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Internet of Things Applications for Agriculture

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18.1 Introduction

The history of agriculture starts at least 22,000 years ago when mankind learned to collect wild grains as food. Various crops have been cultivated as earlier as 9500 BC in Levant according to archaeological discoveries (Hillman, 1996; Walsh, 2009). Over tens of thousands of years since then, significant innovations have been made from time to time to increase the agricultural yield and reduce the heavy human labor needed. However, the demand for more foods from the increasing population will never get satisfied. It is predicted that the world's population will reach 9.7 billion by 2050, which is about 33% more than today (un.org, 2015). Consequently, to keep pace with such population growth, the global production of food has to increase at least 70% to feed the world.

Meanwhile, only a small portion of earth's surface is available for agriculture uses, due to various limitations, including temperature, climate, topography, soil quality, and technologies. Agricultural land use is also shaped by political and economic factors, such as land tenure patterns, environmental regulations, and population density (learner.org, 2016). In fact, the total agricultural land used to produce food has been decreasing for the last few decades. In 2013, total agricultural land used to produce food was around 18.6 million square miles, which covers 37.73% of the world's land area. In comparison, in 1991, these numbers were 19.5 million and 39.47%. So, humanity is facing a daunting challenge of how to feed more people with less land, as shown in Figures 18.1 and 18.2 (WorldBank, 2016).

The answer to the critical issue lays in a new technology "precision agriculture" (PA) that will have a profound effect on the lives of billions of people. The precision agriculture techniques and technologies aim to improve

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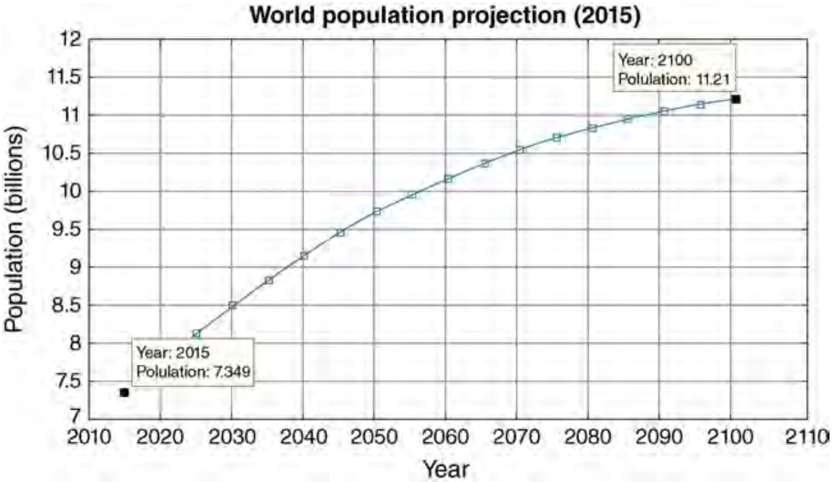

Figure 18.1 World population, 2015–2100.

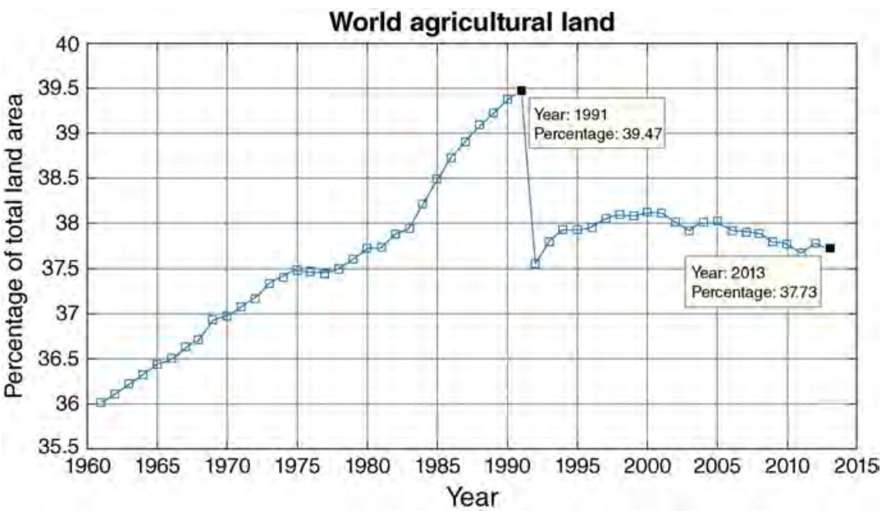

Figure 18.2 World agricultural land, 1961–2013.

the efficiency of agriculture to maximize food production, minimize environmental impact, and reduce cost. Basically, PA, or site-specific agriculture (SA), is integrated information and production-based farming system that can collect precise data on every site in the field and accordingly customize the cultivation of each site independently. In the traditional way, agricultural operations such as planting or harvesting are performed by following a predetermined schedule. However, the effectiveness of practice and schedule could be greatly improved with smarter decisions based on real-time data and predictive analytics on weather, soil quality, crop maturity, equipment, labor costs, and availability. The PA is a farming management system based on observing, measuring, and responding to agricultural variabilities in different aspects. In PA, the large fields are managed as a group of small fields and each small one will be treated precisely and independently with reduced misapplication of water, seed, and nutrients in order to increase crops and farm efficiency.

As an emerging paradigm, the IoT is considered to be *the next big thing* that can have a significant influence on the future of the world. By applying latest IoT technologies in agriculture practice, traditional ways of farming can be fundamentally changed on every aspect, to pave the way to a new agriculture pattern of PA. Briefly, the implementation of PA relies on three stages: (i) the real-time data acquisition, (ii) data analysis and decision-making, and (iii) corresponding precise treatments. All these three stages can be greatly facilitated with the advancing of the IoT technologies in recent years. First of all, IoT provides the fundamental network infrastructure through which enormous smart objects, spanning from microsensors to heavy agricultural vehicles can easily interconnect to each other and to the Internet. This enables the simplest solution of data collection, gathering, exchange, and transmission. Second, backboned by the Internet, IoT provides a revolutionary way in data processing and intelligent decision-making. Solutions for all kinds of services are available online offered by providers all over the world, from industry giants to start-up companies in remote countries. Most of these services, from satellite imaging and processing to chicken health and welfare monitoring, can be cloud based. By this way, they can process data to make an intelligent decision in real-time 24×7 automatically with no human intervention needed. Finally, agricultural treatment decisions and procedures generated from the cloud will be transferred back to the farm. Within the IoT environment, automated agricultural devices, machines, and vehicles will operate accordingly to cultivate crop and livestock in an optimal way (Burrus, 2016). Meanwhile, users can enjoy an unprecedented convenient way of Internet-based data and information access, visualization, and presentation.

Consequently, the seamless integration of IoT technologies into PA raises the agriculture to a new level that was unimaginable before, by which the whole agriculture industry will be reshaped with enormous profits. In general, within the scope of PA, IoT can improve or solve critical issues such as drought response, crop yield optimization, land management, and pest control.

This chapter introduces typical IoT applications in PA, including basic concepts, related technologies, system organization, and the implementation with available products.

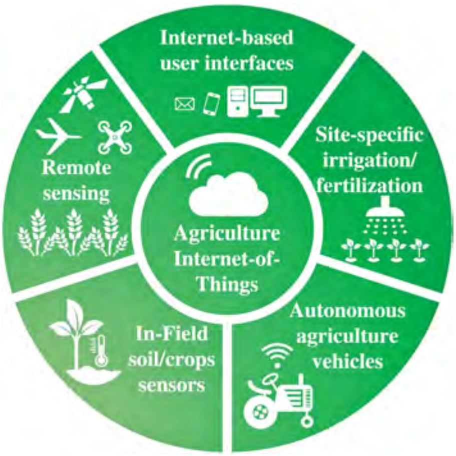

Figure 18.3 IoT-backboned PA.

18.2 Internet of Things-Based Precision Agriculture

Emerging IoT technologies can be integrated into PA in various aspects to improve the agriculture efficiency and productivity. As an overview, Figure 18.3 illustrates typical functions and features provided by this integration.

The IoT technologies can be classified into three categories: data collection, cloud-side data analysis and decision-making, and IoT-assisted agricultural operation.

18.2.1 Data Collection

The goal of PA data collection is to collect soil parameters and crop status/yield data on each site for guiding later operation such as planting, fertilizing, and irrigation. The data collection can be achieved majorly in two ways. The first is through multifunctional imaginary devices equipped with remote sensing platforms, including satellites, agriculture airplanes, balloons, and unmanned aerial vehicles (UAVs). The second is from various sensors installed in different sites across the farmland. Diversified sensors have been developed for the measurement of humidity, temperature, nitrate levels, and so on, to meet requirements of different PA schemes. All data must be tagged with the precise location information, which normally is generated from GPS devices, to support the site-specific treatment later on.

In the next step, all data will feed into a geographic information system (GIS) to generate a crop or soil index map. The GIS can process the data to visualize agricultural environments and status for managing cultivation. In PA scheme, GIS technologies can be used to examine farm conditions, measure and monitor the effects of farm management practices, including crop yield estimates, soil amendment analyses, and erosion identification/remediation. Furthermore, with the help from GIS, reduction in farm input costs such as fertilizer, fuel, seed, labor, and transportation can be achieved (esri.com, 2016).

18.2.2 Site-Specific Operation

Different to the ancient farmer, most agriculture works in modern large-scale agriculture have taken over by equipment such as tractors and harvesters. More specifically, within the scenario of PA, agriculture vehicles will be equipped with GPS and GIS systems, and can operate precisely, site-specifically, and autonomously in dealing with various tasks, including seeding, fertilizing, and harvesting. Another major operation necessity in agriculture is irrigation and the understanding of natural precipitation (e.g., satisfied or unsatisfied water needs of plants). In PA, the irrigation is precisely managed to cover the deficit between crops' optimal water needs and natural supplies on each site independently (CEMA, 2016).

18.2.3 IoT Application in PA

The IoT technologies can play key roles in the PA implementation. IoT provides not only the communication infrastructure to interconnect every smart object from sensor, vehicle, to user mobile device through the Internet, but also functions including local/remote data acquisition, in-cloud intelligent information analysis and decision-making, data access, visualization, user interfacing, and agriculture operation automation.

In general, IoT has two perspectives, to be either Internet centric or smart device centric (Gubbi et al., 2013). Within the PA scenario, the Internet-centric IoT systems have better functionality, flexibility, and extendibility. Systems in this category can take advantage of various Internet services and will have more powerful computing capability from the cloud side. A conceptual schematic architecture of such IoT system is shown in Figure 18.4.

As can be seen in Figure 18.4, the agriculture IoT model has three basic layers. The bottom is the data acquisition layer, in which environmental/crop data are collected through either sensors or remote sensing devices such as UAV then uploaded to the cloud storage through an Internet gateway.

The second layer is the cloud computing function layer (Hassan et al., 2012). Diversified cloud computing functions and services are integrated and provided in this layer. For any required function, there are always multiple solutions available from different providers. In the general process, at first, raw data will be filtered and processed by data analysis tools to abstract information. Then purified information will be converted to essential knowledge by data mining and machine learning tools. With the consideration of

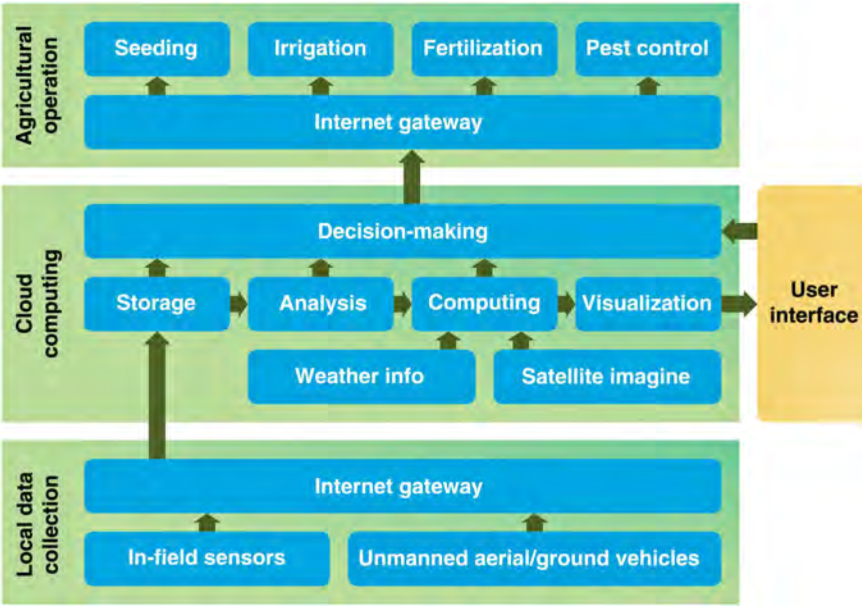

Figure 18.4 Agriculture IoT architecture.

specific factors, such as soil condition, fertilizing pattern, crop state, weather and environment situation and so forth, knowledge derived in the last step will be used for decision-making or the generation of field index maps for different purposes. Such maps will guide agriculture operations in the next stage. Meanwhile, this layer also provides data visualization and presentation services for user access.

Ultimately, the top layer is the control of all agricultural operations, including seeding, irrigation, fertilizing, and harvesting. Corresponding operations are implemented with agricultural devices, machines, vehicles, and irrigation system based on decisions or index maps generated on the cloud side during the last stage. Related control commands will be transmitted through the Internet gateway to agricultural systems. Assisted with GIS, these agriculture systems will treat each atomic plot precisely, by which optimal efficiency and productivity can be expected.

18.3 IoT Application in Agriculture Irrigation

Here are some facts about water. About 71% of the Earth's surface is covered with water, of which about 96.5% of all Earth's water is salt water held by oceans (USGS, 2016). Only the rest 3% is fresh water. Hence, over two thirds is frozen water possessed by glaciers and polar ice caps. Furthermore, most of the remaining unfrozen freshwater is underground, with only a small fraction (0.5%) staying above ground or in the air (GreenFacts, 2016). Shortly, humanity relies on this 0.5% for all of man's and ecosystem's fresh water needs. Furthermore, about 70% of all the accessible freshwater is consumed by agriculture. In comparison, industry consumes about 23% and dwarfing municipal consumes about 8%, which altogether count less than a half of agriculture (UN-Water, 2016).

The traditional ways of water consumption are facing severe challenges on both scarcity and environmental impacts. For example, water has become increasingly scarce in the western U.S. states during the last few decades. In the next 10 years, 40 over 50 states will experience water shortage at different levels (Sunding et al., 2016). And the situation will get worse with the growing demands from cities and industries. Meanwhile, enough fresh water must be kept in rivers and lakes to sustain ecosystems. Consequently, improving water use efficiency or enhancing agricultural water productivity is a critical response to growing water scarcity.

In general, the agricultural water productivity is defined as the ratio of the net benefits obtained from all agriculture sectors, including crop, livestock, fishery, forestry, and so on, to the amount of water consumed during the process that those benefits are produced (Sharma et al., 2015). The key to improving agricultural water productivity is to incorporate crop demand-dependent irrigation schedule that can save water without affecting crop yields. However, practically it is quite challenging to accurately estimate the water demand of crops, which involves many factors such as crop type, irrigation method, soil type, precipitation, crop needs, and soil moisture retention. In fact, even in the year of 2013, crops visual inspection were still playing the key role as a method for irrigation decision-making in nearly 80% of farms with irrigated land in the United States (USDA, 2016).

The current situation is expected to turn around in the next decade with the adoption of emerging IoT technologies. By adopting new IoT-based approaches such as crop water stress index (CWSI)-based irrigation management, the traditional crop watering scheme will be revolutionized to significantly improve the agricultural water productivity.

18.3.1 Crop Water Stress Index

Optimal irrigation relies on the precise measurement of crops' water demand. Since early 1970s, researchers have attempted to monitor crop's water demand by measuring crop's surface temperature. In recent years, this approach has attracted more and more attention, especially with the thriving of remote sensing technologies.

Shortly, crop's water demand of a specific site can be characterized as a CWSI. The CWSI value can be derived in different ways. One popular method to calculate CWSI is based on the following equation (USDA, 2016):

$$\mathrm{CWSI} = \frac{\mathrm{d}T - \mathrm{d}T_{\mathrm{l}}}{\mathrm{d}T_{\mathrm{u}} - \mathrm{d}T_{\mathrm{l}}} \tag{18.1}$$

In Equation 18.1, $\mathrm{d}T$ is the difference between the crop canopy and the air temperature measurements; $\mathrm{d}T_{\mathrm{u}}$ is the difference between the canopy upper limit and the air temperature (nontranspiring crop); and $\mathrm{d}T_{\mathrm{l}}$ is the difference between canopy lower limit and the air temperature (well-watered crop). A CWSI value of 0 indicates that the crops have no water stress, and the CWSI value of 1 represents that crops are suffering the maximum water stress. In conclusion, the crop–water stress signals the site-specific crops' need for irrigation. Moreover, in irrigation management in dealing with crops' water stress, many other factors should be considered, such as yield response to water stress, probable crop price, and water cost (USDA, 2016).

In CWSI-based irrigation management, the first step is to acquire crops' water demand of each site in the entire farmland, in which modern remote sensing technologies can contribute a lot. Then on each site irrigation outlets will be controlled independently based on the crops' water demand; by this way, optimal irrigation efficiency can be achieved.

Various methods have been developed (Idso et al., 1981; Idso, 1982; Maes and Steppe, 2012; Taghvaeian et al., 2012) to determine canopy limits $\mathrm{d}T_{\mathrm{l}}$ and $\mathrm{d}T_{\mathrm{u}}$ in Equation 18.1 in advance. Practically, periodical acquisition of crop canopy and air temperature measurements is needed to calculate the $\mathrm{d}T$ for CWSI derivation.

18.3.2 Data Acquisition

In deriving the value of $\mathrm{d}T$, normally the air temperature can be easily acquired, for example, by the use of a temperature sensor installed meters above ground (Taghvaeian et al., 2012). The difficulty stands on how to measure the crop canopy on each site through the entire farmland with the minimum cost, time delay, and labor needed with an acceptable precision. Different solutions have been developed for this purpose based on different platforms such as satellites, airborne platforms, ground station, and unmanned vehicle.

Thermal infrared imaging data can be acquired via the remote sensing of satellites, for example, the MODIS (Moderate Resolution Imaging Spectroradiometer) system on the Terra and Aqua satellites launched by NASA (NASA, 2016). There are many successful cases of CWSI irrigation management by the use of MODIS data (Xiaoning et al., 2007; Tingting et al., 2008).

Crop canopies may also be obtained by mounting a thermal camera on a balloon or in an aircraft (Jackson, 1982; Hatfield and Pinter, 1993; Jones et al., 2009). Satellite and other airborne platforms offer the highest efficiency on data acquisition. However, none of them are convenient for an individual farmer to access.

Another way to collect crop canopy values is through in-field ground stations. Commercialized devices are available on the market for this temperature measurement. For example, the infrared radiometer products can acquire high accuracy, noncontact surface temperature measurement (ApogeeInstruments, 2016). Coupled with other options, the installation cost is expensive and linear to the area of farmland and could be problematic for the operations of agricultural vehicles due to scattered ground stations. In contrast, the benefit of this approach is that the data collection is local, direct, and 24×7 in real time allowing continuous monitoring.

Technology advancing and cost reduction of unmanned vehicles (UV) especially in recent years have greatly stimulated their applications in many fields, including the agriculture. Equipped with a thermal camera, small-scale UAVs can provide inexpensive solutions for convenient crop canopy measurement (Pipia et al., 2012; Park et al., 2015). Comparing to all the other methods, UAV solution is low cost, user-friendly, flexible, and customizable, with no installation needed.

18.3.3 IoT Irrigation System

The system diagram of a typical IoT irrigation system is shown in Figure 18.5. The system deploys wireless sensor network (WSN) to connect all in-field sensors for crop canopy and air temperature measurements, and then feed all data to the network gateway. Among the many solutions available for this purpose, ZigBee is a popular technology that is easy to setup and configure (Baronti et al., 2007). Due to the low-data transmission bandwidth requirement in this application, the gateway can access the Internet wirelessly by the use of technologies, such as 4G LTE mobile communication network, with

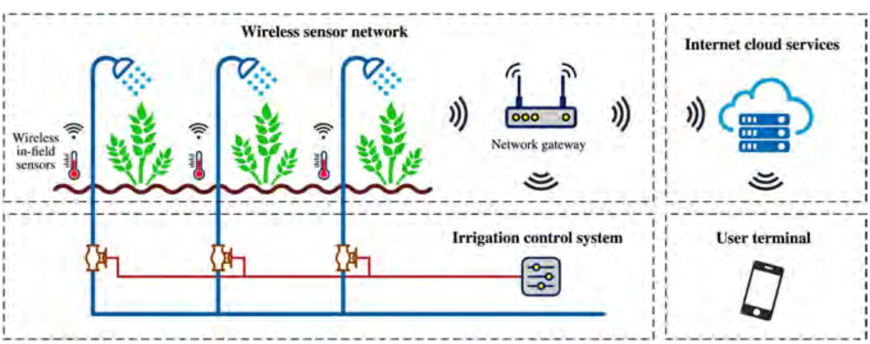

Figure 18.5 IoT irrigation system diagram.

comparatively low cost. The data transmitted over mobile network will be received by subscribed web services on the cloud. Corresponding intelligent software applications will analyze data from farmland, with the consideration of information from other sources, such as weather service and satellite imaging, to apply CWSI models for water need assessment, and finally, produce irrigation index value for each site. These results will be transmitted back to the network gateway, and then forwarded to a controller to manage irrigation. In addition, farmers can access all data and results, and make adjustments with terminals such as smart phones through specifically developed web applications (Zhang, 2011; Guo and Zhong, 2015; Harun et al., 2015; Khelifa et al., 2015).

18.4 IoT Application in Agriculture Fertilization

Thousands of years ago, ancient Egyptians, Romans, and Babylonians have learned to use fertilizers, such as minerals and manure, to enhance the productivity of farms. In general, fertilizer refers to natural or synthetic materials that can supply essential nutrients for plants to grow. The three main macronutrients required by plants are nitrogen (N) for leaf growth; phosphorus (P) for root, flowers, seeds, and fruit development; and potassium (K) for stem growth, water movement, and promotion of flowering and fruiting (Kiiski et al., 2009).

Plants need nutrients from fertilizers to maintain the healthy life. However, applying nutrients improperly can be detrimental or even lead to the death of plants. More important, excess fertilizer is harmful to the environment by depleting the soil quality, poisoning ground water, and even contributing to the climate changes across the globe (Environment.co.za, 2015).

The key to minimizing the negative effects of agricultural fertilizing to the environment stands on precisely applying the required dose of crops, which is known as PA fertilization. The implementation of PA fertilization requires site-specific soil nutrient level measurement. However, practically, the PA fertilization is far more complicated than precise irrigation schemes introduced in previous sections, since the determination of the amount of fertilizer needed for soil patches is a very complicated problem. The fertilizer amount needed relates to various factors, including crop type, soil type and capability of soil absorption, product yield, fertility type, fertilizer utilization rate, weather condition, climate, and agricultural technological factors. The soil nutrient level measurement is expensive, inconvenient, and time consuming, normally involves the sampling and investigation of soil samples at each location.

The advancing of technologies in remote sensing has tremendously strengthened the capability in data collection. With that support, new IoT approaches have been developed for estimating spatial patterns of fertilizing requirements with acceptable accuracy and minimum labor work required. The Normalized Difference Vegetation Index (NDVI) is a powerful method for crop nutrient status monitoring using aerial/satellite photographic images. In brief, NDVI value represents the reflection of visible and near-infrared light from vegetation. NDVI can be used for relative estimation of crops health, vegetation vigor, and density, and can also contribute to the soil nutrient level assessment (Rouse et al., 1974; Rahman et al., 1994; Schumann, 2006).

NDVI can be calculated from individual measurements according to the following equation:

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{VIS}}{\mathrm{NIR} + \mathrm{VIS}} \tag{18.2}$$

In Equation 18.2, VIS and NIR represent the measurement of spectral reflectance acquired in the visible and near-infrared regions, respectively. NDVI value is in the range of $(-1, +1)$ (Weier and Herring, 2011).

The basic procedure of PA fertilization is similar to that shown in Figure 18.5. The first step is to acquire NDVI value by the use of satellite, airborne platforms, or IoT ground stations for generating the site-specific fertilization index map. Then, the application of fertilizers is implemented by automated agriculture machines and vehicles according to the index map. Shortly, such precise fertilization can significantly improve the application efficiency of fertilizers and reduce the side effects to the environment, which has been proved by many successful cases reported (Van Alphen and Stoorvogel, 2000; Tianhong et al., 2003; Schumann, 2006).

There are quite a few new enabling technologies contributing to the IoT-based PA fertilization (CEMA, 2016):

- *High Accuracy Global Positioning System (GPS).* Currently, there are four different satellite-based global positioning systems: GPS (US), GLONASS (Russian), Galileo (EU), and BeiDou (China). Until now, the accuracy of GPS signal is 4 m root mean square (rms) (7.8 m at a 95% confidence level) (DoD, 2001). This is far from meeting the requirements of PA fertilization. The high-precision GPS is a key technology needed for agriculture vehicle to obtain its position in the field based on geographic coordinates (latitude and longitude). Real Time Kinematic (RTK) is a new technique developed in recent years that can significantly improve the GPS precision. Its measurements rely not only on the signal content but also on the phase of the carrier wave of the signal. Moreover, RTK technology uses the signal from reference station or interpolated virtual station for real-time coordinate corrections, to reach up to centimeter-level accuracy (Keller et al., 2001). Currently, there are various RTK GPS products available (Topcon, 2016), with price ranges from a few hundred to tens of thousand dollars.
- *Autonomous Driving System.* The autonomous driving systems for agriculture vehicles are much simpler than those on the road, since its working space is clear and known. Autonomously driving agriculture vehicles can design path,

autosteer, make turns, and follow edges and rows to cover the entire field while applying fertilizers and other matters.

- *Geo Mapping.* Geo mapping tools are required to produce site-specific index maps for input/output data, including soil type, nutrients levels, irrigation, and fertilization (understanding layers for PA data analysis and operation guidance of agriculture vehicles).
- *IoT Communication Infrastructure.* IoT-based communication mechanism is needed to interconnect every object and the commander in the cloud for real-time operation.
- *Variable Rate Technology (VRT).* It denotes the technology that enables the variable rate application of materials, which is required for most PA equipment operations. Simply, VRT is a variable rate (VR) control system on application equipment that can precisely control time and/or location rates of different matters to achieve site-specific application. Through this way, for instance, seed or fertilizer can be applied according to the index map to meet exact variations in crop growth, or soil nutrient needs (CEMA, 2016).

In addition, most water-soluble matters, including fertilizers, soil amendments, and pesticides, can be applied by injecting into irrigation system. This technology is denoted as fertigation (chemigation), which has been widely applied for several years (Threadgill, 1991). Fertigation is recognized as the best management practice to improve effectiveness of various agriculture matters (Wright et al., 2002). Obviously, fertigation system can be seamlessly integrated into the IoT-based PA infrastructure as introduced.

18.5 IoT Application in Crop Disease and Pest Management

Plant diseases and pest have caused severe losses to humans from the birth of agriculture. In history, a crop disease known as "potato blight" had resulted in a significant potato yield reduction in Ireland around 1850, and it led to a famine well known as the "Great Hunger," in which around one million Irish people died (O'Neill, 2010). Even nowadays, every year corn growers in the United States are still experiencing the economic loss of up to one billion dollars due to the crop disease "southern corn leaf blight" (Maloy, 2005). Roughly, direct yield losses caused by animal pests and pathogens are responsible for losses ranging between 16 and 18% of global agricultural productivity (Oerke, 2006; Savary et al., 2012).

The rapid advancement of IoT provides a solid foundation for the development of effective approaches in dealing with crop disease and pest (Iotworm.com, 2016). Compared to the traditional disease/pest control that is calendar or prescription based, the IoT-based modern disease/pest management allows for disease forecasting, modeling, or real-time monitoring, and hence to be more proactive (Maloy, 2005).

The reliability of a crop disease and pest management system depends on three aspects: sensing, evaluation, and treatment (supported by IoT technologies). In an IoT disease/pest management system, the first stage is to collect real-time crop physiopathology-related data. The main approach for disease/pest recognition is image processing, in which raw image can be acquired through either in-field sensors or remote sensing devices on satellite/aircraft (Blakeman, 1990). In general, remote sensing imagery has higher efficiency and less cost, yet higher threshold as well. Meanwhile, in-field sensors can offer more functions in collecting data, information, and even samples of the environment, plant health, and pest situation anytime in every corner. For example, IoT automated traps (Semios, 2016; Spensa, 2016) can capture, count, and characterize insects and upload data to the Cloud for later analysis, which is beyond the capability of remote sensing.

On the second stage, all data collected remotely or locally will be forwarded to the management center sitting in the IoT cloud. The managing center is a combination of sophisticated models and algorithms to process and analyze the raw image and data to provide a batch of related functions such as disease/pest identification, pest behavior prediction, and expert system. Models and algorithms have been developed for dealing with different diseases/pests of different crops. The whole system keeps monitoring the field 24×7, to automatically provide early warning, disease/pest problem report, and even suitable intervention suggestion on an hourly base. This information can be presented to the farmer by the managing center wirelessly in various ways such as text messages or emails to ensure that he/she is notified at the first moment.

The last step of crop disease/pest management is the precise application of corresponding matters required. In disease treatment and pesticide application, similar approaches in PA fertilization can be used, such as autonomous vehicle precise spray or automatic VRT chemigation. Moreover, the advancing of robotic technology provides another solution. Equipped with multispectral sensing devices and precision-spraying effector, an agricultural robot is capable of locating and dealing with crop problems under the manipulation of remote IoT disease/pest management system (Oberti et al., 2016).

18.6 IoT Application in Precision Livestock Farming

A new production pattern denoted as precision livestock farming (PLF) has been practiced in animal husbandry for years, to revolutionize the traditional labor intensive process of animal production (Corkery et al., 2013). Relies on real-time data collection and analyses, PLF offers fully automatic animal health and welfare monitoring and product yields improvement with less environmental impacts. All functions PLF require can find a perfect match in the emerging IoT paradigm that offers various functions, including animal and environmental sensing, in-cloud data analysis and decision-making, and equipment automation. The embedding of IoT into PLF enables optimal animal feeding and nutrient utilization by which higher production efficiency, environmental protection, and high-quality products can be achieved. Related innovative applications such as *smart chicken farm*, *smart cow farm,* and *IoT aquaculture* have been developed all over the globe.

18.6.1 Smart Chicken Farm

Chickens have been domesticated for both eggs and meat for thousands of years (Clauer, 2016). In the twenty-first century, poultry production industries are involved in highly advanced technology (e.g., sophisticated rearing operations). Actually, modern poultry facilities are biological reactor vessels in which numerous inputs, including feeding materials, water, ventilation air, heat, and lighting, will be converted to the output of either meat or eggs (McNulty and Grace, 2009).

In general, the success of a modern poultry production system relies on the knowledge of nutritional requirements, the capability to match these requirements by tuning inputs in real time, and stable the comfort of environmental conditions such as air, temperature, humidity, and lighting. By taking advantages of versatile capabilities offered by IoT technologies, *smart chicken farms* can manage these key factors effectively and efficiently (Corkery et al., 2013).

In daily operation of a poultry facility, first IoT sensors collect live chickens' data through modern methods such as multispectral imagery using internal environmental information that includes air, temperature, humidity, and light. Then, the in-cloud central control system processes collected data to monitor and evaluate chickens' real-time condition, such as distress level, thermal comfort, live weight, behavior, avian influenza evaluation, and so forth. Next, the intelligent algorithms are applied in optimal decision-making to operate automated equipment accordingly in the farm, including mechanized feeding systems, internal environment controllers, mechanical handling and disposal of poultry waste, automation of lighting systems, crate washing and sanitization, and mechanical egg collection and quality control systems (McNulty and Grace, 2009). Comparing with the traditional operation, IoT-based smart farms have much lower cost and higher reliability and extendibility in sensing, better flexibility, updatability and intelligence in data analysis and decision-making, higher capability in machine operation automation, and unprecedented convenience to the user in live/history data access and system remote control. Overall, these advantages will lead to improvements in chicken health and welfare, product quality assurance, and reduction of labor involvement, operation cost, and running risk. Currently, commercialized IoT solutions have been well developed for farmers to build *smart chicken farms* (Iotreecloud, 2016).

18.6.2 Smart Cow Farm

Another application of IoT technology in livestock farming is in cow farm. With IoT sensors attached to cows, farmers can easily locate cows in the field through smartphone or tablet app, and also check more important animal welfare issues such as rumination levels and lameness (Miles, 2016). More and more farmers are adopting IoT technologies to convert their animals into the so-called *Internet of Cows*, *Connected Cows*, or *Smart Cows*.

In general, the IoT paradigm can help livestock farming or ranching to improve the productivity of water, energy, food, and other resources use, while maintaining the well-being of animals. It also helps farmers to make lists, prepare reports, sort cows by category, and track each animal's overall lifetime.

Difficult problems that have been bothering farmers for centuries now found their solutions in IoT scope; for instance, the identification of cow estrus which is critical to milk yields. Normally, a farmer needs to spend 20–30 min each time, four to five times a day in the stables to check if a cow is in heat, which is a sign of estrus. However, over 60% of estrus cases happen at night when the farmer is asleep (Anderson, 2016). Another example is the cattle lameness that has a large impact on a cow's performance in terms of yield, fertility, and longevity (Van Metre et al., 2005).

With the advancing of IoT technologies, these kinds of issues now find their solutions (Ilapakurti and Vuppalapati, 2015; SCR, 2016). Miniaturized IoT sensor tags can be attached to ear, neck, or leg of cows to monitor activity and well-being of each of them, 24 h every day (Miles, 2016). Then sophisticated analytical/empirical models will be applied to analyze the data to identify if a cow has gone into an estrus state. As the direct results, the detection rate of IoT solution can reach up to 95% (Fujitsu, 2016), whereas the detection rate of traditional method is around 55%. In addition, aiming to dynamic lameness detection, fully integrated IoT health monitoring platforms are also developed with available products on the market (Adityan, 2015).

Mostly, in *smart cow farm*, diversified data will be collected from both on-animal sensors and other in-premise sensors. The in-cloud intelligent management system will process data to monitor animal status, control all automated equipment and devices, and provide professional suggestions for user decision-making. With the continuing miniaturization, cost decreasing, and measuring capability increasing of diversified sensors, more and better IoT solutions will be developed to benefit cow farmers further.

18.6.3 IoT Aquaculture

The IoT technology is also reshaping the aquaculture by offering new functions and integrating them into an intelligent autonomous system. Large-scale distributed wireless sensor network comprised of diversified sensors are equipped to collect all kinds of data, including fish behavior, water quality, and equipment status. In a higher level in the IoT system, optimization models and intelligent algorithms are deployed to deal with different jobs, including the following (Zhang et al., 2013; Chen et al., 2015; ShaoHua, 2015):

- Aquaculture water quality monitoring and maintenance
- Fish status monitoring and precise feeding
- Fish behavior analysis, early warning, and disease diagnosis, control, and prevention
- Facility management and fault diagnosis
- Automatic equipment operation
- Information management, storage, visualization, and user access
- Logistics and fishery products quality traceability

The IoT can also help to the better understanding of how industrial fishing impacts important species in the blue water. Advanced aquatic sensor tags have been developed by adopting the latest IoT technologies in RFID Tag and pop-up satellite archival tag (PSAT). These sensor tags can be used to collect data regarding depth, temperature, and moving speed (microwavetelemetry.com, 2016). A sensor tag will be attached to an aquatic animal and held for days, weeks, or months, then released automatically by itself at the end of the measurement period. Then it will float (pop up) to the water's surface and transmit stored data to researchers through the satellite link. Collected data can reveal many facts, including how the fishing operation will change the life of marine animals. The PSAT has been deployed in various marine research projects all around the world (Musyl et al., 2011). Primarily, IoT technologies are penetrating many aspects of livestock farming. Successful applications are reported that span from *Internet of Pigs* (farmingfuture.org, 2016), *Internet of Goats* (Huawei, 2016) to *Smart Oyster Farm* (Microsoft, 2016).

18.7 Conclusion

Agriculture is the basis of human society. Moreover, as Masanobu Fukuoka said, "The ultimate goal of agriculture is not just growing crops, but the cultivation and perfection of human beings" (Fukuoka, 2009). Fortunately, advancing of technologies, especially the combination of the Internet of things and precise agriculture, is paving the road for reaching the goal. Human now is on the cusp of the second green revolution, which is largely built on the IoT and related technologies. IoT-based PA promises to make the farm of the future more productive and efficient with less labor work needed. It is grounded on the use of data to form more efficient and effective farming practices and drive associated environmental and social benefits. The chapter has presented many related technologies developed to serve this purpose, for example, CWSI, NDVI, RTK approaches and advanced sensors. These technologies and associated applications enable farmers to treat crops and animals more precisely. Future implications of data collected through these technologies also allow farmers to make more strategic and effective decisions to increase productivity with fewer environmental impacts. In conclusion, IoT technologies will take center stage on the farm of the future (Sarni et al., 2016). It is predicted that 75 million IoT devices will be used for agricultural purposes by 2020, and the smart agriculture market is expected to reach $18.45 billion in 2022 (Mittal, 2016).

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