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Review

A Review of Applications and Communication Technologies for Internet of Things (IoT) and Unmanned Aerial Vehicle (UAV) Based Sustainable Smart Farming

Nahina Islam [1,2,*], Md Mamunur Rashid [1], Faezeh Pasandideh [3], Biplob Ray [1,2], Steven Moore [1,2] and Rajan Kadel [4]

1 Centre for Intelligent Systems, School of Engineering and Technology, Central Queensland University, Rockhampton 4700, Australia; m.rashid@cqu.edu.au (M.M.R.); b.ray@cqu.edu.au (B.R.); s.moore@cqu.edu.au (S.M.)
2 Institute for Future Farming Systems, Central Queensland University, Bundaberg 4670, Australia
3 Instituto de Informatica, Federal University Rio Grande Do Sul (UFRGS), Porto Alegre 90040-060, Brazil; faezeh.pasandideh@inf.ufrgs.br
4 School of IT and Engineering (SITE), Melbourne Institute of Technology, Melbourne 4000, Australia; rkadel@mit.edu.au
* Correspondence: n.islam@cqu.edu.au; Tel.: +61-3-9616-0415

Abstract: To reach the goal of sustainable agriculture, smart farming is taking advantage of the Unmanned Aerial Vehicles (UAVs) and Internet of Things (IoT) paradigm. These smart farms are designed to be run by interconnected devices and vehicles. Some enormous potentials can be achieved by the integration of different IoT technologies to achieve automated operations with minimum supervision. This paper outlines some major applications of IoT and UAV in smart farming, explores the communication technologies, network functionalities and connectivity requirements for Smart farming. The connectivity limitations of smart agriculture and it's solutions are analysed with two case studies. In case study-1, we propose and evaluate meshed Long Range Wide Area Network (LoRaWAN) gateways to address connectivity limitations of Smart Farming. While in case study-2, we explore satellite communication systems to provide connectivity to smart farms in remote areas of Australia. Finally, we conclude the paper by identifying future research challenges on this topic and outlining directions to address those challenges.

Keywords: agriculture; Internet of Things (IoT); smart farming; sustainable future; sustainable smart farming; Unmanned Aerial Vehicles (UAVs)

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1. Introduction

The goal of sustainable farming is to increase agricultural yield to meet the food demand of 10 billion people by 2050, as reported by World Resources Institutes (WRI) in 2018 [1] and smart farming is the inevitable approach to reach this goal. Smart farming is defined as the farming system where smart and cutting-edge technologies are integrated with traditional farming approaches to improve quality and quantity of agricultural production, while at the same time lowering the inputs significantly [2]. The aim of smart farming is to improve productivity, increase yields and profitability and reduce the environmental footprint by utilizing different techniques such as efficient irrigation, targeted and precise use of pesticides and fertilizers for crops, etc. Evolution of Internet of Things (IoT) and Unmanned Aerial Vehicles (UAVs) has enabled the vision of sustainable smart farming. Being a key technology of smart farming, IoT adds value to obtained data by automatic processing, analysis and access by ensuring data flow between different devices such as sensors, relays and gateways. Hence more cost-efficient and timely production and management practices are enabled in smart farms [3]. Furthermore, IoT reduces the inherent climate impact by enabling real-time reactions to infestations such as weed, pest or disease detection, monitoring and predicting weather conditions, soil conditions, etc. As a consequence, UAV and IoT based technologies facilitate adequate use of resources such as water, pesticides or agro-chemicals. Additionally, these smart technologies have proven to increase the quality of crop yield [4] and reduce environmental footprint from agricultural sector [2]. Some major features of IoT and UAV based smart farming includes, but are not limited to, the following [5]:

- Field Monitoring: Smart farming helps in reducing crop waste by adapting better monitoring, accurate data obtaining and data processing.
- Livestock Monitoring and Tracking: Smart farming helps to identify the location of animals grazing in open area within big stables. Technology also helps to measure the status of ventilation and air quality in farms and detect harmful gases from excrement.
- Application in Green Houses: Smart farming controls micro-climate conditions towards the aim of maximizing the production and quality of fruits and vegetables within green houses.
- Compost Management: As a measure of preventing fungus and other microbial contaminants, smart farming helps to control the level of humidity and temperature in crops such as straw, hay, etc.
- Offspring Care: Smart farming controls the growing conditions of the offspring in animal farms, hence ensuring their survival and health.

On the other hand, UAVs have been incorporated into smart farming towards the aim of providing additional perspectives, such as, imagery analysis and agricultural surveillance [6]. UAVs not only facilitate image analysis and processing of the agricultural area, but also, offer in-depth situation awareness by patrolling over an area of interest [7]. Moreover, UAVs can also be used to provide important information to grounded monitoring stations by traversing data towards them. The applications UAVs are expanded to many areas of agriculture, including insecticide and fertilizer prospecting and spraying, seed planting, weed recognition, fertility assessment, mapping, and crop forecasting.

These recent advancements of IoT and UAV based smart farming are helping the world to reach the goals of “The 2030 Agenda for Sustainable Development”, where the United Nation (UN) and international community set a target to eliminate Hunger by 2030 [8]. However, there are many factors that limit the advantage of smart farming, where connectivity is one of the most crucial factors that may affect the benefits of IoT and UAVs in smart agriculture [1,9]. In order to achieve a seamless operation of the IoT and UAV-based smart farming, it is very important to ensure seamless connectivity and high level of communication efficiency among sensors-equipped devices.

The contributions of this paper are summarized as follows:

- Exploring two emerging technologies: IoT and UAV, which will be the pioneers of smart farming in the coming years.
- Outlining some major applications of IoT and UAV in smart farming as well as the agricultural industry.
- Exploring the communication technologies, network functionalities and connectivity requirements needed to ensure seamless connectivity for Smart farming
- Identifying the connectivity limitations and challenges of smart agriculture in remote areas with two case studies. In case study-1, we propose and evaluate meshed Long Range Wide Area Network (LoRaWAN) gateways to address connectivity limitations of Smart Farming—while, in case study-2, we explore satellite communication systems to provide connectivity to smart farms in remote areas in Australia.
- Identifying future research challenges on this topic and outlining directions to address those challenges.

Table 1 presents the acronyms used in this paper. The remainder of the paper is structured as follows. Section 2 explains how IoT and UAVs are used in smart farming, while Section 3 explores various applications of IoT and UAV in smart farming. Section 4 explicitly discusses the smart communication technologies along with network functionalities and connectivity requirements. Section 5 presents connectivity limitations of smart farming in remote areas with two case studies on smart farming. Section 6 discusses some open research issues on this topic and finally, Section 7 concludes the paper.

Table 1. Acronyms used in this paper.

Acronym	Definition
3GPP	3rd Generation Partnership Project
AI	Artificial Intelligence
AIoT	Agricultural IoT
BPSK	Binary Phase Shif Keying
GCS	Ground control station
IoT	Internet of Things
LPWAN	Low Power Wide Area Network
LOS	Line of Sight
LoRa	Long Range
LoRaWAN	Long Range Wide Area Network
M2M	Machine to machine
NFC	Near Field Communication
NBIoT	Narrow Band IoT
QoS	Quality of Service
RFID	Radio Frequency IDentification
UAV	Unmanned Aerial Vehicle
UNB	Ultra Narrow Band
UWB	Ultra WideBand
WSN	Wireless Sensor Network

2. IoT and UAVs in Sustainable Smart Farming

Authors in [10] anticipated that the world population will reach around 10 billion by 2050; Consequently, the food production needs to be increased by 70%. In order to meet this huge food demand, the agriculture industry requires information services, automation, robotics, and intelligence that combines Information and Communication Technologies, drones, robotics, Artificial Intelligence (AI), IoT and big data. In this section, we will discuss how IoT and UAVs in smart agriculture can take agricultural outcomes to new levels that were beyond imagination in the pre-IoT era.

2.1. IoT in Smart Farming

There are some important components of Agricultural IoT (AIoT), such as sensor equipped devices, internet connectivity, wireless communication technology, sensed and transmitted data, etc. The wireless communication technology plays a pivotal role in the successful deployment of IoT systems, which can be categorized based on spectrum, transmission distance, and application scenarios.

As shown in Figure 1, the structure of IoT is primarily based on three layers; namely, the perception layer where the sensing is done, the network layer which deals with data transfer, and the application layer where data storage and data manipulation is done [5].

Perception layer: The perception layer consists of various terminal devices, sensors, Wireless Sensor Networks (WSN), RFID tags and readers, Near Field Communications (NFC) devices, etc. [11]. At this layer, sensors are used to collect information about temperature, wind speed, humidity, nutrient level, plant diseases, insect pests, etc. The collected information is being processed through embedded devices and are uploaded to a higher layer through the network layer for further processing and analysis. These terminal devices and sensors are used to monitor, control, identify and track agricultural and livestock products. For instance, WSNs are often used to climate control and monitoring of storage and logistics facilities [11]. On the other hand, RFID technologies are the most crucial example of interconnected devices. RFID tags store data in the form of the Electronic Product Code (EPC), which are then read, triggered and manipulated by RFID Readers [12].

Hence, by offering object identification, tracking and data storage on active or passive tags; WSN, RFID and NFC technologies play an important role in the agricultural domain.

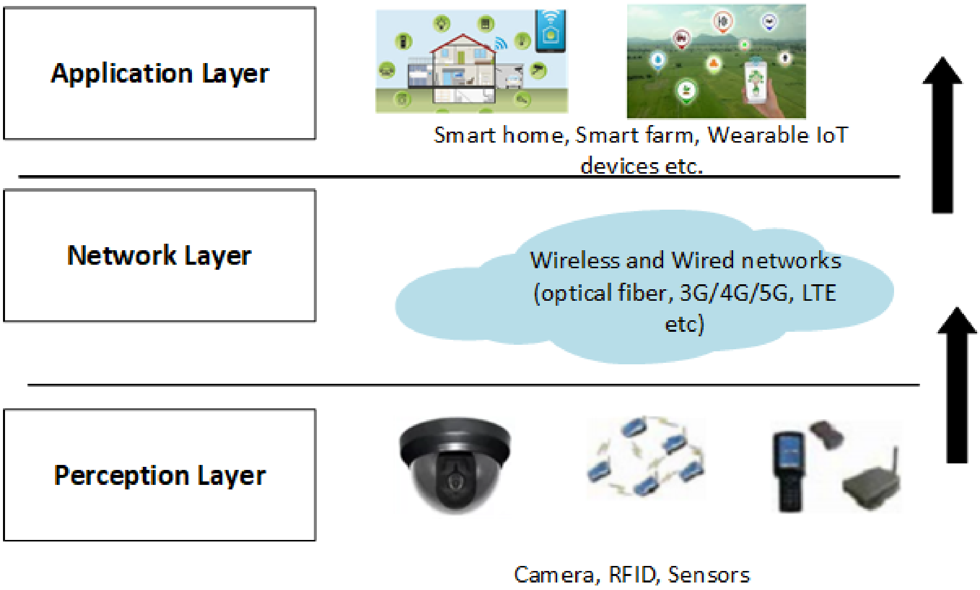

Figure 1. The architecture of IoT.

Network Layer: In this paper, we focus on the network layer of IoT where the sensors and devices need to be connected to their neighbouring nodes and a gateway in order to build a network. At this layer, the sensor nodes interact and communicate with other nodes and gateways within a network in order to forward data towards a remote infrastructure; where these data are stored, further analysed, processed and disseminated to useful information [13]. A large scientific literature has been conducted on wireless networks, addressing several problems, such as reducing energy consumption, improving networking features, increasing scalability and robustness [11]; however, the connectivity limitations in remote areas have not been addressed extensively.

Wireless protocols and standards sets the protocol for wireless communication. For instance, IEEE 802.15.4 is a wireless standard which facilitate the interconnection between internet-enabled gateways and end-nodes. A few other examples of such protocols are ZigBee, Sigfox, ONE-NET, WirelessHART, ISA100.11a, LoRaWAN, Bluetooth Low Energy (BLE), DASH7, etc. [14]. These standards are categorized in terms of transmission distances as follows [15]:

- Wireless connectivity technologies with short-distance communication range (at most 10 m): Examples include Bluetooth, RFID, UWB technologies [15].
- Wireless connectivity technologies with medium distance range (10 to 100 m): This category includes ZigBee [16] and Wi-Fi [17] technologies.
- Wireless connectivity technologies with a long-distance range (100 m and above): Cellular networks, and Low Power Wide Area (LPWA) technologies which are classified to Non-3GPP (LoRa [18], Sigfox [19] and Weightless) and 3GPP (NB-IoT [20], LTE-M, EC-GSM) technologies that are considered in the long-distance communication range category.

Figure 2 is a graphical representation of the classification of communication technologies.

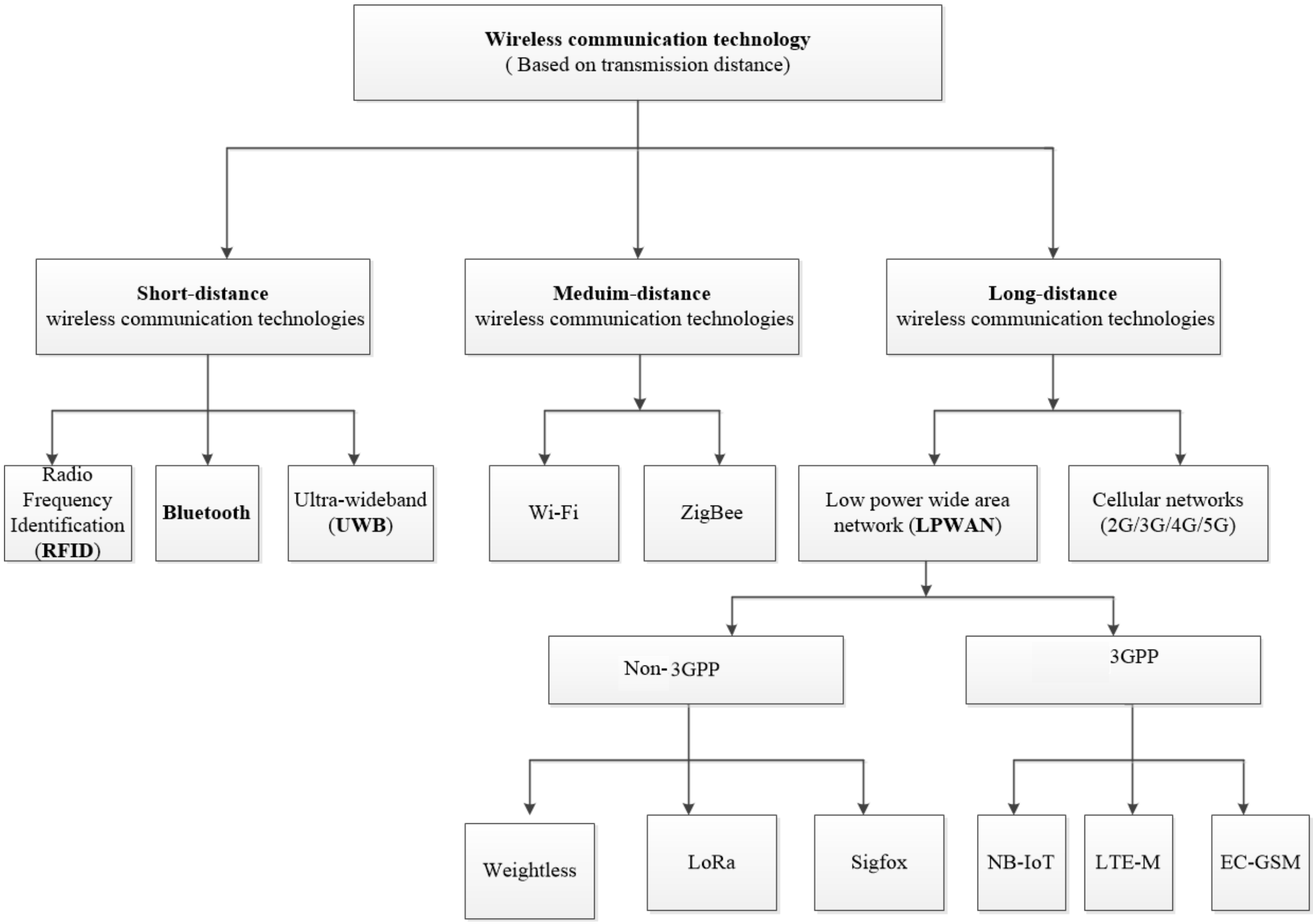

Figure 2. A classification of communication technologies used in Internet of Things (IoT) based Smart Farming.

Classifying Standards based on Communication Distance: For short-range applications, IEEE 802.15.4-based protocols are the preferred choice [11], which are intended for Low-Power Wide-Area Networks (LPWANs). It offers a data rate between 20 kbps to 250 kbps, operates over different frequency bands such as 433 MHz, 868 MHz, 915 MHZ and 2.4 GHz; and supports a maximum outdoor Line of Sight (LoS) range of 100 m [21]. On the contrary, IEEE 802.11 standard are suitable for applications that need medium range connectivity. The 2010 release of this standard, namely IEEE 802.11p, incorporate scenarios with a high mobility requirements. This particular release appears to be of large interest in agriculture scenarios because of it's large transmission range, maximal legal transmission power of 1 W, and the less interfered band of 5.9 GHz ISM frequency [9].

When coverage is concerned, long-range technologies are the only reliable and desired solutions. Cellular communication technologies such as 3G, 4G, Long Term Evolution (LTE), and 5G are most suitable and a reliable standard for precision agriculture, where a large amount real-time data needs to be transmitted and processed [22]. For instance, the data rate of LTE data rate is up to 3 Gbps for downlink and up to 500 Mbps for uplink, while the latency is than 10 ms in the LTE-Advanced Release 10 [9]. In addition, the 5G communication system is expected to provide real-time Device to Device (D2D) communication, which will enable vehicle positioning. Additionally, a huge number of devices can be supported per square kilometer [23]. In comparison to LTE, 5G can operate on higher frequency bands, and hence can offer wider channel bandwidths. Particularly for rural areas, 5G technology may enable new capabilities on farm equipment by offering higher data rates and longer transmission distances under the paradigm of real-time connectivity. However, the availability of the cellular network and the economical feasibility of 5G technology in rural areas is still a questionable concern.

Among long-range communication technologies of IoT, IEEE 802.11ah and LoRa/LoRaWAN are the most reliable. The first one is an amendment of the IEEE 802.11 family, which was published in 2017 to support IoT scenarios such as smart metering [9]. It uses 900 MHz license-exempt bands, provide wider coverage range and consumes lower energy compared to Bluetooth and IEEE 802.15.4. It provides connectivity to thousands of devices with a single access point up to one-kilometer radius of coverage. On the contrary, LoRaWAN is one of the most promising LPWAN specifications intended for a network of battery-operated wireless nodes. More information on LoRaWAN is provided in later sections.

Application layer: The highest level of the IoT architecture is the application layer, where the benefits and utilities of IoT are most apparent. There are lots of intelligent platforms or systems in this layer for the purpose of monitoring and controlling of soil condition, water and nutrition level, plants and animals. This layers also supports the early warning and management of diseases and insect pests, infestation and agricultural product safety tractability; as a result, production efficiency can be improved.

2.2. UAVs in Smart Farming

One of the most useful innovations of smart farming are the agricultural robots, among which, UAV, also called drones, have been extensively applied [7,24]. Drones or UAVs are being widely used by farmers for farm growth monitoring and controlling. Some UAVs are being used to spray water and other pesticides efficiently in the tough terrains were human movement is not easy and the crops possess different heights. This is why UAVs were defined as a 'green-tech' tool in smart farming by the Massachusetts Institute of Technology in 2014 [25]. Figure 3 shows an example of different types of agricultural UAVs used for various agricultural applications.

With recent advances in swarm technology and mission-based control, groups of drones equipped with heterogeneous sensors and 3D cameras, can work together to provide farmers with comprehensive capabilities to manage their land. These agricultural UAVs are making it possible for the farmers to have a bird's eye view over their farms to manage and control the farms well by significantly reducing working hours, resulting in increased stability, productivity and measurement accuracy. Moreover, their applications have contributed to the expansion of many areas of agriculture, such as fertilizer and pesticide prospecting and spraying, weed detection and removal, seed planting, fertility assessment, mapping etc. [7,25]. For instance, the authors in [26] used UAV images for early weed detection in a chilli field located in Australia. UAV images were also used to measure the crop height of maize and sorghum plants in an agricultural field [27]. A similar application of UAVs is found in [28], where the authors proposed a novel technique to register UAV images of agricultural crops and reconstruct 3D models of the crop to monitor growth parameters of the plants. In smart farming, UAVs have also been integrated with smart sensors to perform many applications such as monitoring field conditions [29], yield quantity and quality [25], meteorological parameters such as temperature, humidity, wind speed, wind direction etc. [30]. For instance, a wireless sensor network (WSN) was integrated with a smart UAV platform to perform real-time measurement influencing quantity and quality of grape yield [31]. The researchers in [32] developed a UAV mounted smart flying sensor to map the volume of grain inside a trailer during forage harvesting. UAVs have also been effectively used for agricultural crop yield management. For example, the researchers in [33] have shown application of UAVs to address various issues of palm oil plantations, such as yield prediction, disease detection, pest monitoring, etc.

In-spite of the advancements of UAVs, there are some unsolved challenges that need attention for better implementation of UAVs such as battery efficiency, low flight time, communication distance and payload [24,34]. For instance, researchers have focused on reducing energy consumption in UAVs [35] since energy is a scarce resource of UAVs. However addressing the connectivity limitation still requires more attention. Therefore, in this paper, we are identifying the connectivity limitations of agricultural UAVs so that researchers can conduct research to solve these issues.

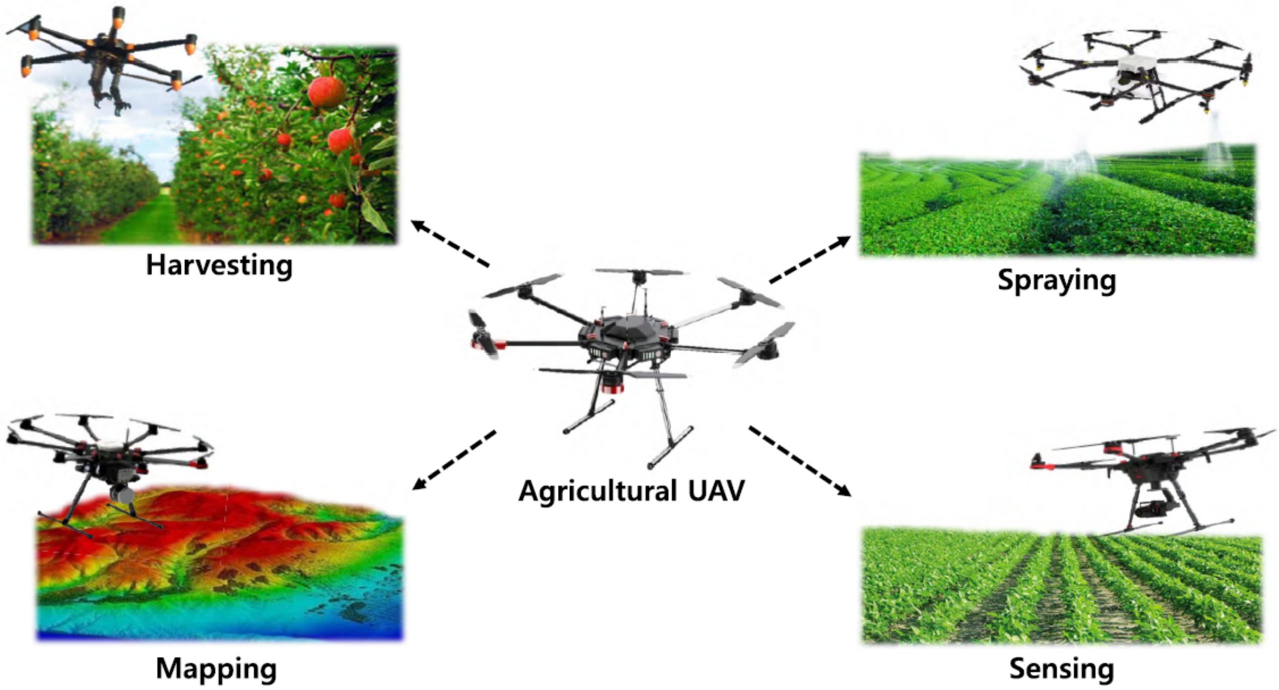

Figure 3. Different types of agricultural UAVs (Harvesting UAV, Spraying UAV, Mapping UAV, Sensing UAV) [6].

3. Application Areas of IoT and UAV in Smart Farming

IoT and UAVs can be implemented in many application areas of smart farming. This section discusses a few common applications of smart farming.

3.1. Monitoring

Monitoring refers to timely sensing of different parameters of a farm. Automatic monitoring is one of the preliminary features of smart agriculture. Strategically placed sensors can automatically sense and transmit data to a gateway for further analysis and processing. Sensors are used to monitor crop parameters such as leaf area index [36], plant height, colour, shape and size of leaves [37]. They are also useful in monitoring soil moisture [38,39]; irrigation water parameters such as salinity and pH level [40]; and weather parameters such as air pressure, temperature, relative humidity, wind speed, wind direction, rainfall, radiation, etc. [41,42]. Furthermore, remote sensing is also being used very effectively. Due to the light weight of sensors, remote sensors are installed in lower altitude UAVs and consequently can monitor crops effectively and cost-efficiently. Thus, high-resolution data are being obtained by eliminating different types of constrained such as weather condition. For instance, authors in [43] conducted an experiment to collect 3D data from lightweight snapshot cameras mounted in aerial vehicles.

3.2. Mapping

UAVs are used to create useful 2D or 3D maps of an agricultural field. For example, the area of the farmland, soil conditions, and status of the crops, infestation within the crop can be detected in these maps [44]. For instance, the authors in [45] obtained high-resolution maps delineating the spatial variations of radiation interception using UAV images. These maps are used for profitable precision agriculture tasks, such as the separation of fruit quality areas, identifying the area of deforestation and the agronomic control of homogeneous zones.

3.3. Detecting Weed and Infestation

Another most useful sector of smart farming is weed and infestation detection using UAVs. As per a study conducted in the United States, approximately $33 billion of annual damage is caused by pest infestations and infections [46] in crops. Hence, early diagnosis is essential to minimise this damage. Authors in [47] conducted a study to analyze the vegetation index of grapes by acquiring data from vineyards using UAV mounted multi-spectral cameras. These vegetation indices can be used in various applications such as weed detection, infestation detection, weed mapping, etc. Many researchers have used RGB cameras, hyper spectral camera and multi-spectrum sensors mounted on UAVs to detect weed and infestation in plants and crops [26,48,49].

3.4. Planting Seeds and Seedlings

Undoubtedly plantation of seeds and seedlings can be made more efficient using UAVs. For instance, authors in [50] shows an effective use of UAVs on a large area of uneven rice paddies. They used a UAV based system for effective and timely distribution of seeds, fertilizers and plant nutrients. Plantation of seed and seedlings using UAVs is still in development stage, the researchers are developing UAVs equipped with image recognition technology and an optimized planting technique [6].

3.5. Spraying Pesticides and Fertilizers

UAVs have proven to effectively and quickly spray pesticide and fertilizers compared to a speed sprayer or a wide-area sprayer. The measure of pesticides per hectare of farmland correlates to the risks of worker ailments and environmental pollution. The use of pesticides can be minimized with UAVs by achieving large-scale decontamination of up to 50 hectares per day and requires only about 10 min of work per 0.5 hectare area [6]. One of the major motives of using UAVs is to reduce labor requirements. For instance, authors in [51] conducted a study in citrus farms to determine the optimum level of preventive work by spraying fertilizers from various heights using a UAV.

3.6. Forecasting

Forecasting is one of the major features of smart farming that uses real-time data and historical data to forecast and predict some important parameters. Scientific modelling and machine learning are examples of tools employed for forecasting. Different machine learning models have been employed, such as the regression model, Artificial Neural Networks for forecasting maximum and minimum temperatures at field level [52]; forecasting soil moisture or plant disease detection [48]; for estimating phosphorus level in the soil [53], etc.

3.7. Controlling

In IoT based smart agriculture, controlling is the result of active monitoring in an automated system, where the monitored variables are automatically adjusted to predefined thresholds. Forecasting can also play an important role in controlling. For instance, in smart irrigation systems, irrigation is activated by forecasting drought conditions, hence yield losses can be reduced. Weather forecasts in combination with real-time sensing of soil moisture and soil temperature has been used to control a fully autonomous irrigation scheme in [54]. Sensors installed in tractors and UAVs can also be used to control variable rate of nutrition, fertilisation and site specific weed control technologies [5].

4. Communication Technologies for Seamless Connectivity in Smart Farming

Seamless connectivity is a vital part of IoT-based smart farming. The provision of connectivity and value-added services have a large effect on the entire chain. The connectivity services that are offered by cellular operators only indicate the small portion of the entire intelligent farming market. Telecom operators should provide a new range of services, in rural regions in particular, due to increasing the demands.

4.1. Network Functionality and Connectivity Requirements

For large farms, high bandwidth is necessary because of large amount of data processing, such as large amount of precision farming data and telemetric data to be collected in the farm servers and download/update operations of the geographic maps. In case of greenhouses and horticulture lands, a totally different scenario must be analysed. Greenhouses are connected to the electrical grid [9], which has the requirement of using gateways. These gateways are very power consuming, hence batteries cannot be used as the power source. Therefore, cellular technologies such as LTE, 4G and 5G connections can substitute fixed lines, whereas WiFi can be considered for Internet connection. Similarly, a gateway between the WSN and the infrastructure can be available, so that small agricultural nodes can exchange data. On contrary, Livestock farming may have two different scenarios: one of for shaded animals and another is for free animals pasture in the fields. The former one is very similar to greenhouse, where wireless sensors are worn by the animals. Whereas, the latter one is an expensive option, where the data from animal sensors needs to be collected since the animals are scattered around the field. These information sometime rely on UAVs, drones or agricultural machines. Ensuring a safe travel of agricultural machines in public roads is another issue that needs to be addressed. The solution is to provide a Machine to Machine (M2M) communication notifying the presence of slow machines, where Intelligent Transportation Systems (ITS) standards [55] need to be included. The protocols for both Internet infrastructured connectivity and long range communications are cellular technologies such as 3G, 4G, 5G and LPWAN air interfaces which enable IoT data management paradigms.

For agricultural UAVs, the Micro Air Vehicle Link (MAVLink) is a common communication protocol allowing UAVs to communicate with Ground Control Station (GCS). It communicates between computing platform (such as Raspberry Pi, Arduino, and UDOO), control platform (such as Pixhawk and Ardupilot) of UAV and application (such as mission planner and Qground control) of GCS [56]. MAVLink transmits directions, position of global navigation satellite system (GNSS) and speeds of the UAV. The communication distance between the UAV and the GCS depends on specifications of the UAV, However, it can communicate up to 2 km when the UAV is within LOS [6]. Currently, UAVs are programmed to operate at return-to-launch mode, which means the UAVs will automatically return to its first position when communication is interrupted. This mode is activated to prevent unwanted accidents or lost of UAVs [6,57,58]. Few other types of communication systems are also available for communicating between GCS and UAVs such as ZigBee, radio-frequency modules, and other transmitting medias. The communication distance can be increased with the addition of technologies, including phone apps. Moreover, the emergence of 5G cellular technology promises to greatly improve communications and data-processing speeds, which will be useful for high-definition mapping [59,60].

4.2. Availability and Challenges of Communication Technologies

In smart farming, UAVs are deployed with mounted gateway to gather data from sensors and nodes spread over the farm areas. The UAVs can fly over obstacles such as trees in the wide farm areas. Various physical and systemic conditions of the agriculture, ranging from wide outdoor area to power life should be considered. In this case sending and receiving data should be carried out over a long distance with low power consumption. For this reason, we will focus on long-distance wireless connectivity challenges in agriculture and farm areas and decide to investigate the limitations of cellular networks and LPWAN (Sigfox, LoRa/LoRaWAN and NB-IoT) technologies [61].

4.2.1. Cellular Networks

Cellular technologies (2G/3G/4G/5G) have been considered as the possible option for long range wireless connectivity. However, using cellular connectivity leads to some limitations related to Low-Power WAN. The high power consumption that makes battery operation not-allowed for long periods of time causes one of these limitations. When it comes to using cellular modules, people should pay the charge per month to subscribe to the cellular operator or service providers. Thus, such modules are rather more expensive [62]. 5G is the newest technology for the mobile world and IoT communications [63]. However, there are not many explanations on how to combine the high-speed technology of 5G with the low power consumption, which is essential for IoT applications [64]. In fact, 5G has the capability of enabling ultra-high-speed communications through a wide bandwidth [63] and high frequency. This is not suitable for energy constrained IoT devices. Moreover, the Massive Machine-Type Communications (mMTC) and critical Machine-Type Communications (cMTC) are two objectives of 5G to leverage Ultra Reliable and Low Latency Communications (URLLC). The mMTC has been developed for IoT, while the cMTC requirements are too limited. The mMTC 5G necessities are fulfilled using LTE-M and NB-IoT developed by 3GGP, and there are no other dedicated solutions to be specified for 5G IoT [65].

4.2.2. LPWAN Technologies

When it comes to LPWAN technologies, lower power consumption and data rate, wider coverage, more massive connection are provided in comparison with traditional cellular systems [62]. These traditional technologies provide proper connectivity for devices that only transfer a small amount of data, but they are not recommended to use for audio or video data streaming [66]. LPWANs take advantage of highly constrained radio links that the size of packets are very limited. In our preliminary work [40], we have evaluated the suitability of LPWAN technologies for smart farming in remote areas. In this paper, we have presented that analysis elaborately. This subsection discusses three popular LPWAN technologies, namely LoRaWAN, Sigfox and NB-IoT:

- **LoRaWAN (Long Range Wide Area Network):** LoRaWAN was defined by Alliance in article [67]. The network and media access control protocols are both defined on top of the physical layer of LoRa by LoRaWAN, the required parameters at the physical layer are defined by LoRa [61,64,66,68]. The radio frequency bands (169, 443, 868, and 915 MHz) with 0.25 and 12.5 kbps data rates are used in LoRaWAN [9]. LoRaWAN communication connects the LoRa gateway to a number of sensors. Drones (UAVs) equipped LoRa gateways are able to fly over the agriculture regions and gather data from sensors placed on the bottom of the farm. By doing this, users will be able to access the remote and inaccessible areas. In addition, this provides a larger coverage using a single gateway. Some applications cannot take advantage of the LoRa technology because there are still some restrictions in using such a technology. One of the main drawbacks of IoT applications is that a device with LoRa technology can only transmit at most 36 seconds per hour. This is the main limitation that can affect not only the time among messages but also the payload. Therefore the IoT application equipped with LoRa should be programmed in such a way that can adapt itself with these limitations. Moreover, only the half-duplex communication can be supported by the latest LoRa modules, which means a device with LoRa cannot receive and send data at the same time [69].
  Some of the limitations of LoRaWAN are considered as follows: Firstly, LoRaWAN uses the ALOHA Protocol which is not slotted, in its MAC layer. This means Clear Channel Assessment (CCA) is not performed at all, and packets can be transmitted at any arbitrary time. The collision avoidance mechanism, which is employed in order to cost reduction and simplicity provision, is not used in this mechanism. Secondly, if the devices in LoRaWAN are mobile, there is no certain handover method, as these devices are not associated with a specific gateway. Finally, there are three classes in LoRaWAN including, Class All, Beacon, and Continuous which are called A, B, and C, respectively. Class A is intended to enhance the power efficiency of the sensors, which work with a battery. Actuator nodes use Class B that inherits and performs all the functionality of Class A. The periodic receiving windows are also being opened and are allowed to receive the downlink messages by Class B. Devices in Class C are

listening without interruption to receive the messages, hence these devices should have a lot of power.

- **Narrow-Band IoT (NB-IoT):** NB-IoT is a protocol in mobile communications, especially standardized by the 3GPP standardization group with a 180 kHz bandwidth. Using this bandwidth, the down-link and up-link data rates are considerably reduced around 20 and 250 kbps, respectively. As a result of this, updating Firmware over the Air (FotA) will be hard to reach using NB-IoT. As NB-IoT does not support the handover, considering NB-IoT for mobile IoT applications will be difficult, as well. In addition, current LTE infrastructures need to be upgraded when it comes to using NB-IoT. Therefore, deploying NB-IoT is a difficult task [64,68].
- **Sigfox:** Sigfox [70] is a LPWAN technology that takes advantage of Ultra-Narrow-Band modulation (UNB) which decreases the levels of noise then the communication rate will increase. It is proper for the lightweight and low data rate IoT based devices. The typical structure of the modulation is Binary Phase Shift Keying (BPSK). In addition, the down-link and up-link communications of each device are limited by Sigfox. Moreover, many countries have used Sigfox and there is no roaming involved.

4.2.3. Comparison in Terms of IoT Factors

Some parameters including, device lifetime and latency, quality of service, coverage and range, cost, payload length, and scalability should be taken into consideration when it comes to using a proper LPWAN technology for IoT applications [71]. These parameters for NB-IoT, Sigfox and LoRaWAN are compared in Table 2 and discussed below:

- **Coverage and Range:** The highest coverage range (at least 40 km) is related to Sigfox, and only one Base Station is enough to cover the entire area. The lowest range (at most 10 km) is obtained using NB-IoT which is not adapted for rural regions, and it is only used for LTE infrastructure. LoRaWAN has a coverage range of at most 20 km [72].
- **Latency:** NB-IoT offers a low IoT latency connectivity, while a low bidirectional latency is provided by Sigfox and LoRaWAN at the expense of increased energy consumption [73]. As a result, the best solution for IoT applications with low latency connectivity and latency insensitive applications can be NB-IoT, LoRaWAN-Class-C, and LoRaWANClass-A and Sigfox, respectively.
- **Battery life:** The lifetime of NB-IoT based devices is lower than LoRaWAN and Sigfox ones. This is because the energy consumption of NBIoT based devices is more than Sigfox and LoRaWAN devices, as they need to handle QoS and synchronous communication [40].
- **Quality of service (QoS):** Some applications need the Qos requirements, Sigfox and LoRaWAN are suitable for such applications, while for those applications that need QoS requirements NB-IoT is preferred [74].
- **Scalability and Payload length:** Sigfox, NB-IoT, and LoRaWAN provide high scalability. NB-IoT not only provides higher scalability than LoRaWAN and Sigfox but also maximum payload length. About 50K connected devices per Base Station is supported by RaWAN and Sigfox while NB-IoT supports twice as much as this number of users [70]. NB-IoT allows the highest payload length of 1600 bytes, while the Sigfox allows the lowest data transmission up to 12 bytes.
- **Deployment model:** Many countries and cities take advantage of completed LoRaWAN and Sigfoxs' ecosystems. LoRaWAN is deployed in 42 countries while Sigfox is used in 31 ones [72]. However, NB-IoT was published under rollout to set up its network over the world. Sigfox, NB-IoT, and LoRaWAN technologies are still in the final phase. Public network operation and local network placement via Base Stations are provided by these three technologies.

Table 2. Overview of Long range connectivity technologies [61].

	NB-IoT	SigFox	LoRa
Modulation	QPSK	BPSK	CSS
Interference immunity	Low	Very High	Very High
Localization	Yes (TDOA)	Yes (RSSI)	Not supported
Standardization	3GPP	SigFox company with ETSI	LoRa-Alliance
Maximum data rate	200 kbps	100 kbps	50 kbps
Bidirectional	Yes/Half-duplex	Limited/Half-duplex	Yes/Half-duplex
Maximum message/day	Unlimited	140 (UL), 4 (DL)	Unlimited
Maximum payload length	1600 bytes	12 bytes (UL) 8 bytes (DL)	243 bytes
Coverage	164 dB	160 dB	157 dB
Power Consumption	Very low	Low	Low
Security	Very High	Low	Low
Bandwidth	200 kHz	100 kHz	250 kHz and 125 kHz
Frequency	Licensed LTE Frequency	ISM Band 433, 868, 915 MHZ	ISM Band 433, 868, 915 MHZ
Technology	OpenLTE	Proprietary	Proprietary
Spectrum	Licensed	Unlicensed	Unlicensed
Topology	Star	Star	Star
Downlink Data Rate	0.5–200 kbps	0.1 kbps	0.3–50 kbps
Uplink Data Rate	0.2–180 kbps	0.1 kbps	0.3–50 kbps
Range	1 km (urban) 10 km (rural)	10 km (urban) 40 km (rural)	5 km (urban) 20 km (rural)
Duty Cycle Restriction	No	Yes	Yes
Output Power	23 dBm	14 dBm	14d Bm
Battery Lifespan	15 years	10 years	10 years

5. Connectivity Limitations of Smart Farming in Remote Areas

The aim of IoT is to connect beyond restrictions of geographical boundaries; therefore, network connectivity in remote areas is an important silo for wider acceptance of the technology. The remote connectivity is also more important to get full advantage of smart agriculture as agricultural lands are extremely large and located in remote areas. For most of the cases, the remote agricultural lands are not fully covered with mobile networks and other forms of internet connectivity. Therefore, in remote areas, the IoT gateway must support longer communication capability to extend coverage to the nearest internet, not be power hungry and offer multiple powering options. One of the core component of IoT technology is openness; therefore, we are considering an open standard of LPWA named LoRaWAN for evaluating connectivity limitations in remote areas. To date, the LoRaWAN protocol can cover 10 km [75] in a laboratory testing environment and 5–7 km in remote areas [75]. The connectivity of LoRaWAN in rural areas is limited to 2–3 km only [75]. In remote smart farming scenarios, connectivity of 5–7 km is not enough to reach a connection to the internet nearby. Therefore, it creates a connectivity problem to extend the remote farm's IoT network to rest of the world. Furthermore, maintaining IoT connectivity devices/equipment in remote locations is a challenging task, which limits the options of deploying IoT devices. Furthermore, the remote deployment of IoT devices must support long life span and multi mode power source [76]. Below is a list of the connectivity limitations for remote smart farming:

- **Longer range connectivity with redundant connections:** In remote areas, the IoT devices need to be spread out over a larger area to cover an entire farm. These devices often fail to get connected to nearby internet sources due to their limited communication range. Therefore, existing connectivity range of IoT gateways need to be improved to reduce dependency on backhaul systems.
- **Self sustained power source:** current IoT system must reduce dependency on traditional main grid power source to make it usable in remote setting. A sensor system could use renewable energy with adaptive energy sharing and management.
- **Low and remote maintenance requirement:** Inaccessibility is one of the major limitations of remote areas. Hence the IoT devices set in remote locations should have higher durability, improved reliability and low maintenance requirement. They should be equipped with proactive and remote management and maintenance for remote areas.
- **Minimal power usages using optimised techniques:** Power is a scarce resource in remote area. Therefore, low power consuming techniques are desirable for battery operated nodes in remote areas.
- **Privacy assurance:** Many of the existing IoT systems ignored users and objects privacy requirement. For sustainable growth and trust, the IoT system must assure privacy of users and objects at minimum.

The recent development of LoRaWAN technologies is working to address some limitations mentioned in the list above, but others requires more attention from researchers in this area.

In this subsection, we present two case studies addressing this issue. In the first case study, we propose meshed LoRaWAN gateways to address connectivity limitations of Smart Farming in remote areas, and, in the second case study, we present satellite communication systems to provide connectivity to smart farms in remote areas of Australia. The following subsections describe the details of these case studies:

5.1. Case Study 1: Meshed LoRaWAN Gateways for Smart Farming in Remote Areas

To address longer coverage and redundant connections, the meshed LoRaWAN gateway [77,78] was tested to get city wide coverage. This study [77] has used 18 channels LoRaWAN gateway [79] with overlapping area to ensure redundant communication support between gateways as illustrated in Figure 4.

Few researches also looked into the performance and reliability of meshed LoRaWAN gateways [78,80,81] for remote and large scale deployment. Based on these existing research, current technology of the meshed LoRaWAN gateways perform poorly and low reliability [80].

There is work to implement offline mobile computing at the edge [76] to process collected data onsite from a local LoRaWAN gateway. This reduces the requirement of getting IoT networks connected to the internet directly. However, the offline mobile computing at the edge reduces the capability of the high computational decision-making process with the help of existing global knowledge.

There have been some attempts to use renewable power sources for LoRaWAN gateways, but little or no work have been done towards self sustained power sources for gateways in remote areas. Although there has been work done to optimise power usages during active and passive communication of gateways, no work exists for LoRaWAN IoT gateways specifically in meshed network scenarios. Moreover, the remote maintenance of networked IoT gateways requires further investigation for a sustainable smart farming system in remote areas. Although some connectivity challenges for remote smart farming are getting investigated, other challenges listed above need further attention from the research community and industry to evolve smart farming into becoming suitable for remote areas. Therefore, it will be useful to see some innovation towards a networked IoT gateway which ensure adaptive channel distribution, full duplex communication, data transmission, and user privacy for a trusted object network in remote setup.

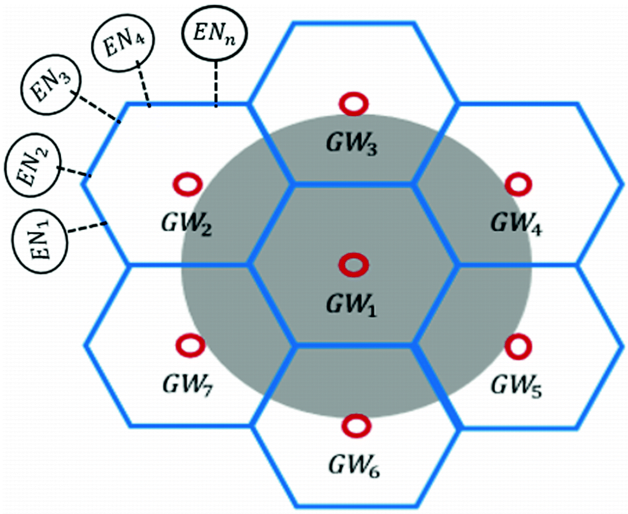

Figure 4. Meshed IoT gateways adapted from [78].

5.2. Case Study 2: Satellite Communication Systems to Provide Connectivity to Smart Farms in Remote Areas of Australia

In remote areas where connectivity via cellular communication is not available, satellite systems are considered to be the better alternative of cellular systems to provide connectivity to IoTs and UAVs. In Australia, there are few providers of satellite communications services in rural and regional Australia, which can support the connectivity of smart devices. A popular communication satellite is Low earth orbit (LEO) satellites, which are placed at heights between 100 km to 2000 km and orbit very quickly [82]. As a consequence, they move in and out within Line of sight (LOS) regularly during every 9–10 min. In order to have continuous access (e.g., LOS), the service providers must have a large numbers of satellites in orbit in a given location. This allows a hand-over from one satellite to another as they depart line of sight from a given user. A common LEO satellite system in Australia is U.S. based Iridium [83,84] with a constellation of 66 LEO satellites. In the Iridium, each satellite in the constellation not only maintains communication with the ground user, but they also maintain contact with two to four adjacent satellites and routes data between them, hence effectively creating a large mesh network. LEO communications satellites have comparatively low latency times and can support high bandwidth due to their proximity to ground. For instance, Iridium offers a low-latency Short Burst Data (SBD) service that is specialized for the M2M and IoT market. Another LEO satellite communications system is Globalstar, where the data and calls are passed from satellite to local gateways located in some places in Australia such as Meekatharra, Dubbo and Mt Isa [85]. They use 24 satellites that need to be within the range of ground stations during data or call exchange. As a consequence, these satellites are prone to interruptions, especially for areas closer to the equator such as the gulf country of northern Australia [82].

Another category of satellite communications is the geostationary satellites, which are placed directly over the equator at approximately 35,800 km high [82] and revolve in the direction of earth's rotation. These satellites appear to 'hover' in the sky and hence can be accessed using a directional antenna pointing at a fixed direction in the sky. One of the major Australian telecommunication providers, namely Optus, operates a fleet of 5 geostationary satellites over Australia and New Zealand with access to another nine third-party satellites in the Pacific and Indian Ocean regions [86]. IoT and machine to machine (M2M) applications are supported by these satellites. A British satellite telecommunications system, Inmarsat [87], provides data and voice communications via 12 geostationary satellites. Inmarsat provides satellite connectivity to Vodafone's IoT platform all over Australia including regional areas. Another group of geostationary satellites are the Sky Muster satellites (NCN Co 1A and NBN Co 1B) of NBN [88], which maintain each of their 101 fixed spot beams on specific regions over Australia. However, these particular satellites do not support IoT directly as access is provided to satellite dishes located on residential and business premises. Additionally, a network named Thuraya, covers 140 countries and relies on two geostationary satellites [89]. Their reception exists in LOS areas in Australia. Thus, the available satellite communication systems provide connectivity to IoTs and UAVs in some rural parts of Australia. For our future work, we set a milestone to extensively analyse on which type of connectivity option is suitable for farming in different parts of Australia depending on several criterion, such as location, network coverage, communication delay, energy consumption etc.

6. Open Research Issues

Despite of the immense popularity of IoT and UAV based smart farming, there are few challenges that need to be addressed. This section presents the open research issues related to IoT and UAV for sustainable smart farming.

- Hardware maintenance and limited energy resources:
  The perception layer's hardware are setup in harsh environment, like farms and mining field, which have extreme weather conditions like high temperature, rain, strong wind and extreme humidity, etc. As a result, the electronic circuits of these hardware devices get damaged. Therefore, stronger hardware devices need to be designed that will be less damaged by the harsh environment. Additionally, these devices operate on inadequate battery power consistently for a long period. Hence, alternative energy efficient solutions are required for the end devices because, in case of any program failure, instant battery replacement is complicated, especially in remote areas [35]. Authors in [90,91] suggested energy efficient approaches for the network side; however, energy efficient solutions for the end devices are also desirable.
- Security and privacy issues:
  The use of IoT contributes to widespread exposure to cyber security risks and vulnerabilities in smart farming. Gupta et al. in [92], introduced some key challenges for security and privacy in smart farming: access control and trust, data, network and compliance, and supply chain. The architecture of smart farming recognizes the high chance of cyber attacks, which needs to be addressed. A smart farm which is a highly connected system and generates a huge amount of data. Since most of the devices used in smart farming are unattended therefore, they can be easily targeted by the attacker. If the attacker is able to compromise a device, then, through that infected device, attacks can spread through the whole network and infected all other devices. In the literature, several machine learning assisted Intrusion Detection Systems (IDS) [93,94] have been proposed to identify the infected device by analysing the network traffic. However, none of them have considered the smart farming specific solution. Therefore, smart farm-specific sophisticated access control and machine learning-based IDS development can be an effective solution in this regard.
- Big data in smart farming:
  A massive volume of data with a wide variety are captured, stored and analysed for decision-making in IoT and UAV based smart farming. Big data are used to provide predictive insights in farming operation by providing real-time operational decisions. The scope of Big Data applications in Smart Farming goes beyond primary production; rather, it influences the entire food supply chain. The major issues with data analysis are data quality, intelligent processing and analysis, sustainable integration of Big Data sources, etc. [95]. The openness of the platform is also very important since it can empower farmers in their position in supply chains.
- Weed detection and management:
  Weed control is an important aspect of horticultural crop management. Failure to

adequately control weeds leads to reduced yields and product quality. Use of chemical and cultural control strategies can lead to adverse environmental impacts when not managed carefully, and effective weed management strategies that minimise environmental risks through strategic application of control measures can be expensive to implement. Hence, low cost smart tools for identification and mapping of weeds at early growth stages will contribute to more effective, sustainable weed management approaches. Existing studies [26,96,97] have shown some approaches to detect weeds using UAV images; however, they only could achieve less than 90% of accuracy, hence more accurate weed detection approaches are desirable. The authors in [4] presented a shielded band sprayer to spray herbicides in weed, avoiding to spray on crops, hence increase the food quality and reduce the use of plant protection products. However, further research should be carried out, which may indicate the occurrence of statistical differences in the production yield between various weed control methods in crops. It is recommended to continue crop tests based on the band spraying method in terms of the effectiveness of weed control and to extend the scope of tests with the quantitative analysis of the used herbicides and their possible residues in crop yield.

- Multi/hyper-spectral imagery for disease and pest control:
  Multi spectral and Hyper-spectral image based remote sensing techniques have demonstrated high potentiality in detecting pests and diseases in crops. A multi-disciplinary approach—including plant pathology, engineering, data analytic and informatics—is required [98,99] to utilise the full potential of these highly dimensional, sophisticated and innovative technologies. Besides precision crop protection, plant phenotyping for fungicide screening and resistance breeding can be optimized by these innovative technologies.
- Automated watering control and management in remote areas:
  the right amount of water usages is important to maintain aesthetic requirements of parks and sport groups. Farms need to water based on the crop's need. Moreover, efficient water management needs to be implemented to reduce nutrient leaching in the stream by an excessive amount of water in the lower layer of the soil. Using live monitoring of moisture at various soil depths, watering based on Artificial Intelligent (AI), automating of watering and water management using IoT and UAV technology can address most of the above-mentioned objectives.

7. Conclusions

This paper explores different use cases of smart farming, the advantages and application of implementing IoT and UAVs in agriculture, the various communication technologies and identifies the issues and limitations of connectivity of IoT and UAVs in remote areas. We have outlined the connectivity limitations in terms of communication technology and transmission distance, and have discussed the special case of implementing IoT for smart farming in remote areas. We have also discussed how satellite communication can be used to offer connectivity of IoT and UAVs in rural parts of Australia. The paper provides an overview of applications of smart farming, as well as helps the researchers to identify the challenges and open research issues of smart farming, hence will be helpful in identifying the prospects and gaps of sustainable smart farming.

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