in terms of reducing waste in farms, control of pests, and regulating greenhouse microclimates to mitigate the adverse effects associated with extreme weather (Li et al., 2018a; Kavga et al., 2021; Sagheer *et al.*, 2021; Ullah et al., 2021). The feasibility of IoT-based data-driven decision support systems for intelligent application of agrochemicals and fertilizers has been demonstrated in Europe (Sinha, Shrivastava, and Kumar, 2019), where intelligent systems for fertilizer and pesticide application have been extensively employed; this has helped to minimize wastage at the point of application. The progress documented by Sinha, Shrivastava, and Kumar (2019) across Europe was in line with Symeonaki, Arvanitis, and Piromalis (2019), who projected that the demand for IoT infrastructure would increase to 16 million units by 2025. The beneficial ecological effects of IoT infrastructure in agriculture suggest that there was adequate room for improvement, and it was improper to consider the adverse consequences of 5G technology before it is rolled out on a larger scale.

5. Conclusion

The rigorous appraisal of scholarly research concerning IoT in agriculture demonstrated that emerging technologies such as artificial intelligence sensors, actuators, uncrewed aerial vehicles, satellites, big data analytics, intelligent machines, and radio-frequency identification devices had multiple and practical areas of application in smart greenhouses and precision agriculture. Theoretical evidence shows the progress made in research and development coupled with would catalyze the uptake of these technologies. Commercial farms have demonstrated that it was practical to improve crop yield and monitor growth conditions (temperature, humidity, and nutritional content). On the downside, the transition to agriculture 4.0 would be impeded by the technological challenges, nascent nature of the industry, cost, and unequal availability of IoT infrastructure in developed and emerging nations.

At present, it is challenging to manufacture affordable sensors with high functionality. The commercially available sensors are expensive. The costs were variable ranging between \$150 to \$1,000+ per sensor; this makes it unfeasible for smallholder farmers to invest in IoT. Other studies had documented the availability of low-cost sensors. The impact of cost is validated by the fact that smart greenhouses require multiple sensors for water, soil pH, and nutrition monitoring, and microclimate regulation. Even though the cost was a factor, it could be offset through the exploitation of the synergistic benefits associated with IoT systems. For example, IoT infrastructure can enhance energy saving through the integration of PV panels and optimal utilization of agricultural resources through demand-driven and intelligent irrigation of crops, and fertilizer application, and data-driven decision support systems for fungicide and pesticide application, analysis of soil water balance, and soil water content. New research has also confirmed that IoT was indispensable in carbon dioxide enrichment within a greenhouse, which is beneficial in improving crop yields through better photosynthesis. Additionally, sensors linked with IoT systems were integral to the regulation of the greenhouse microclimate (humidity, light intensity, soil nutritional content, water and temperature, and plant physiology). The optimization of these parameters translated to better crop yields. The traditional farming methods have made it challenging to achieve the desired temperature, humidity, soil nutritional content without cost-intensive human labor.

Even though edge computing offers practical benefits compared to cloud computing, the technology was nascent and unavailable in farms. Cost is another barrier. The installation of IoT infrastructure is capital-intensive and often out of the reach of smallholder farmers compared to large-scale producers. In light of the available evidence, it can be argued that the transition from Agriculture 3.0 to Agriculture 4.0 is sustainable given the higher initial costs are offset by energy and water saving and the actualization of global sustainable development goals.

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.

References

Abosrra, L., Ashour, A.F., Youseffi, M., 2011. Corrosion of steel reinforcement in concrete of different compressive strengths. Constr. Build. Mater. 25 (10), 3915–3925. https://doi.org/10.1016/j.conbuildmat.2011.04.023.

Achour, Y., Ouammi, A., Zejli, D., 2021. 'Technological progresses in modern sustainable greenhouses cultivation as the path towards precision agriculture. Renew. Sustain. Energy Rev. 147, 111251 https://doi.org/10.1016/j.rser.2021.111251.

Aggarwal, S., Kumar, N., Tanwar, S., 2021. Blockchain-envisioned UAV communication using 6G networks: open issues, use cases, and future directions. IEEE Internet Things J. 8 (7), 5416–5441. https://doi.org/10.1109/JIOT.2020.3020819.

Agrawal, H., et al., 2016. Smart feeding in farming through IoT in silos. Adv. Intell. Syst. Comput. 530, 355–366. https://doi.org/10.1007/978-3-319-47952-1_28.

Ahamed, S., Guo, H., Taylor, L., Tanino, K., 2018. Heating demand and economic feasibility analysis for year-round vegetable production in Canadian Prairies greenhouses Heating demand and economic feasibility analysis for year-round vegetable production in Canadian Prairies greenhouses, Information Processing in Agriculture. China Agricultural University, pp. 1–10. doi: 10.1016/j.inpa.2018.08.005.

Akhtar, M.N., Shaikh, A.J., Khan, A., Awais, H., Bakar, E.A., Othman, A.R., 2021. Smart sensing with edge computing in precision agriculture for soil assessment and heavy metal monitoring: a review. Agriculture (Switzerland) 11 (6), 1–37. https://doi.org/10.3390/agriculture11060475.

Akram, R., Natasha, Fahad, S., Hashmi, M. Z., Wahid, A., Adnan, M., Nasim, W., 2019. Trends of electronic waste pollution and its impact on the global environment and ecosystem', Environmental Science and Pollution Research, 26(17), pp. 16923–16938. doi: 10.1007/s11356-019-04998-2.

Aktar, M.W., Sengupta, D., Chowdhury, A., 2009. Impact of pesticides use in agriculture: their benefits and hazards', Interdisciplinary toxicology. Slovak Toxicol. Soc. SETOX 2 (1), 1–12. https://doi.org/10.2478/v10102-009-0001-7.

Ali, A., Hassanein, H.S., 2020. Time-Series Prediction for Sensing in Smart Greenhouses. In: GLOBECOM 2020–2020 IEEE Global Communications Conference, pp. 1–6. https://doi.org/10.1109/GLOBECOM42002.2020.9322549.

Al-Masri, E., et al., 2020. Investigating messaging protocols for the internet of things (IoT). IEEE Access 8, 94880–94911. https://doi.org/10.1109/ACCESS.2020.2993363.

An, W. et al. (2017) 'Agriculture Cyber-Physical Systems', in Cyber-Physical Systems: Foundations, Principles and Applications Intelligent Data-Centric Systems, pp. 399–417. doi: 10.1016/B978-0-12-803801-7.00025-0.

Antony, A.P., Leith, K., Jolley, C., Lu, J., Sweeney, D.J., 2020. A review of practice and implementation of the internet of things (IoT) for smallholder agriculture. Sustainability (Switzerland) 12 (9), 1–19. https://doi.org/10.3390/su12093750.

Arabkoohsar, A., Farzaneh, M., Ghezelbash, G.R., 2016. Energy consumption pattern modification in greenhouses by a hybrid solar – geothermal heating system. Journal of the Brazilian Society of Mechanical Sciences and Engineering. Springer Berlin Heidelberg. doi: 10.1007/s40430-016-0569-8.

Awani, S., et al., 2017. 'Numerical and experimental study of a closed loop for ground heat exchanger coupled with heat pump system and a solar collector for heating a glass greenhouse in north of Tunisia Étude numérique et expérimentale d ' une boucle fermée pour un échangeur de chaleur géothermique couplé à un système de pompe à chaleur et un capteur solaire pour chauffer une serre en verre au nord de la Tunisie'. Int. J. Refrigerat. 76, 328–341. https://doi.org/10.1016/j.ijrefrig.2017.01.030.

Ayhan, B.U., Tokdemir, O.B., 2019. Safety assessment in megaprojects using artificial intelligence. Saf. Sci. 118 (May), 273–287. https://doi.org/10.1016/j.ssci.2019.05.027.

Badenhop, C.W., et al., 2017. The Z-Wave routing protocol and its security implications. Comput. Secur. 68, 112–129. https://doi.org/10.1016/j.cose.2017.04.004.

Bamini, A., Shanmugadevi, M., 2021. Smart Pesticides Using Robotics and IoT. IJSDR2104108 International Journal of Scientific Development and Research (IJSDR) 6 (4), 665–667.

Bao, J., Lu, W.-H., Zhao, J., Bi, X.T., 2018. Greenhouses for CO2 sequestration from atmosphere. Carbon Resources Convers. 1 (2), 183–190. https://doi.org/10.1016/j.crcon.2018.08.002.

Baruah, S., Dutta, Æ.J., 2009. Nanotechnology applications in pollution sensing and degradation in agriculture: a review'. Environ. Chem. Lett. 7, 191–204. https://doi.org/10.1007/s10311-009-0228-8.

Beckmann, K., Dedi, O., 2015. sDDS: A portable data distribution service implementation for WSN and IoT platforms. In: in 2015 12th International Workshop on Intelligent Solutions in Embedded Systems (WISES), pp. 115–120.

Behzadi, A., Arabkoohsar, A., 2020. Feasibility study of a smart building energy system comprising solar PV/T panels and a heat storage unit. Energy 210, 118528. https://doi.org/10.1016/j.energy.2020.118528.

Ben Slama, S., 2021. Prosumer in smart grids based on intelligent edge computing: A review on Artificial Intelligence Scheduling Techniques', Ain Shams Engineering Journal. THE AUTHOR, (xxxx). doi: 10.1016/j.asej.2021.05.018.

Bersani, C., Ouammi, A., Sacile, R., Zero, E., 2020. Model predictive control of smart greenhouses as the path towards near zero energy consumption. Energies 13 (14), 1–17. https://doi.org/10.3390/en13143647.

Bilbao-Osorio, B., Dutta, S. and Lanvin, B. 2014. The Global Information Technology Report 2014 Rewards and Risks of Big Data.

Bo, Y. and Wang, H. 2011. The application of cloud computing and the internet of things in agriculture and forestry, Proceedings - 2011 International Joint Conference on Service Sciences, IJCSS 2011. IEEE, pp. 168–172. doi: 10.1109/IJCSS.2011.40.

Bottaccioli, L. et al. (2017) 'Building energy modelling and monitoring by integration of IoT', in Building Digital Autonomy for a Sustainable World (COMPSAC). doi: 10.1109/COMPSAC.2017.75.

Bravo-arrabal, J., García-cerezo, A., Serón, J., Gomez-ruiz, J.A., 2021. Development and implementation of a hybrid wireless sensor network of low power and long range for urban environments. Sensors 21 (567), 1–27.

Canakci, M., Emekli, N.Y., Bilgin, S., Caglayan, N., 2013. Heating requirement and its costs in greenhouse structures: a case study for Mediterranean region of Turkey Heating requirement and its costs in greenhouse structures: a case study for Mediterranean region of Turkey. Renew. Sustain. Energy Rev. 24, 483–490. https://doi.org/10.1016/j.rser.2013.03.026.

Changqing, C., Hui, L., Wenjun, H., 2018. Internet of agriculture-based low cost smart greenhouse remote monitor system, 2018 Chinese Automation Congress (CAC). IEEE 3940–3945. https://doi.org/10.1109/CAC.2018.8623230.

Chao, Z., Shi, G., Jian, S., Rui-fa, H.U., 2015. Productivity effect and overuse of pesticide in crop production in China. J. Integrat. Agric. Chinese Acad. Agric. Sci. 14 (9), 1903–1910. https://doi.org/10.1016/S2095-3119(15)61056-5.

Chaudhary, G., Kaur, S., Mehta, B., Tewani, R., 2019. Observer based fuzzy and PID controlled smart greenhouse. J. Statist. Manage. Syst. 22 (2), 393–401. https://doi.org/10.1080/09720510.2019.1582880.

Chauhan, Y.K., Ratan, R., 2019. Study on Placement of Sensors for Readings Accuracy Level Enhancement in Greenhouse, in: Applications of Computing, Automation and Wireless Systems in Electrical Engineering, p. 245.

Chaurasia, R., Mohindru, V., 2021. Unmanned aerial vehicle (UAV): a comprehensive survey. Unmanned Aerial Vehicles for Internet of Things (IoT) 1–27. https://doi.org/10.1002/9781119769170.ch1.

Chen, C., Huang, Y., Li, Y., Chang, C., and Huang, Y. 2020. An AIoT Based Smart Agricultural System for Pests Detection, 8. doi: 10.1109/ACCESS.2020.3024891.

Chen, J.H., Sung, W.T., Lin, G.Y., 2016. Automated Monitoring System for the Fish Farm Aquaculture Environment', in: Proceedings - 2015 IEEE International Conference on Systems, Man, and Cybernetics, SMC 2015. IEEE, pp. 1161–1166. doi: 10.1109/SMC.2015.208.

Chen, M., Wan, J., Li, F., 2012. Machine-to-machine communications: architectures, standards and applications. KSII Trans. Internet Informat. Syst. 6 (2), 480–497. https://doi.org/10.3837/tiis.2012.02.002.

Chen, Y., et al., 2019. Experimental study on the effect of dust deposition on photovoltaic panels. Energy Procedia 158, 483–489. https://doi.org/10.1016/j.egypro.2019.01.139.

Chen, Z., Sivaparthipan, C.B., Muthu, B., 2022. IoT based smart and intelligent smart city energy optimization. Sustain. Energy Technol. Asses. 49, 101724 https://doi.org/10.1016/j.seta.2021.101724.

Chiesa, G. et al., 2020. A fuzzy-logic IoT lighting and shading control system for smart buildings', Automation in Construction. Elsevier, 120(July), p. 103397. doi: 10.1016/j.autcon.2020.103397.

Chiriboga, G. et al., 2021. Harnessing of geothermal energy for a greenhouse in Ecuador employing a heat pump : design, construction, and feasibility assessment, Heliyon, 7, pp. 1–13. doi: 10.1016/j.heliyon.2021.e08608.

Choudhary, S., Jadoun, R., Mandoriya, H., 2016. Role of cloud computing technology in agriculture fields. Computing 7 (3), 1–7.

Chowdhury, M., Kiraga, S., Islam, N., Ali, M., Reza, N., Lee, W., and Chung, S. 2021. Effects of Temperature, Relative Humidity, and Carbon Dioxide Concentration on Growth and Glucosinolate Content of Kale Grown in a Plant Factory, Foods, 10 (1524), pp. 1–19.

Cisco and the International Telecommunication Union (ITU). 2015. Harnessing the Internet of Things for Global Development.

Compte, S.S., 2019. LoRa-based WSN and its applications'. In: in 6th International Electronic Conference on Sensors and Applications, pp. 1–71.

da Cruz, M.A.A., et al., 2018. A Proposal for Bridging the Message Queuing Telemetry Transport Protocol to HTTP on IoT Solutions. In: in 2018 3rd International Conference on Smart and Sustainable Technologies (SpliTech), pp. 1–5.

Curran, C. 2020. What Will 5G Mean for the Environment?, The Henry M. Jackson School of International Studies, University of Washington. [Online] Available at: https://jsis.washington.edu/news/what-will-5g-mean-for-the-environment/ (Accessed: 17 October 2021).

Dachyar, M., Zagloel, T.Y.M., Saragih, L.R., 2019. Knowledge growth and development: internet of things (IoT) research, 2006–2018. Heliyon 5 (8), e02264. https://doi.org/10.1016/j.heliyon.2019.e02264.

Dahlqvist, M., Nilsson-Hedman, T., 2015. Self-Aligning Solar Panel: Construction of a self-aligning platform for solar panels. KTH 1–46.

DeLay, N.D., Thompson, N.M., Mintert, J.R., 2021. Precision agriculture technology adoption and technical efficiency'. J. Agric. Econ. 1–10. https://doi.org/10.1111/1477-9552.12440.

Dimov, D. et al. (2018) 'Ultrahigh Performance Nanoengineered Graphene–Concrete Composites for Multifunctional Applications', Advanced Functional Materials. John Wiley & Sons, Ltd, 28(23), p. 1705183. doi: https://doi.org/10.1002/adfm.201705183.

Elijah, O., et al., 2018. An Overview of Internet of Things (IoT) and Data Analytics in Agriculture: Benefits and Challenges. IEEE Internet of Things Journal. IEEE 5 (5), 3758–3773. https://doi.org/10.1109/JIOT.2018.2844296.

Envira IOT (2021) Structural health monitoring of buildings. Available at: https://enviraiot.com/structural-health-monitoring-of-buildings/.

Parliament, E., 2021. The use of pesticides in developing countries and their impact on health and the right to food. Policy Department for External Relations Directorate General for External Policies of the Union 1–56.

Ferkoun, M. 2015. Cloud computing helps agriculture industry grow, IBM. [Online] Available at: https://www.ibm.com/blogs/cloud-computing/2015/01/23/cloud-computing-helps-agriculture-industry-grow/. [Accessed 17 October 2021].

Food and Agricultural Organization of the United Nations. 2017. The possibilities of Internet of Things (IoT) for Agriculture. [Online] Available at: https://www.fao.org/e-agriculture/news/possibilities-internet-things-iot-agriculture [Accessed: 16 October 2021].

Foresti, R., et al., 2020. Smart society and artificial intelligence: big data scheduling and the global standard method applied to smart maintenance. Engineering. The Authors 6 (7), 835–846. https://doi.org/10.1016/j.eng.2019.11.014.

Friha, O., Ferrag, M.A., Shu, L., Maglaras, L., Wang, X., 2021. Internet of things for the future of smart agriculture: a comprehensive survey of emerging technologies. IEEE/CAA J. Autom. Sin. 8 (4), 718–752. https://doi.org/10.1109/JAS.2021.1003925.

Gai, H., et al., 2020. Alternative emission monitoring technologies and industrial internet of things–based process monitoring technologies for achieving operational excellence. Curr. Opin. Green Sustain. Chem. 23, 31–37. https://doi.org/10.1016/j.cogsc.2020.04.009.

Gassner, A., Coe, R. and Sinclair, F. 2013. Improving food security through increasing the precision of agricultural development, Precision Agriculture for Sustainability and Environmental Protection, pp. 34–57. doi: 10.4324/9780203128329.

Ghoulem, M., et al., 2020. 'Analysis of passive downdraught evaporative cooling windcatcher for greenhouses in hot climatic conditions: Parametric study and impact of neighbouring structures. Biosyst. Eng. 197, 105–121. https://doi.org/10.1016/j.biosystemseng.2020.06.016.

Goedde, L., Katz, J., Ménard, A., Revellat, J. 2020. Agriculture's connected future: How technology can yield new growth, McKinsey and Company. [Online] Available at: https://www.mckinsey.com/industries/agriculture/our-insights/agricultures-connected-future-how-technology-can-yield-new-growth [Accessed: 16 October 2021].

Government Office for Science. 2014. The Internet of Things: making the most of the Second Digital Revolution.

Gupta Chatterjee, S., Chatterjee, S., Ray, A.K., Chakraborty, A.K., 2015. Graphene–metal oxide nanohybrids for toxic gas sensor: a review. Sens. Actuat. B 221, 1170–1181. https://doi.org/10.1016/j.snb.2015.07.070.

Hakiri, A., et al., 2015. Publish/subscribe-enabled software defined networking for efficient and scalable IoT communications. IEEE Commun. Mag. 53 (9), 48–54. https://doi.org/10.1109/MCOM.2015.7263372.

Halhoul Merabet, G. et al., 2021. Intelligent building control systems for thermal comfort and energy-efficiency: A systematic review of artificial intelligence-assisted techniques', Renew. Sustain. Energy Rev. Elsevier Ltd, 144(August 2020), p. 110969. doi: 10.1016/j.rser.2021.110969.

Hall, R., Scoones, I., Tsikata, D., 2017. Plantations, outgrowers and commercial farming in Africa: agricultural commercialisation and implications for agrarian change. J. Peasant Stud. Taylor & Francis 44 (3), 515–537. https://doi.org/10.1080/03066150.2016.1263187.

Hassan, A., Elkady, H., Shaaban, I.G., 2019. Effect of Adding Carbon Nanotubes on Corrosion Rates and Steel- Concrete Bond, Scientific Reports, pp. 1–12. doi: 10.1038/s41598-019-42761-2.

He, M., Shi, J., 2021. Circulation traceability system of Chinese herbal medicine supply chain based on internet of things agricultural sensor. Sustain. Comput. Inf. Syst. 30, 1–8. https://doi.org/10.1016/j.suscom.2021.100518.

Hebel, M.A., 2006. Control Challenges Through Zigbee Wireless Network Technology', in Computers in Agriculture and Natural Resources, 4th World Congress, pp. 234–239.

Hernández-morales, C.A., Luna-rivera, J.M., Perez-jimenez, R., 2022. Design and deployment of a practical IoT-based monitoring system for protected cultivations. Comput. Commun. 186, 51–64. https://doi.org/10.1016/j.comcom.2022.01.009.

Hossard, L., Philibert, A., Bertrand, M., Debaeke, P., Jeuffroy, M.H., Richard, G., Makowski, D., 2013. Effects of halving pesticide use on wheat production'. Sci. Rep. 1–7. https://doi.org/10.1038/srep04405.

Howard, D.A., et al., 2020. Data Architecture for Digital Twin of Commercial Greenhouse Production. In: 2020 RIVF International Conference on Computing and Communication Technologies (RIVF), pp. 1–7. https://doi.org/10.1109/RIVF48685.2020.9140726.

Huang, T.-S., et al., 2015. Surface modification of TiNi-based shape memory alloys by dry electrical discharge machining. J. Mater. Process. Technol. 221, 279–284. https://doi.org/10.1016/j.jmatprotec.2015.02.025.

Industrial Shields. 2020. Arduino Greenhouse Automation with Open Mote, Industrial Arduino Controller & Raspberry Pi Panel PC. [Online] Available at: https://www.industrialshields.com/case-study-iot-greenhouse-control-monitoring-arduino-industrial-raspberry-pi-panel-pc-gr [Accessed: 21 October 2021].

Jamil, F. et al. (2022) 'Optimal smart contract for autonomous greenhouse environment based on IoT blockchain network in agriculture', *Computers and Electronics in Agriculture*. Elsevier B.V., 192(December 2021), p. 106573. doi: 10.1016/j.compag.2021.106573.

Jawad, H.M., Nordin, R., Gharghan, S.K., Jawad, A.M., Ismail, M., 2017. Energy-efficient wireless sensor networks for precision agriculture: a review. Sensors (Switzerland) 17 (8), 1–45. https://doi.org/10.3390/s17081781.

Jin, C., Du, S., Wang, Y., Condon, J., Lin, X., Zhang, Y., 2009. Carbon dioxide enrichment by composting in greenhouses and its effect on vegetable production. J. Plant Nutr. Soil Sci. 172, 418–424. https://doi.org/10.1002/jpln.200700220.

Jumaah, H.J., Kalantar, B., Halin, A.A., Mansor, S., Ueda, N., Jumaah, S.J., 2021. Development of UAV-based PM 2. 5 monitoring system. Drones 5 (60), 1–12.

Kang, K.D., Kang, H., Ilankoon, I.M.S.K., Chong, C.Y., 2020. Electronic waste collection systems using Internet of Things (IoT): household electronic waste management in Malaysia. J. Cleaner Prod. 252, 119801 https://doi.org/10.1016/j.jclepro.2019.119801.

Karthikeyan, P.R., Chandrasekaran, G., Kumar, N.S., Sengottaiyan, E., Mani, P., Kalavathi, D.T., Gowrishankar, V., 2021. IoT based moisture control and temperature monitoring in smart farming'. J. Phys. Conf. Ser. 1964 (6), 1–7. https://doi.org/10.1088/1742-6596/1964/6/062056.

Kavga, A., Thomopoulos, V., Barouchas, P., Stefanakis, N., Liopa-Tsakalidi, A., 2021. Research on innovative training on smart greenhouse technologies for economic and environmental sustainability. Sustainability (Switzerland) 13 (19), 1–22. https://doi.org/10.3390/su131910536.

Kazeem, O.O., Akintade, O.O., Kehinde, L.O., 2017. Comparative study of communication interfaces for sensors and actuators in the cloud of internet of things. Int. J. Internet Things 6 (1), 9–13. https://doi.org/10.5923/j.ijit.20170601.02.

Kelsh, M.A., Shum, M., Sheppard, A.R., Mcneely, M., Kuster, N., 2011. Measured radiofrequency exposure during various mobile-phone use scenarios. J. Exposure Sci. Environ. Epidemiol. 21, 343–354. https://doi.org/10.1038/jes.2010.12.

Khavalko, V., Baranovska, S., Geliznyak, G., 2019. Investment feasibility of building the architecture of greenhouse automated control system based on the IoT and cloud technologies. CEUR Workshop Proceedings 2588.

Khudoyberdiev, A., Ullah, I., Kim, D., 2021. Optimization-assisted water supplement mechanism with energy efficiency in IoT based greenhouse. J. Intell. Fuzzy Syst. 40 (5), 10163–10182. https://doi.org/10.3233/JIFS-200618.

Khujamatov, K.E., Toshtemirov, T.K., 2020. Wireless sensor networks based Agriculture 4.0: challenges and apportions. In: 2020 International Conference on Information Science and Communications Technologies (ICISCT), pp. 1–5. https://doi.org/10.1109/ICISCT50599.2020.9351411.

Kirsche, M., Klauck, R., 2012. Unify to bridge gaps: Bringing XMPP into the Internet of Things. In: 2012 IEEE International Conference on Pervasive Computing and Communications Workshops, pp. 455–458. https://doi.org/10.1109/PerComW.2012.6197534.

Kishore, H., 2020. Economic and Environmental Impact of AI and IOT Based Precision Agriculture On Small and Mid-Scale Farmers Economic and Environmental Impact of AI and IOT Based Precision Agriculture On Small and Mid-Scale Farmers. Bournemouth University 1–4.

Köksal, Ö., Tekinerdogan, B., 2017. Obstacles in data distribution service middleware: a systematic review. Future Generation Computer Systems 68, 191–210. https://doi.org/10.1016/j.future.2016.09.020.

Kotsovos, M.D., 2017. Reinforced concrete shear design: shortcomings and remedy. ACI Struct. J. 114 (4), 1055–1066.

Lal, R., 2001. Potential of desertification control to sequester carbon and mitigate the greenhouse effect. Clim. Change 51 (1), 35–72. https://doi.org/10.1023/A:1017529816140.

Lehr, W., Queder, F., Haucap, J., 2021. 5G: a new future for mobile network operators, or not? Telecommun. Pol. 45 (3), 102086 https://doi.org/10.1016/j.telpol.2020.102086.

Lemayian, J.P., Hamamreh, J.M., 2020. Drone-based smart rescue system for critical situation management in future wireless networks. RS Open J. Innovative Commun. Technol. 4, 1–12.

Li, J. et al. (2010) 'Design on the monitoring system of physical characteristics of dairy cattle based on zigbee technology', in 2010 World Automation Congress, pp. 63–66.

Li, Y., Ding, Y., Li, D., Miao, Z., 2018a. Automatic carbon dioxide enrichment strategies in the greenhouse: a review. Biosyst. Eng. 171, 101–119. https://doi.org/10.1016/j.biosystemseng.2018.04.018.

Li, Y., Ding, Y., Li, D., Miao, Z., 2018b. Automatic carbon dioxide enrichment strategies in the greenhouse: a review. Biosyst. Eng. 171, 101–119. https://doi.org/10.1016/j.biosystemseng.2018.04.018.

Liao, M., et al., 2017. On precisely relating the growth of Phalaenopsis leaves to greenhouse environmental factors by using an IoT-based monitoring system. Comput. Electron. Agric. 136, 125–139. https://doi.org/10.1016/j.compag.2017.03.003.

Liu, Y., Yang, Y., Li, Y., Li, J., 2017. Conversion from rural settlements and arable land under rapid urbanization in Beijing during 1985–2010. J. Rural Stud. 51, 141–150. https://doi.org/10.1016/j.jrurstud.2017.02.008.

Madushanki, A.A.R., Halgamuge, M.N., Wirasagoda, W.A.H.S., Syed, A., 2019. Adoption of the Internet of Things (IoT) in agriculture and smart farming towards urban greening: a review. Int. J. Adv. Comput. Sci. Appl. 10 (4), 11–28. https://doi.org/10.14569/ijacsa.2019.0100402.

Maier, M., 2020. The effect of moisture and reinforcement on the self-sensing properties of hybrid-fiber-reinforced concrete. Eng. Res. Express. IOP Publishing 1–12.

Mainetti, L., Mele, F., Patrono, L., Simone, F., Stefanizzi, M. L., and Vergallo, R. 2013. An RFID-Based Tracing and Tracking System for the Fresh Vegetables Supply Chain, International Journal of Antennas and Propagation. Edited by I. Cuiñas. Hindawi Publishing Corporation, p. 531364.

Mainetti, L., Patrono, L., Vilei, A., 2011. Evolution of Wireless Sensor Networks towards the Internet of Things: a Survey. In: 19th International Conference on Software, Telecommunications and Computer Networks. IEEE, pp. 1–6.

Maraveas, C., 2020. Durability issues and corrosion of structural materials and systems in farm environment. Appl. Sci. (Switzerland) 10 (3). https://doi.org/10.3390/app10030990.

Maraveas, C., Bartnazas, T., 2021a. Application of internet of things for optimized greenhouse environments, Agri Engineering.

Maraveas, C., Bartzanas, T., 2021b. Sensors for structural health monitoring of agricultural structures'. Sensors (Switzerland) 21 (1), 1–32. https://doi.org/10.3390/s21010314.

Mavrakis, A., Papavasileiou, C., Salvati, L., 2015. Towards (Un)sustainable urban growth? Industrial development, land-use, soil depletion and climate aridity in a Greek agro-forest area. J. Arid Environ. 121, 1–6. https://doi.org/10.1016/j.jaridenv.2015.05.003.

Mazzaro, R., Vomiero, A., 2018. The Renaissance of Luminescent Solar Concentrators : The Role of Inorganic Nanomaterials, 1801903, pp. 1–19. doi: 10.1002/aenm.201801903.

Mazzei, F., Montilla, S., Pilloton, R., Botre, F., Botre, C., Podesta, E., 2004. Alkaline phosphatase inhibition based electrochemical sensors for the detection of pesticides. J. Electroanal. Chem. 574, 95–100. https://doi.org/10.1016/j.jelechem.2004.08.004.

Miller, M.A., Cappuccio, F.P., 2021. A systematic review of COVID-19 and obstructive sleep apnoea. Sleep Med. Rev. 55, 101382 https://doi.org/10.1016/j.smrv.2020.101382.

Mishra, B., Kertesz, A., 2020. The use of MQTT in M2M and IoT systems: A survey. IEEE Access 8, 201071–201086. https://doi.org/10.1109/ACCESS.2020.3035849.

Mohsen, M.O., Ansari, M.S. Al, Taha, R., Nuaimi, N.A., 2019. Carbon Nanotube Effect on the Ductility, Flexural Strength, and Permeability of Concrete', Journal of Nanomaterials, 2019, pp. 1–12.

Molinara, M., Bria, A., De Vito, S., Marrocco, C., 2021. Artificial intelligence for distributed smart systems'. Pattern Recogn. Lett. 142, 48–50. https://doi.org/10.1016/j.patrec.2020.12.006.

Monteiro, J., et al., 2018. Towards Sustainable Digital Twins for Vertical Farming. In: 2018 Thirteenth International Conference on Digital Information Management (ICDIM), pp. 234–239. https://doi.org/10.1109/ICDIM.2018.8847169.

Moretti, S., Marucci, A., 2019. A photovoltaic greenhouse with variable shading for the optimization of agricultural and energy production. Energies 12 (13). https://doi.org/10.3390/en12132589.

Motlagh, N. H. and Mohammadrezaei, M. 2020. Internet of Things (IoT) and the Energy Sector, Energies, pp. 1–27. doi: 10.3390/en13020494.

Mukherjee, A. et al., 2021. Application of smart materials in civil engineering: A review', Materials Today: Proceedings. Elsevier Ltd, (xxxx). doi: 10.1016/j.matpr.2021.03.304.

Murugesan, P., et al., 2017. Adopting Attribute-Based Access Control to Data Distribution Service. In: in 2017 International Conference on Software Security and Assurance (ICSSA), pp. 112–115. https://doi.org/10.1109/ICSSA.2017.23.

Naser, M.Z., 2019. 'Fire resistance evaluation through artificial intelligence - A case for timber structures. Fire Saf. J. 105, 1–18. https://doi.org/10.1016/j.firesaf.2019.02.002.

Navarro, E., Costa, N., Pereira, A., 2020. A systematic review of IoT solutions for smart farming. Sensors (Basel, Switzerland) MDPI 20 (15), 4231. https://doi.org/10.3390/s20154231.

O'Grady, M.J., Langton, D., O'Hare, G.M.P., 2019. Edge computing: a tractable model for smart agriculture? Artificial Intelligence in Agriculture 3, 42–51. https://doi.org/10.1016/j.aiia.2019.12.001.

OneWeb. 2021. Connect with Confidence. [Online] Available at: https://oneweb.net/our-markets (Accessed: 17 October 2021).

Oreggioni, G.D., Luberti, M., Tassou, S.A., 2019. Agricultural greenhouse CO2 utilization in anaerobic-digestion-based biomethane production plants: A techno-economic and environmental assessment and comparison with CO2 geological storage. Appl. Energy 242, 1753–1766. https://doi.org/10.1016/j.apenergy.2019.03.045.

Ou, C., Yang, J., Du, Z., Liu, Y., Feng, Q., 2019. Long-term mapping of a greenhouse in a typical protected agricultural region using landsat imagery and the google earth engine. Remote Sensing 12 (55), 1–23. https://doi.org/10.3390/rs12010055.

Pack, M., Mehta, K., 2012. Design of affordable greenhouses for East Africa. Proceedings - 2012 IEEE Global Humanitarian Technology Conference GHTC 2012, 104–110. https://doi.org/10.1109/GHTC.2012.66.

Pan, T., Ding, J., Qin, G., Wang, Y., Xi, L., 2019. Interaction of supplementary light and CO2 enrichment improves growth, photosynthesis, yield, and quality of tomato in autumn through spring greenhouse production'. HortScience 54 (2), 246–252.

Pan, Y., Zhang, L., 2021. Roles of artificial intelligence in construction engineering and management: A critical review and future trends', Automation in Construction. Elsevier B.V., 122(November 2020), p. 103517. doi: 10.1016/j.autcon.2020.103517.

Park, J.H., et al., 2019. Dependable fire detection system with multifunctional artificial intelligence framework. Sensors (Switzerland) 19 (9). https://doi.org/10.3390/s19092025.

Patil, V.C., Al-Gaadi, K.A., Biradar, D.P., Rangaswamy, M., 2012. Internet of things (Iot) and cloud computing for agriculture: an overview. Agro-Informat. Precision Agricult. 292–296.

Peña, A., Peralta, M., Mar, P., 2020. Design and testing of a structural monitoring system in an almeria-type tensioned structure greenhouse. Sensors 20 (258), 1–19.

Pérez-Lucas, G., Vela, N., Aatik, A.E., Navarro, S., 2018. Environmental Risk of Groundwater Pollution by Pesticide Leaching through the Soil Profile, in Pesticides -. Use and Misuse and Their Impact in the Environment. Intechopen.

Piromalis, D., Arvanitis, K.G., Papageorgas, P., Ferentinos, K.P., 2018. Smart precision lighting for urban and landscape closed controlled horticultural environments. In: Nandwani, D. (Ed.), Urban Horticulture. Sustainable Development and Biodiversity, vol. 18. Springer. https://doi.org/10.1007/978-3-319-67017-1_6.

Piromalis, D., Arvanitis, K., 2016. SensoTube: a scalable hardware design architecture for wireless sensors and actuators networks nodes in the agricultural domain. Sensors 16, 1227. https://doi.org/10.3390/s16081227.

Placidi, P., Morbidelli, R., Fortunati, D., Papini, N., Gobbi, F., Scorzoni, A., 2021. Monitoring soil and ambient parameters in the iot precision agriculture scenario: an original modeling approach dedicated to low-cost soil water content sensors'. Sensors 21 (15), 1–28. https://doi.org/10.3390/s21155110.

Popović, T., Latinović, N., Pešić, A., Zečević, Ž., Krstajić, B., Djukanović, S., 2017. Architecting an IoT-enabled platform for precision agriculture and ecological monitoring: a case study. Comput. Electron. Agric. 140, 255–265. https://doi.org/10.1016/j.compag.2017.06.008.

PrecisionAg Alliance. 2020. Six Levels of Precision Agriculture Adoption Identified by the PrecisionAg Institute. [Online] Available at: https://www.precisionag.com/institute/six-levels-of-precision-agriculture-adoption-identified-by-the-precisionag-institute/ (Accessed: 17 October 2021).

Ramasubramanian, S., Arumugam, S. and Sasikala, A. (2020) 'Fire Detection using Artificial Intelligence for Fire-Fighting Robots', in Proceedings of the International Conference on Intelligent Computing and Control Systems (ICICCS 2020), pp. 180–185.

Raviteja, K., Supriya, M., 2020. Greenhouse monitoring system based on internet of things. Lecture Notes Electr. Eng. 637, 581–591. https://doi.org/10.1007/978-981-15-2612-1_56.

Rayhana, R., Xiao, G., Liu, Z., 2020. Internet of Things Empowered Smart Greenhouse Farming, IEEE Journal of Radio Frequency Identification. IEEE 4 (3), 195–211. https://doi.org/10.1109/jrfid.2020.2984391.

Raza, M.Q., Khosravi, A., 2015. 'A review on artificial intelligence based load demand forecasting techniques for smart grid and buildings. Renew. Sustain. Energy Rev. 50, 1352–1372. https://doi.org/10.1016/j.rser.2015.04.065.

Risius, M., Spohrer, K., 2017. A blockchain research framework: what we (don't) know, where we go from here, and how we will get there. Bus. Inform. Syst. Eng. 59 (6), 385–409. https://doi.org/10.1007/s12599-017-0506-0.

Rodríguez-Mosqueda, R., Bramer, E.A., Brem, G., 2018. CO2 capture from ambient air using hydrated Na2CO3 supported on activated carbon honeycombs with application to CO2 enrichment in greenhouses'. Chem. Eng. Sci. 189, 114–122. https://doi.org/10.1016/j.ces.2018.05.043.

Rojas, A., 2015. Smart agriculture IoT with cloud computing. Revista de Historia de América 29, 37–66.

Ruan, J., Hu, X., Huo, X., Shi, Y., Chan, F.T.S., Wang, X., Zhao, X., 2020. An IoT-based E-business model of intelligent vegetable greenhouses and its key operations management issues. Neural Comput. Appl. 32 (19), 15341–15356. https://doi.org/10.1007/s00521-019-04123-x.

Ruan, J., Wang, Y., Chan, F.T.S., Hu, X., Zhao, M., Zhu, F., Lin, F., 2019. A life cycle framework of green IoT-based agriculture and its finance, operation, and management issues. IEEE Commun. Mag. 57 (3), 90–96.

Runkle, B.E. 2015. Interactions of Light, CO2 and Temperature on Photosynthesis', Michigan State University's department of horticulture, p. 54.

Sagheer, A., Mohammed, M., Riad, K., Alhajhoj, M., 2020. A cloud-based IoT platform for precision control of soilless greenhouse cultivation, sensors (Basel, Switzerland). MDPI 21 (1), 223. https://doi.org/10.3390/s21010223.

Said Mohamed, E., Belal, A.A., Kotb Abd-Elmabod, S., El-Shirbeny, M.A., Gad, A., Zahran, M.B., 2021. Smart farming for improving agricultural management. The Egypt. J. Remote Sens. Space Sci.

Salerno, I., et al., 2021. Adaptable energy management system for smart buildings. J. Build. Eng. 44, 1–21. https://doi.org/10.1016/j.jobe.2021.102748.

Sanjuan, E.B., et al., 2020. Message queuing telemetry transport (MQTT) security: a cryptographic smart card approach. IEEE Access 8, 115051–115062. https://doi.org/10.1109/ACCESS.2020.3003998.

Saxena, S., et al., 2018. Design and Field Implementation of a Multi-Agent System for Voltage Regulation Using Smart Inverters and Data Distribution Service (DDS). In: in 2018 IEEE Electrical Power and Energy Conference (EPEC), pp. 1–6. https://doi.org/10.1109/EPEC.2018.8598367.

Saxena, S., Farag, H.E.Z., El-Taweel, N., 2021. A distributed communication framework for smart Grid control applications based on data distribution service. Electr. Power Syst. Res. 201, 107547 https://doi.org/10.1016/j.epsr.2021.107547.

Seitllari, A., Naser, M.Z., 2018. Leveraging artificial intelligence to predict fire-induced explosive spalling in concrete. Comput. Concr. 24, 1–24. https://doi.org/10.12989/cac.2019.24.3.271.

Sendra, S., Garc, L., Lloret, J., Bosch, I., Vega-rodr, R., 2020. LoRaWAN network for fire monitoring in rural environments. Sensors 9 (531), 1–29.

Shamshiri, R.R., Hameed, I.A., Thorp, K.R., Balasundram, S.K., Shafian, S., Fatemieh, M., Samiei, S., 2020. Greenhouse automation using wireless sensors and IoT instruments integrated with artificial intelligence. Next-Generation Greenhouses Food Secur. Intechopen 1–20.

Singh, K., Arora, G., Singh, P., Gupta, A., 2021. IoT-based collection vendor machine (CVM) for E-waste management. J. Reliable Intell. Environ. 7 (1), 35–47. https://doi.org/10.1007/s40860-020-00124-z.

Singh, R.K., Berkvens, R., Weyn, M., 2020. Energy efficient wireless communication for IoT enabled Greenhouses. In: in 12th International Conference on Communication Systems & Networks. IEEE, pp. 2020–2022.

Sinha, A., Shrivastava, G., Kumar, P., 2019. Architecting user-centric internet of things for smart agriculture. Sustain. Comput. Inf. Syst. 23, 88–102. https://doi.org/10.1016/j.suscom.2019.07.001.

Sivakumar, M.V.K., 2007. Interactions between climate and desertification. Agric. For. Meteorol. 142 (2), 143–155. https://doi.org/10.1016/j.agrformet.2006.03.025.

Song, Y., Chen, J., Sun, M., Gong, C., Shen, Y., Song, Y., Wang, L., 2015. Simple electrochemical biosensor based on AuNPs / MPS / Au electrode sensing layer for monitoring carbamate pesticides in real samples'. J. Hazard. Mater. 304 (5), 103–109. https://doi.org/10.1016/j.jhazmat.2015.10.058.

Spitfire. 2021. IoT (Internet of Things). [Online] Available at: https://www.spitfire.co.uk/products/engineering-solutions/iot-internet-of-things/?ppc_keyword=iot&gclid=CjwKCAjwn8SLBhAyEiwAHNTJbRnm_Jio0DzYP-MSJ8wMH4o5xlj7wZXRtz0IX1FbpZ6nqNHTjm1fnxoCHZIQAvD_BwE (Accessed: 17 October 2021).

Starlink. 2020. High-speed, low latency broadband internet. Available at: https://www.starlink.com/ (Accessed: 17 October 2021).

Su, S., He, Y., Zhang, M., Yang, K., Song, S., Zhang, X., Lee, S.-T., 2008. High-sensitivity pesticide detection via silicon nanowires-supported acetylcholinesterase-based electrochemical sensors. Appl. Phys. Lett. Am. Inst. Phys. 93 (2), 23113. https://doi.org/10.1063/1.2959827.

Suradhaniwar, S., Kar, S., Durbha, S.S., Jagarlapudi, A., 2021. Time series forecasting of univariate agrometeorological data: a comparative performance evaluation via one-step and multi-step ahead forecasting strategies. Sensors 21 (7), 1–34. https://doi.org/10.3390/s21072430.

Syafarinda, Y., Akhadin, F., Fitri, Z. E., Yogiswara, Widiawanl, B., and Rosdiana, E. 2018. The Precision Agriculture Based on Wireless Sensor Network with MQTT Protocol, IOP Conference Series: Earth and Environmental Science, 207(1), pp. 1–9. doi: 10.1088/1755-1315/207/1/012059.

Symeonaki, E.G., Arvanitis, K.G., Piromalis, D.D., 2019. Current trends and challenges in the deployment of IoT technologies for climate smart facility agriculture. Int. J. Sustain. Agric. Manage. Informat. 5 (2–3), 181–200. https://doi.org/10.1504/IJSAMI.2019.101673.

Tan, X., Hu, Q., Wu, J., Li, X., Li, P., Yu, H., Lei, F., 2015. Sensors and Actuators B : Chemical Electrochemical sensor based on molecularly imprinted polymer reduced graphene oxide and gold nanoparticles modified electrode for detection of carbofuran. Sens. Actuat. B 220, 216–221. https://doi.org/10.1016/j.snb.2015.05.048.

Tekinerdogan, B., Köksal, Ö. and Çelik, T. (2017) 'Data Distribution Service-Based Architecture Design for the Internet of Things Systems BT - Connected Environments for the Internet of Things: Challenges and Solutions', in Mahmood, Z. (ed.). Cham: Springer International Publishing, pp. 269–285. doi: 10.1007/978-3-319-70102-8_13.

Tiwari, S., Bhatti, J., Tiwari, G.N., Al-helal, I.M., 2016. Thermal modelling of photovoltaic thermal (PVT) integrated greenhouse system for biogas heating. Sol. Energy 136, 639–649. https://doi.org/10.1016/j.solener.2016.07.048.

Tournier, J., et al., 2021. A survey of IoT protocols and their security issues through the lens of a generic IoT stack. Internet of Things 16, 100264. https://doi.org/10.1016/j.iot.2020.100264.

Tzounis, A., et al., 2017. Internet of Things in agriculture, recent advances and future challenges. Biosyst. Eng. 164, 31–48. https://doi.org/10.1016/j.biosystemseng.2017.09.007.

Ullah, I., Fayaz, M., Aman, M., and Kim, D. H. 2021. An optimization scheme for IoT based smart greenhouse climate control with efficient energy consumption, Computing. Springer Vienna. doi: 10.1007/s00607-021-00963-5.

Ullah, Z., Al-Turjman, F., Mostarda, L., 2020. Cognition in UAV-aided 5g and beyond communications: a survey. IEEE Trans. Cognit. Commun. Networking 6 (3), 872–891. https://doi.org/10.1109/TCCN.2020.2968311.

United States Geological Survey. 2021. Pesticides in Groundwater. [Online] Available at: https://www.google.com/search?client=firefox-b-d&q=USGC (Accessed: 20 October 2021).

University of Massachusetts Amherst. 2021. Pesticides and Groundwater Protection. [Online] Available at: https://ag.umass.edu/greenhouse-floriculture/greenhouse-best-management-practices-bmp-manual/pesticides-groundwater (Accessed: 20 October 2021).

US Environmental Protection Agency. 2020. Climate Impacts on Agriculture and Food Supply. [Online] Available at: https://19january2017snapshot.epa.gov/climate-impacts/climate-impacts-agriculture-and-food-supply_.html (Accessed: 5 October 2021).

Varjovi, A.E., Babaie, S., 2020. Green Internet of Things (GIoT): vision, applications and research challenges. Sustain. Comput. Inf. Syst. 28, 100448 https://doi.org/10.1016/j.suscom.2020.100448.

Verma, S. et al., 2020. Recent advancements in multimedia big data computing for IoT applications in precision agriculture : opportunities, issues, and challenges', in: Multimedia Big Data Computing for IoT Applications. Springer Singapore, pp. 391–416. doi: 10.1007/978-981-13-8759-3.

Villa-Henriksen, A., Edwards, G.T.C., Pesonen, L.A., Green, O., Sørensen, C.A.G., 2020. Internet of Things in arable farming: Implementation, applications, challenges and potential. Biosyst. Eng. 191, 60–84. https://doi.org/10.1016/j.biosystemseng.2019.12.013.

Wan, J., Chen, M., Xia, F., Li, D., Zhou, K., 2013. From machine-to-machine communications towards cyber-physical systems. ComSIS 10 (3), 1106–1128. https://doi.org/10.2298/CSIS120326018W.

Wang, H., et al., 2017. A lightweight XMPP publish/subscribe scheme for resource-constrained IoT devices. IEEE Access 5, 16393–16405. https://doi.org/10.1109/ACCESS.2017.2742020.

Wang, J., Chen, M., Zhou, J., Li, P., 2020a. Data communication mechanism for greenhouse environment monitoring and control: an agent-based IoT system. Inform. Process. Agric. 7 (3), 444–455. https://doi.org/10.1016/j.inpa.2019.11.002.

Wang, W., Wang, X., Cheng, N., Luo, Y., Lin, Y., Xu, W., Du, D., 2020b. Recent advances in nanomaterials-based electrochemical (bio)sensors for pesticides detection. TrAC, Trends Anal. Chem. 132, 116041 https://doi.org/10.1016/j.trac.2020.116041.

Wang, Z., Wang, X., Cong, S., Geng, F., Zhao, Z., 2020c. Fusing electrochromic technology with other advanced technologies: a new roadmap for future development. Mater. Sci. Eng. R 140, 1–26. https://doi.org/10.1016/j.mser.2019.100524.

Wang, K., Khoo, K.S., Leong, H.Y., Nagarajan, D., Chew, K.W., Ting, H.Y., Show, P.L., 2021. How does the Internet of Things (IoT) help in microalgae biorefinery? Biotechnology Advances 107819. https://doi.org/10.1016/j.biotechadv.2021.107819.

Wong, A., Silva, T.A., Marcolino-junior, L.H., Fatibello-filho, O., Janegitz, B.C., 2017. An overview of pesticide monitoring at environmental samples using carbon nanotubes-based electrochemical sensors. J. Carbon Res. 3 (8), 1–18. https://doi.org/10.3390/c3010008.

Yaïci, W., et al., 2021a. Recent advances in internet of things (IoT) Infrastructures for building energy systems: a review. Sensors 21, 1–40.

Yaïci, W., Krishnamurthy, K., Entchev, E., Longo, M., 2021b. Recent advances in internet of things (IoT) infrastructures for building energy systems: a review. Sensors 21, 1–40.

Yang, I.-C., Chen, S., Huang, Y.-I., Wen Hsieh, K.-, Chen, C.-T., Lu, H.-C., and Martin, Y.-M., 2008. RFID-integrated Multi-Functional Remote Sensing System for Seedling Production Management, in Food Processing Automation Conference Proceedings, 28-29 June 2008, Providence, Rhode Island. St. Joseph, MI: ASABE, p. 15.

Zamora-Izquierdo, M.A., Martı, J.A., Skarmeta, A.F., 2018. Intelligent systems for environmental applications smart farming IoT platform based on edge and cloud computing. Biosyst. Eng. 177, 4–17. https://doi.org/10.1016/j.biosystemseng.2018.10.014.

Zamora-Sequeira, R., Starbird-Pérez, R., Rojas-Carillo, O., Vargas-Villalobos, S., 2019. What are the main sensor methods for quantifying pesticides in agricultural activities? A review. Molecules 24 (14), 1–26. https://doi.org/10.3390/molecules24142659.

Zeed, A.T.A., Ali, A.H., Baghdadi, M.A.R.S.A., 2019. A cost-effective IoT-based control system for smart greenhouses powered by solar energy. Int. J. Energy Environ. 10 (3), 103.

Zhang, X., Cao, Z., Dong, W., 2020. Overview of edge computing in the agricultural internet of things: key technologies. Appl. Challenges, IEEE Access 8, 141748–141761.

Zhang, C., Guanming, S., Shen, J., Hu, R., 2015. Productivity effect and overuse of pesticide in crop production in China. J. Integrative Agric. 14 (9), 1903–1910.

Zhang, Y., et al., 2021. Big data and artificial intelligence based early risk warning system of fire hazard for smart cities. Sustain. Energy Technol. Assess. 45, 100986 https://doi.org/10.1016/j.seta.2020.100986.

Zhao, X., Askari, H., Chen, J., 2021. Nanogenerators for smart cities in the era of 5G and Internet of Things. Joule. Elsevier Inc. 5 (6), 1391–1431. https://doi.org/10.1016/j.joule.2021.03.013.

Zisis, C., Pechlivani, E.M., Tsimikli, S., Mekeridis, E., Laskarakis, A., 2019. Organic photovoltaics on greenhouse rooftops: effects on plant growth. Mater. Today:. Proc. 19, 65–72. https://doi.org/10.1016/j.matpr.2019.07.658.

Zu, X., Bai, Y., Yao, X., 2016. Data-centric publish-subscribe approach for Distributed Complex Event Processing deployment in smart grid Internet of Things. In: in 2016 7th IEEE International Conference on Software Engineering and Service Science (ICSESS), pp. 710–713. https://doi.org/10.1109/ICSESS.2016.7883166.

Further reading

Agrawal, N., Katna, R., 2019. Applications of Computing, Automation and Wireless Systems in Electrical Engineering. Springer Singapore. doi: 10.1007/978-981-13-6772-4.

Almadani, B. and Mostafa, S. M. (2019) 'Optimized RTPS platform for IIoT based smart farming systems', 2019 IEEE Asia-Pacific Conference on Computer Science and Data Engineering, CSDE 2019. doi: 10.1109/CSDE48274.2019.9162424.

Wan, X., Zhang, F., Liu, Y., Leng, J., 2019. CNT-based electro-responsive shape memory functionalized 3D printed nanocomposites for liquid sensors. Carbon 155, 77–87. https://doi.org/10.1016/j.carbon.2019.08.047.

Wang, D., Weisz, J. D., Muller, M., Ram, P., Geyer, W., Dugan, C., ... and Gray, A., 2019. Human-AI collaboration in data science: Exploring data scientists' perceptions of automated AI. Proceedings of the ACM on Human-Computer Interaction, 3(CSCW), pp.1-24.