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Internet of Things in Agricultural Innovation and Security

Abdul Salam
Purdue University, salama@purdue.edu

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Chapter 3
Internet of Things in Agricultural Innovation and Security

Abstract The agricultural Internet of Things (Ag-IoT) paradigm has tremendous potential in transparent integration of underground soil sensing, farm machinery, and sensor-guided irrigation systems with the complex social network of growers, agronomists, crop consultants, and advisors. The aim of the IoT in agricultural innovation and security chapter is to present agricultural IoT research and paradigm to promote sustainable production of safe, healthy, and profitable crop and animal agricultural products. This chapter covers the IoT platform to test optimized management strategies, engage farmer and industry groups, and investigate new and traditional technology drivers that will enhance resilience of the farmers to the socio-environmental changes. A review of state-of-the-art communication architectures and underlying sensing technologies and communication mechanisms is presented with coverage of recent advances in the theory and applications of wireless underground communications. Major challenges in Ag-IoT design and implementation are also discussed.

3.1 Introduction

One of the biggest sustainability challenges of the twenty-first century is to ensure proper food and water to the growing population of the world [140, 182]. Management of these resources is vital in our response to these challenges. The climate change has negatively impacted the agricultural production in last four decades [6, 12, 35, 87, 110, 127, 127]. Various factors such as stresses related to crops, droughts, weeds, crop diseases have caused decline in crop production and yields [45, 67, 85, 93, 119, 129]. Particular, the geographic areas and crops that depend on rain and precipitation are impacted the most due to losses in soil and water related resources caused by extreme weather patterns [121, 132]. These weather patterns are making it hard to adapt to the climate changes in agriculture and stress on critical threshold is already at maximum [86, 122, 206].

The rapid adoption rate in agriculture will be able to keep pace with climate related changes [44, 102, 172, 205]. The innovations in the field of decision agriculture (also called digit, smart, and precision agriculture) are needed to ensure global sustainable agriculture and food security [113, 164] through higher crop yields and resource conservation [39, 72, 92]. In the decades to come, sensing and wireless communication in the precision agriculture will play an important role to measure soil moisture accurately over larger landscapes [13, 202]. The accurate soil water content measurements are vital to improve crop yield, better water and irrigation management hence providing food security to our society [4]. Plant productivity also heavily depends on the soil moisture. From the field level to networked landscapes of farms to regional level, there is need to scale point based measurements to remote sensing measurement [161]. Moreover, the lack of interconnection in these measurement paradigms creates errors in models which propagate all the way up to hydrology, vegetation, soil surface, soil saturation, and runoff models [132] and creates challenges for accurate prediction and sustainability over a scale.

3.1.1 Decision Agriculture

The precision agriculture as defined by International Society of Precision Agriculture (ISPA) is [81]:

> a management strategy that gathers, processes, and analyzes temporal, spatial, and individual data and combines it with other information to support management decisions according to estimated variability for improved resource use efficiency, productivity, quality, profitability, and sustainability of agricultural production [81].

Recently, for sustainable agricultural practices, the field of precision agriculture has witnessed a lot of development in the areas of technology and concept [8, 25, 42, 64, 107, 142–151, 154–158, 161, 192]. It is beneficial in terms of reduced cost production with high outputs. It is driving in innovations in different agricultural areas such as farm equipment and machinery, crop, plant, and soil sensing, seeding, and harvesting. These technologies in decision agriculture are being used to make informed decisions for sustainable agriculture in real time that helps to reduce input and resource conservation through applications of variable-rate techniques in the field such as variable-rate irrigation. Moreover, the pesticides, fertilizer, and nutrients inputs can be tailored accordingly based on the field conditions. Accordingly, the accurate applications are done for critical areas which leads to economic benefits (e.g., improved crop yields with low cost). Through sensor-guided decisions, the costs reduce at different stages of the crop growth such as types and density of seeds, inter-plant spacing, and planting depth, rates and schedule of fertilizer, pesticide applications, and customized harvesting. The important

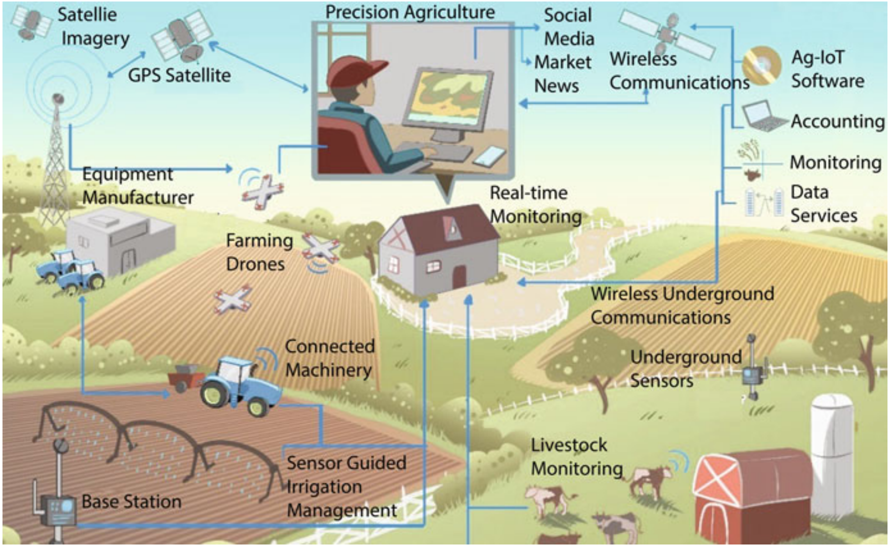

Fig. 3.1 An overview of the precision agriculture technologies

precision agriculture technologies are in situ and remote sensing, geo-location, soil mapping, and variable rate technologies. (see Fig. 3.1). The custom application of seeding, fertilizer, herbicides, chemicals, and pesticides technologies are manual control GPS guidance system, automatic control GPS guidance system [50], automatic control of nozzle and sprayer boom [208], sprayer turn compensation [111], and variable-rate prescription maps [141]. Currently, precision agronomist services available to farmers are soil sampling and field mapping. Soil sampling is done using whole field approach based traditional methods, grid patterns, and through management zones. The management zones for soil sampling are determined by electrical conductivity, and soil mapping unit. The yield dependent field mapping is done using GIS and soil EC, pH sensing, chlorophyll sensors for N, and profit/cost analysis.

3.1.2 Main Barriers to Digital Agriculture Technologies Adoption

There are many barriers to adoptions and expansion of digital agriculture technologies. The precision agriculture technology adoption in maize production is shown in Fig. 3.2. First major issue in adoption is return on investment. Still the cost of digital agriculture equipment and services is higher than the benefits. This also affects the motivation levels of the farmers because there is more emphasis on increasing farm income as compared to adoption of the technology digital agriculture technology

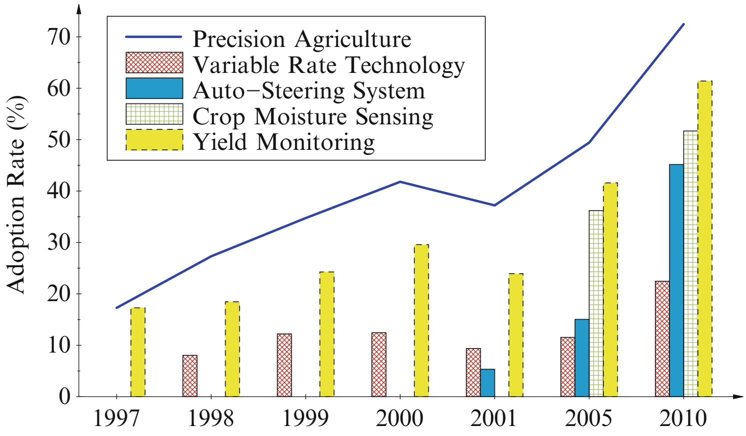

Fig. 3.2 Precision agriculture technology adoption in maize production [202]

business is mostly targeted to the big farms and smaller farm owners are left behind. Moreover, the use of digital agriculture technology in diverse topographic and soil texture fields is milted. Due to enormous data being generated from the farm and lack of decision tools, interception and decision making are very time consuming for the farmers. Farmers trust more the educated guess based on experience rather than having confidence in the recommendations made based on the sensing (in situ and remote), yield maps, and soil maps. Because of these barriers the digital agriculture business is not profitable. The cost and availability of specialists for complex equipment, lack of manufacturer support, difficulty in putting up encompassing high value, precision portfolios are the limiting factors for precision business.

3.2 Internet of Things for Sustainable Agriculture

Internet of Underground Things (IOUT) has numerous applications in the field of digital agriculture [8, 25, 42, 64, 107, 142–151, 154–158, 161, 190, 192]. It is a paradigm in which technology is being used to effectively manage agriculture by understanding the temporal and spatial changes in soil, crop, production, and management through innovative techniques. A multitude of wireless devices is employed for sensing and communications on the field [202] in smart farming. With the development of novel soil sensing methods, adaptive input application (e.g., fertilizer and lime), and soil mapping techniques, there is a higher demand for increased data rates and long-range underground communications. Another important application is in the area of border monitoring, where this technology is being employed for border enforcement and to curtail infiltration [9, 181]. Moreover, IOUT is also being utilized for landslide and pipeline monitoring [64, 179, 180].

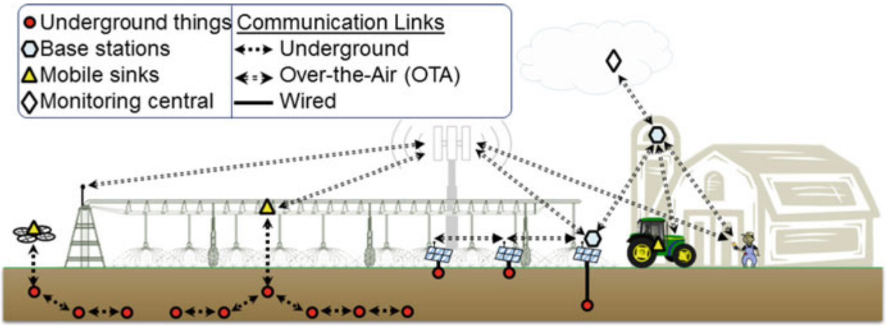

Fig. 3.3 IOUT paradigm in precision agriculture [202]

The IOUT delivers consistent access to data garnered from the farming areas via underground networking, aboveground networks, and the Internet. IOUT Paradigm in precision agriculture is shown in Fig. 3.3. IOUT incorporates in situ underground sensing [4] of soil physical, chemical, and biological factors which includes water content sensing, salinity sensing, pH and nitrogen sensing, and temperature sensing. It also has the communication capabilities built-in as one of the integral components to provide the sensing data from the plants, roots, and the soil. Moreover, it has the ability to include the environmental sensing capability to provide the real-time data pertaining to the diverse environmental phenomena such as wind data, rain information, and solar potential [203]. When integrated with agricultural machinery and farm equipment on the field (e.g., seeding equipment, irrigation controllers, harvesting machines and combines), the IOUT leads to the full self-sufficiency on the smart farming fields, and has the strong potential of development of enhanced food production solutions and applications in the area of digital agriculture [202]. The IOUT is also being utilized to provide useful decision making information to the growers in the field in real time.

The sustainable agricultural-IoT in the subsurface environment has the potential to transform soil and natural resources management systems. The improved knowledge gained through development of this underground sensing system will contribute to the development of better management techniques in the field of digital agriculture. Effective and reliable soil moisture sensing and irrigation management techniques will lead to advances in underground sensing and communication technology. To build technology-aware, advanced digital agriculture practices, this innovation and automation in underground sensing and secure communications, data collection, analysis, and visualization will play a vital role. Based on the IoT systems, sensors for soil and water quality across networked landscapes can be developed. Moreover, it will also facilitate integration of advances in digital agriculture data analytics, in situ and remote sensing into working systems, indigenous and local information.

The development and application of novel sensing and communication techniques for water resource conservation and enhancement of the crop yield is a major area in need of technology innovations. A large-scale field Ag-IoT built using these wired and wireless technologies and sensing solutions will also aid in advancing the fields of subsurface radio wave propagation, underground communications and networking, and digital agriculture data analytics. It enables novel way of studying soil properties will facilitate efficient resource usage (e.g., improved water conservation, improved crop yield) leading to health and sustainable communities. Creation of networked collection of existing soil type and moisture related databases will improve access to large-scale consolidated data for decision making.

3.3 Wireless Underground Communications

An accurate analysis of wireless underground channel model is vital for any efficient wireless subsurface communications system design. The prospect of completely underground sensing and communications network, without any footprint on the soil surface and support from nodes mounted on aboveground infrastructure, has therefore fueled interest in underground channel propagation measurements. Since many of the smart farming future applications will need high data rate and long-range connectivity between underground and aboveground nodes, a lack of detailed measurements is affecting the design of next generation soil sensing systems [150, 156, 161].

Not only the subsurface path loss as compared to over-the-air (OTA) is higher in the wireless underground channel [41, 144, 152], but also the underground antenna design is highly sensitive to many soil factors such as soil texture, bulk density, soil moisture, depth, and the air-soil interface [157]. Furthermore, at lower frequencies in the underground channel, the time domain channel characteristics such as root mean square (RMS) delay spread and coherence bandwidth of the wireless underground channel are of the utmost importance. Because the underground communication system design is highly dependent on these characteristics to overcome higher path loss due to complex permittivity of the soil and also to achieve higher data rate underground communications [144, 153].

The development of a wireless underground channel path loss model that accounts for the soil type and moisture impact is important because of many factors such as the operation frequency, communications protocol, modulation scheme, network layout, connectivity, and other important operational parameters can be ascertained based on the model. Moreover, to evaluate IOUT solutions, a reliable UG channel model is required. Existing over-the-air (OTA) channel models cannot be used in subsurface communications because of the high path loss that is caused by complex permittivity of the soil in the lossy propagation medium. Moreover, spatial and temporal changes in the soil permittivity also lead to path loss variations, a phenomenon not observed in OTA communications.

Impact of soil moisture variations on permittivity and wavenumber in soil is analyzed in this section. The β_s and β_0 are the phase constants in soil and air, respectively. The λ_s and λ_0 are wavelengths in soil and air. Effects of the change in β_s/β_0 and λ_s/λ_0, parameters with change in soil moisture in silt loam, sandy,

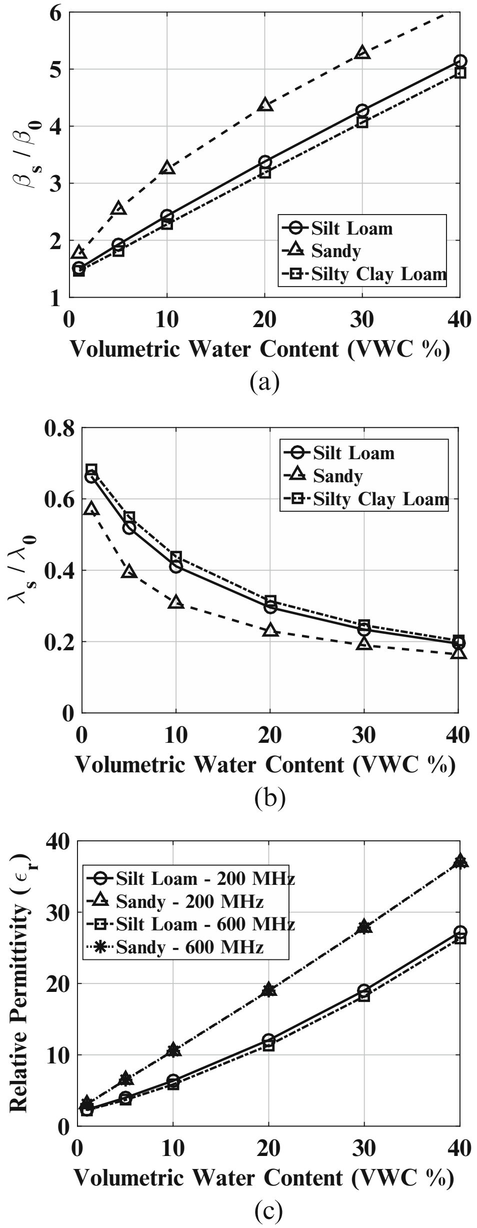

Fig. 3.4 (**a**) Change in β_s/β_0, (**b**) λ_s/λ_0, parameters with change in soil moisture in silt loam, sandy, and silty clay loam soil types, (**c**) Relative permittivity of silt loam and sandy soil with change is soil moisture at 200 and 600 MHz frequency

and silty clay loam soil types, obtained from complex wavenumber $k_s = \beta_s + i\alpha_s$, are shown in Fig. 3.4 (where α_s is the attenuation constant in soil). From Fig. 3.4, it can be observed that β_s/β_0 increases with increase in soil moisture. At 40 % soil moisture level, in silt loam, and silty clay loam soil, phase shift is 5 times higher as compared to the free space β_0. This effect is more significant in the sandy soil.

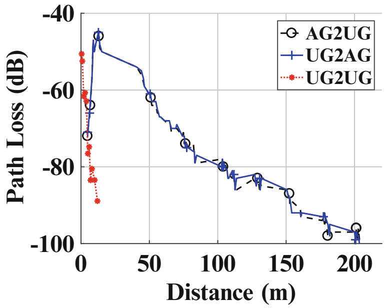

Fig. 3.5 The path loss of different wireless channels in underground communications [202]

Effects of change in wavelength, λ_s/λ_0, as compared to OTA wavelength are shown in Fig. 3.4b. Frequency shift as compared to the OTA is less for lower soil moisture levels, and it increases with increase in soil moisture level. It can be observed that at higher soil moisture levels, due to higher permittivity of the soil, the difference in frequency shift between different soils is also low. In Fig. 3.4c, relative permittivity of silt loam and sandy soil with change in soil moisture at 200 and 600 MHz is shown. It can be seen that change in soil moisture affects the relative permittivity of the soil. Sandy soil has larger effect due to the change of soil moisture as compared to silt loam soil. It can be also observed that sandy soil permittivity does not change with frequency. This is caused by two different physical phenomenon, namely dielectric and conduction losses. Soil moisture variations happens due to dielectric losses in soil as a result of relaxation process of water particles held in the soil medium [40].

There are three different paths that contribute to propagation in wireless underground communications. Through-the-soil paths are direct and reflected. For both components, the wave path remains completely in the soil. The third wave, lateral component, moves along the air-soil interface above the soil surface. The path loss of different wireless channels in underground communications is shown in Fig. 3.5. An in-depth discussion of these components of UG channel is presented in [41, 159].

3.4 Underground Antennas and Beamforming

In [145], an empirical investigation of propagation path loss variations with frequency in sandy and silty clay loam soils has been done using planar and dipole antennas. The path loss experiments are conducted using vector network analyzer (VNA) in sandy soil testbed, and greenhouse outdoor silty clay loam testbed for different operation frequencies and communication distances. The results show that the planar antenna can be used for subsurface communications in a wide range of operation frequencies. The comparison paves the way for development of sensor-guided irrigation system in the field of digital agriculture. Moreover, a model has been developed to predict the resonant frequency of the underground dipole antenna at different soil moisture levels and depths [157]. The textural triangles containing resonant frequencies for all soil types are shown in Fig. 3.6.

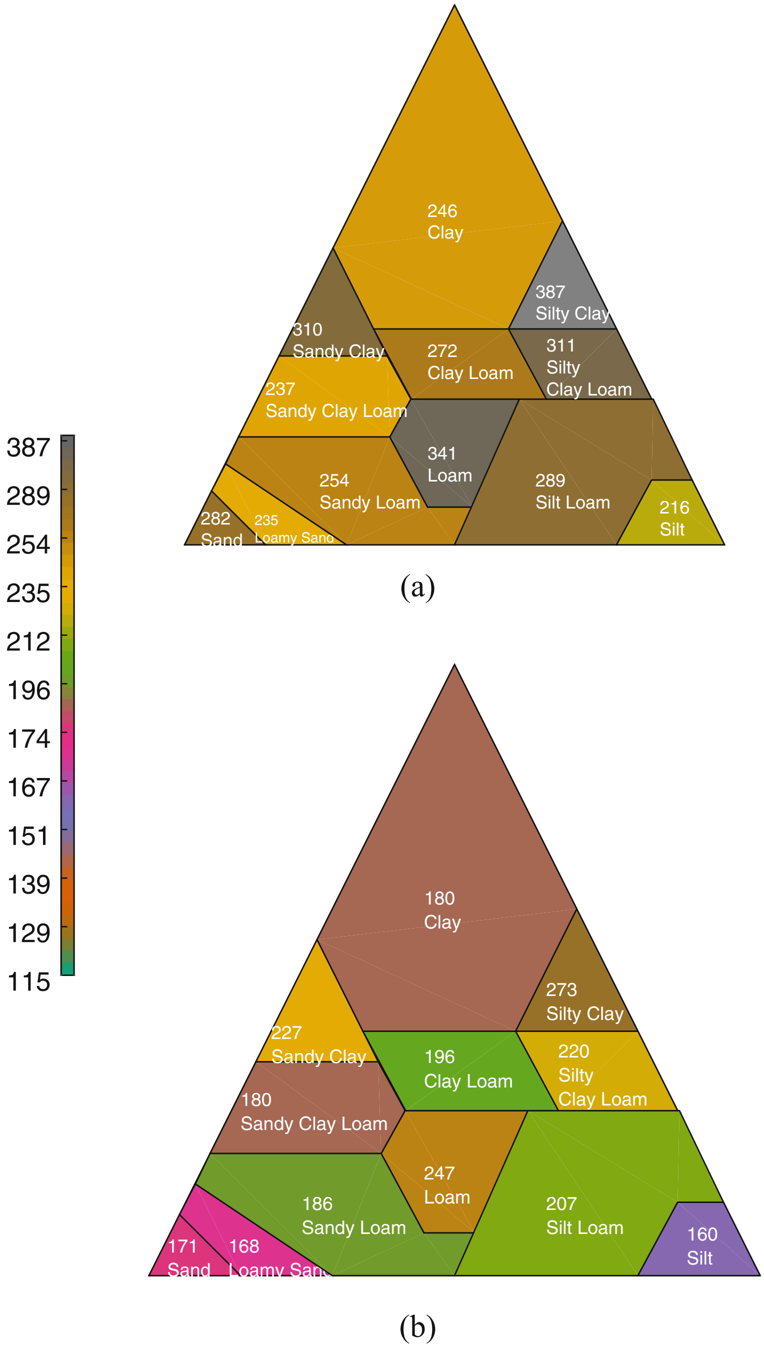

Fig. 3.6 Resonant frequency (MHz) of different soils in textural triangle at different soil moisture levels for a 433 MHz OTA antenna [157]. (**a**) 10% VWC. (**b**) 20% VWC. (**c**) 30% VWC. (**d**) 40% VWC

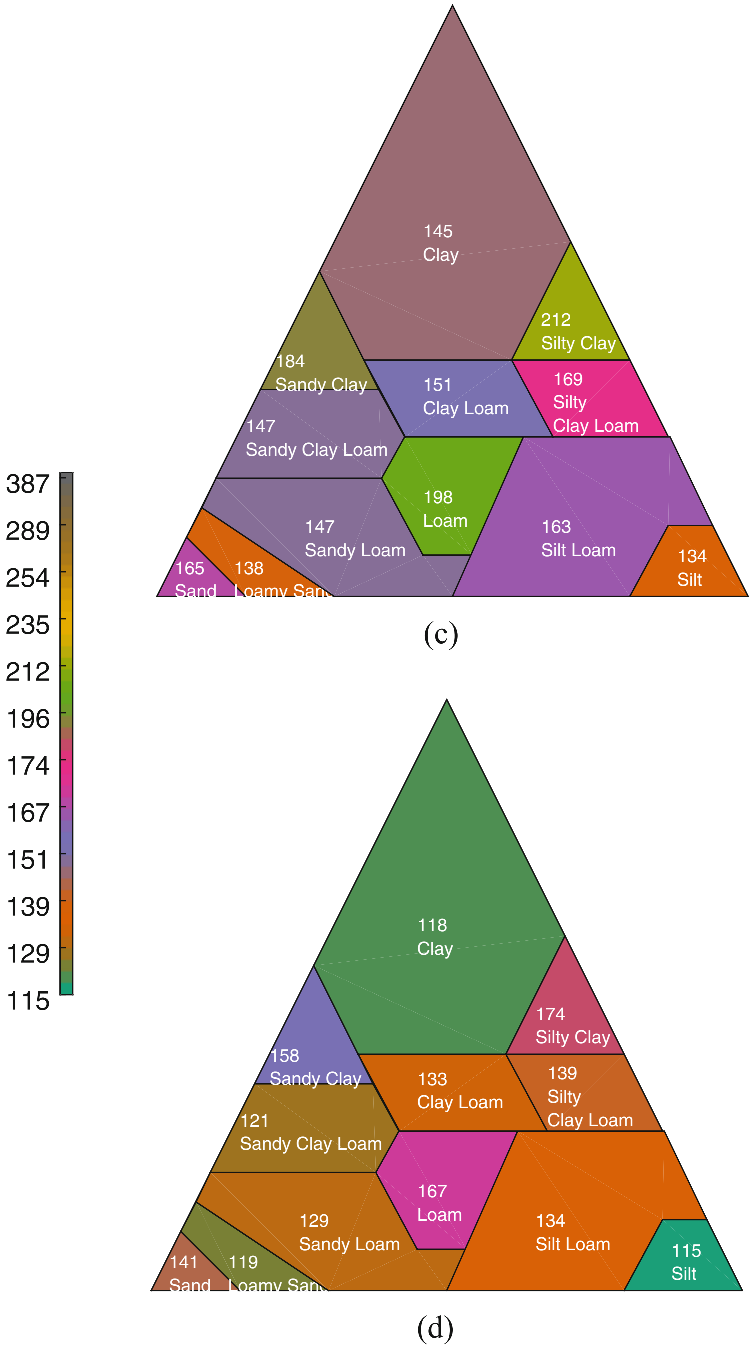

Fig. 3.6 (continued)

The UG transmit beamforming using array antennas at the transmitter can be employed in the underground (UG) communications to maximize the lateral wave by transmitting energy at a particular angle [154, 159]. By using this approach, the energy wastage by sending signals in isotropic direction can be reduced by forming the narrow-width beam and steering it accordingly [198]. In underground wireless communications, the aim is to enhance the received signal strength and reduce the interference at receiver [154]. In underground phased array antennas, the soil moisture adaptive weights, based on soil moisture sensing, feedback signals, are used to adjust the weights by using the array gain feedback loops. This problem is formulated as to maximize the array gain by using the pilot signals. In this method, phased array at the transmitter receives the pilot signal in receive mode and then accordingly adjust its parameters for the transmit mode. In receive mode at the transmitter, scan angles are varied to get the estimate of channel state. The best SNR statistics are used, and accordingly, with change in soil moisture, parameters are adjusted for optimum performance.

3.5 Soil Sensing for Sustainable Ag-IoT

With change in soil structure and particles over time, the process based and empirical models are needed to understand the relation of soil texture with its water cycle [48, 117]. The global climate and change in rain patterns, in addition to the lack of crop rotation, microbes and organic matter, has accelerated the process of changes in pore size, compaction, and structure of soil [131]. The analysis and corresponding analysis will help us to better sensing through the soil communication techniques in response to such biochemical changes in soil [132]. Different factors (e.g., crop and soil type, climate, hydrophilic and bio-geo-chemical properties, pore size evaluation at pedon scale) should be considered together for development of such models. The development of these models will also lead long-term soil sustainability and development of better response to deterioration of soil caused by global climate changes. Currently, there is dearth of novel soil sensing techniques to measure the chemical, biological, and properties of the soil. Accordingly, novel sensing mechanisms are needed to understand these physical, chemical, and biological phenomena in soil. The soil sensing for sustainable Ag-IoT is discussed in this section.

Soil Sensor Requirements The soil moisture and temperature sensors should have the capability to calibrate itself because currently the major challenge in soil moisture measurements is sensor calibration [36, 221, 223]. The understanding of the carbon nutrient cycle, leaching, and uptake process of nitrogen can be improved by development of hydrological flow models. The development of sensors for agricultural purposes should also include to sense salinity and nutrients. The di-electric based and electrophoretic nitrate based signal processing approaches [124] are of particular interest to enhance the soil sensing capabilities for agricultural applications. The pH and measurements of dissolved oxygen need to be integrated with low-cost low-power systems, advanced power management on single circuit boards [30, 219].

The energy conservation issues are also important in the development of such sensor systems. For prolonged uninterrupted operation soil, these sensor systems should have the capability to harvest the energy from the environment as well as able to wirelessly receive power from soil surface and other aboveground sources (recharge). This wireless transmission of power to these sensing systems can be achieved through the propagation of subsurface radio frequency transverse magnetic mode (TM) where soil-air interface serves as a waveguide. The performance efficiency of this scheme can be increased twofold by using multiple transmitters on and below the soil-air interface, creating two such modes hence maximizing transfer using lateral (Zenneck) waves.

Different sensing and modeling approaches (e.g., remote sensing, field scale tools, in situ sensing, crop models and coefficients, transport models, nutrients and microbes, subsurface soil data) also need to be integrated in the digital agriculture. It will improve our understanding of the physical, chemical, and biological processes of the soil and will also improve soil-crop management practices and health.

Self-Deploying Sensors There is also a need of further development of sensors with self-boring capability to overcome installation challenges in excavation, penetration, and replacement of sensors in heterogeneous environments [99]. The use of robots is a potential candidate for the development and auto deployment of these with this capability with minimum soil and crop during the growing season aided with GPS technology. The major advantage of this approach is ability to auto relocate sensors without human innervation for spatial temporal sensing of physical, chemical, and biological properties of the soil. The major challenges in self-deploying and relocating sensors are ability to adjust to varying field terrain, maintaining connectivity within the optimal deployment region and requirement of different deployment hardware for different type of soils.

Acoustic Soil Sensors Acoustic soil sensors is also being envisioned as the alternative to the wire based sensor techniques [116]. One major limitation of wire based sensors is that low sensor density per unit in agricultural fields as limited number of wires can be connected from the underground hole. Because of the changes in the surrounding environment of these sensors, these connections become gradually weak which leads to loss of connectivity due to cable degradation. Moreover, these exposed cables also offer an attractive target to field animals. Acoustic connections offer opportunity to remove these cables completely for underground to aboveground communications. However, the major challenges in this area are higher path loss because of the higher soil moisture content. Moreover, currently only sea based underwater acoustic and through the animal tissue acoustics communication techniques are being applied and there is need to tailor these underwater communication techniques to groundwater, soil moisture, pesticide chemicals, agricultural machinery, farm equipment, and foot traffic [23, 173, 186, 201]. The surface acoustic wave sensors can be used to manufacture soil nutrients sensors by using acoustic wave delay lines [103] and polymer based conductive impedance detectors [168].

Seismometers in Soil A related approach is based upon the use of the soundscapes and seismic signals by using the seismometers to study the movement of soil particles [137]. The main challenge in this approach is to pick the signal of interest (elastic waves) form the background noise by using state-of-the-art seismic arrays in geological, ecological, and biological landscapes. These type of measurements because of their high temporal and spatial resolution can provide insights into the different geomorphic bioturbation factors contributing to spoil erosion and landscape changes on surface (e.g., animals, plants, deposit rocks, foot and machinery traffic).

Root Sensing New non-invasive soil sensor systems are needed to understand the root chemistry. Using current methods this information cannot be obtained without disturbing soil. Development of root sensors will make available the real-time information about roots which can be used to model the impacts of soil type and irrigation cycle on the root growth [178]. Current practices for soil root imaging include minirhizotrons [183] and planar optodes [100]. In the first approach, a transparent plastic tube is buried into the soil root growth zone to obtain contusion images of plant roots. The later approach is based on the use of optical fluoresce sensing mechanism [7]. The big size and high deployment cost of these approaches are major factors limiting the use of these techniques in precision agriculture. Moreover, it can also be used at small-scale plant based level. To address these challenges there is need of development EM-based root imaging and growth sensing techniques that can be used at large scale in a cost effective way.

On-the-Go Soil Sensors Depending on the soil minerals and texture, there is an emission of gamma radiation based on the radioactive decay in soil. Gamma radiation is the electromagnetic photons in the visible light spectrum. These are also being used at top soil mapping. However, these cannot be used as real time on-the-go sensing apparatus in soil because one measurement is not sufficient rather multiple measurements are required. The soil pH can also be used to real-time on-the-go soil mapping [4, 5, 171]. A soil pH based autonomous soil sampling and mapping system has been developed in [171] that used ion-selective electrodes technology for pH sensing and soil mapping. The prototype has demonstrated the effectiveness of the system for lime application. A lime is a soil supplement developed from chalk and limestone. There is also need of sensors to measure mechanical impedance of the soil [5]. This mechanical resistance can be used for selection of no-till or chiseled soil treatment based on the soil impedance measurements.

Topography Soil Sensors There is need of development of topography soil sensors for precision agriculture application. The topography soil sensors in the field can be used to measure slop and corresponding water flow. Currently GPS and LIDAR technologies are being used for mapping topography of soil [162].

Microbial Sensors There are many different species of microbes present in the soil ecosystem. These organisms play a vital role in our support system. Development of new sensing approaches can provide us with the better capability into crop growth control cycle and energy influx. In literature, there is no existing work to support the use of microbes as an input parameters into major models (e.g., waste management, soil health, and climate), therefore there is need of inexpensive, real time, capable of highly dense deployment of microbial sensors [26]. Development of new microbial sensing techniques will help in development of better soil models coupled with maximum entropy production from the thermodynamic perspective. It can also provide much needed insights into the microbe organization and composition changes.

The other major candidates for development of novel microbial sensing approaches are methanogenesis, thermodynamically controlled metabolic sensing approach, chronoamperometry, methanthropy, electrochemical and piezoelectric quartz crystal micro-balance (E-QCM) [54]. A network of microbial sensors working together for sensing will improve the reliability and will contribute to decreasing the cost and amount of field inputs in the field of digital agriculture. It can also lead to better crop health. Because, currently, excess or improper application of fertilizers in agricultural fields is causing nitrogen runoff, which not only contaminates drinking water but is creating troubles for commercial sector (e.g., tourism and fishing) [138]. The algae outbreak and reduction of dissolved water oxygen also results from over-fertilization [59, 114]. The phosphorous cycle is also important for sustainable agriculture. The increase in human activity in the field leads to development of hazardous phosphorous in environment. Therefore, growers can benefits through these advanced soil nutrient sensing systems by application of correct amount of fertilizers.

Soil Nutrient Sensing The soil nitrogen sensing techniques require high field density for correct prediction and development of nitrogen models. Moreover, for better accuracy these sensors should be buried at different depths in the soil. Development of low-cost sensors to sense the concentration levels of nitrate, heavy metal ions, and ammonium will help to overcome these challenges. Carbon based low-cost graphene (ionosphere membranes) can be used to fabricate these sensors in a cost effective way to detect nitrate and ammonium in soil [189]. This knowledge along with NDVI will help in improving crop productivity.

The process of soil erosion can be understood and effective mitigation approaches can be developed by sensing soil iron and oxygen. The erosion of topsoil by physical tillage, wind, climate change, and forces of water is a major issue in agriculture [48, 212]. Better insight into the erosion process can be gained from interaction of soil with iron and oxygen. The information combined with surface water lateral flow models can also illuminate the interaction of microorganisms and resulting seismic change in soil chemistry in managed and unmanaged soil.

Photonic Sensors Macro fabricated photonic sensors work on the principle of detecting changes to the environmental reflective index and can be used to measure soil nutrients. Photo or electron beam lithography based photonic sensors developed on silicon can be used to detect the nitrate and phosphate [10]. This approach has been used in metal sensing but can be tailored to soil nutrients sensing. Zinc oxide nanorods allow spatial high resolution sensing of soil nutrients. These nanorods when combined with Raman spectroscopy can provide highly reliable soil nutrient sensing for abundant and rare nutrients in soil. The major challenges in this area are difficulty in developing standard methods for sensing, calibration, and validation across different nutrient types and soils.

Biosensors Another potential approach for sensing the presence of hazardous microorganisms and chemicals is based on engineered bacterial spores (complete cell-sensors) [106]. Traditionally spores can be used to store biosensors for extended period of time. These biosensors can sense microbial activity based on bacteria can be tailored to adopt to change in the microbial activity in soil. These can be muted as well (dormant mode) and be reused across different sensing cycles. The self-sustainability of these biosensors is an important challenge to achieve long-term field operation to monitor crop health. The underground microbial fuel cell (MFC) is being used effectively to supply power to these sensors [222]. The impedance spectroscopy sensors (ISS) [94] can also be developed by using the MFCs. The ISS sensors are based on detection of change of permittivity of soil to detect ionic concentrations in soil. Therefore, it can be used to monitor the soil nutrients. However, there is need to develop and validate models to connect these permittivity changes to microbial activity and changes in soil.

Micro-Electro Mechanical System (MEMS) Array The soil health can be better characterized by bio-chemical processes and volatile organic compounds produced by them. The detection of soil chemical properties is currently restricted to the pH. The micro-electro mechanical system technology consists of miniature transducers which can be used to sense concentrations of these chemicals at different frequencies. These combined with other sensors can provide a full spectrum soil health sensing capability in digital agriculture. A schematic of the cantilever-array nutrients sensor is shown in Fig. 3.7.

Soil Organic Matter Sensing The soil organic matter (SOM) constitutes the 2% of the soil particles but is not generally accounted as part of the soil texture, which sometimes lead to error in soil models. The sensing of the subsurface biotic factors (e.g., plants, algae, animals, bacteria, and fungi) and abiotic factors (e.g., soil type, mineral weathering, temperature, soil water content, sunlight, oxygen present in the soil pore space, wind speed, water flux, carbon nitrogen cycle, carbon dioxide, ammonia, and nutrients) can provide decision making information in the real time. Among these the soil respiratory quotient (RQ) [29] is a strong indicator of soil metabolism. An understanding of water-gas exchange and diffusion can also provide better information into the gases composition in soil. The pore space sensing for presence of azane, carbon dioxide, and oxygen can be used to assess nitrification process, gas water exchange, and diffusion in different soil textures. Variation in these also need to be investigated over large spatial and temporal scale in agricultural fields.

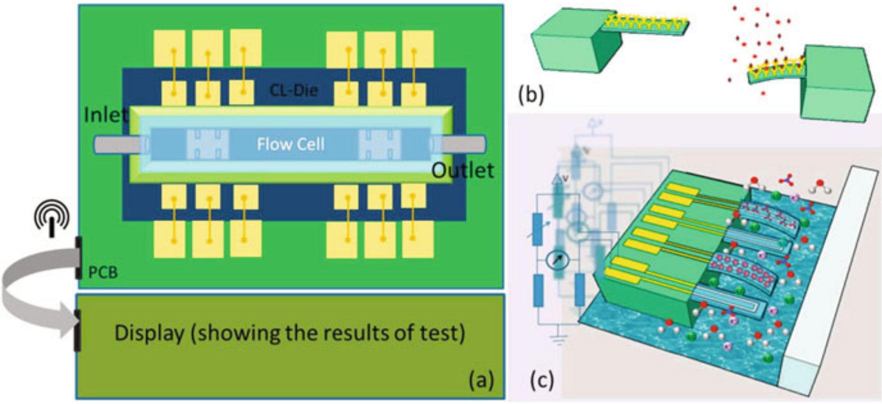

Fig. 3.7 A schematic of the cantilever-array nutrients sensor [125], (**a**) a lab-on-a-chip system (LOC), (**b**) sensing principle of a micro cantilever, (**c**) microcantilever array depicting the sensing of multiple macronutrients

Stress Sensing The lack of enough nutrients, water shortage, improper irrigation, crop diseases, and weeds leads to crop stress. Proper identification of factors causing the crop stresses is vital for insights into phenology and crop physiology. The multi-spectral and hyper-spectral sensing approaches can be used chlorophyll concentration sensing and biomass estimation. However, systematic research and empirical evaluations in the areas of multiple view plant geometry and RGB are required to show effectiveness of these approaches in crop stress identification.

Weed Sensing The weed sensing is another area of digital agriculture that requires major research because weeds have a significant impact on the crop yield. The satellite based imaging for weed sensing has not been promising because of low accuracy, reliability, and resolution. Therefore, new techniques need to be developed for GPS guided high resolution to effectively sense different types of weeds. High quality weeds map can help identification, classification, and proper elimination of weeds.

Autonomous Disease Sensing There is almost total lack of literature on use of technology in digital agriculture for autonomous disease detection. Although the problem of disease sensing has been investigated from the vegetation index perspective by comparing and contrasting the normal and anomalous crop growth pattern. However, models are required which can link these abnormalities to the automatic early stage disease identification.

Plant Temperature and Physiological Properties Sensing The vital physiological properties of the plants can be estimated through the chlorophyll fluorescence sensing. It requires light-saturating photosystem technology with high beam intensity. Lasers that can produce this high intensity beam cannot be used for plants. Traditionally, satellite imagery has been used for chlorophyll fluorescence sensing but suffers from low resolution problems. Another alternative is micro-hyperspectral sensing technology. However, it is expensive and it is not possible to use it for large farms. Therefore, novel inexpensive fine resolution chlorophyll fluorescence sensing techniques need to be developed.

The plant temperature sensing via thermal sensing is done to assess the water stress. This sensing is important to analyze the important process of photosynthesis. Thermal sensors offer very low resolutions and have to be placed close to the plant for correct assessment of water stress. By mounting un-cooled thermal sensors on mobile farm machinery can lead to this assessment but it is not possible for all crop types. But it results in slowing the speed of that particular machinery on which these sensors are mounted, because an instantaneous thermal sensor imagery cannot be used to measure water stress. Rather multiple images are required which are then processed off-line to assess water shortage. Therefore, advanced technology is required for real-time in situ processing of the data and estimation of deficiency of water pressure and CWSI. Moreover, interferences (e.g., the machinery heat generated from the field operation, soil emissions, and plant temperature) are some of challenges that limit applications of this approach to the field of the precision agriculture.

3.6 Aerial Sensing

In digital agriculture, UAVs are becoming ubiquitous as an IoT platform for sensing, data collection, and real-time decision making. Because of flexible design and lower footprint, these can be adopted for use in different types of fields in different terrains UAVs are high quality, inexpensive, higher resolution, and high rate data collection as compared to the remote sensing where performance suffers from the bad weather conditions. Other advantages of UAVs in precision agriculture are ability to select and integrate different sensors on the UAV In terms of modeling, UAVs offer better alternatives to the traditional agricultural modeling processes. Potential applications of UAVs are monitoring the nitrogen status for building nutritional nitrogen index and map, and evaluation of crop growth during the growing season using regression for making SAVI, NDVI, NDRE index indicators of vegetation growth UAVs in precision agriculture is also being used for plant height and biomass analysis with very higher accuracy using multiple UAV trips in the field in real time. The approach of photogrammetry is very helpful for this types of height analysis. A detailed analysis of this approach has been presented in [70]. A stand count analysis in crop field via UAV photos combined with proximal soil sensing and satellite photos has been done. Digital agriculture can be benefited from automation of UAV flights for safe operation, integration of different sensors and sensing techniques across disciplines under a standard protocol, and development of business planning models and supervised learning for effective and optimum field operation. Other novel applications of UAVs include disease and water stress and weed detection, biomass and yield prediction, assessment of deficiency of nutrients, and crop modeling and classification.

The crop ripeness and weed analysis using UAVS have been done in [70] for prolonged field operation and predictive models have been done based on this analysis. In [177], UAVs are utilized, in cotton fields, for canopy response observation and residue management using a thermal camera mounted on the craft. The nitrogen and correlation of LAI and biomass have been analyzed using different UAVs in [14, 71, 75, 184, 197]. Applications to the effective in-field irrigation management and soil sensing using UAVS are shown in [3, 62]. The idea of multiple micro UAV platoons has been presented in [62]. The use of UAVs for fertilizer management in the crop field has been done in [76, 118]. The superior capabilities of spatio-temporal sensing of the UAVs as compared to the remote sensing are demonstrated in [20, 22, 165] using thermal and multi-spectral sensing systems mounted on UAVs. The correlation between the remotely sensed soil moisture and in situ soil moisture measurements is done in [18]. The analysis of plant structure and canopy and plant height was carried out in [11, 95, 218]. In [218], the drainage management has been done using crop scouting. Plant pathogen mapping using UAVs has been done in [120, 188] in a potato field. Applications of UAVs in the area of canopy cover and temperature are tested in [21, 109]. The weed detection and management using UAVs have been explored in [37, 53, 60, 74, 126, 174, 193]. The effectiveness of the crop disease detection using UAVs has been studied in [28, 163, 176]. The characterization of plant growth parameters and yield prediction has been done in [15, 57]. The biological and physical parameters of the soil were estimated using UAVs in [217]. The application of UAVs in the area of vegetation maps and for creating different Indices (NDVI, LAI, GAI, GNDVI, CWSSI, PCRI) using UAVs have been carried out in [27, 56, 108, 194, 199]. Use of UAV imaging in precision agriculture has been discussed in great details in [2, 51, 56, 58, 73, 97, 101, 108, 120, 211]. A detailed analysis of UAV based pest management has been done in [133].

3.7 Big Data

The decision making parameters at the farm includes nitrogen, P and K, liming, hybrid variety selection, placement in field, crop planting rates, variable seeding rate prescriptions, pesticide selection (e.g., herbicides, insecticides, fungicides), cropping sequence/rotation, and irrigation. The data obtained from soil testing, yield and soil maps, EC at farm level and through satellites. It can be managed at different levels. At local level, the data obtained from farmer is restricted to farmer use only at the field level and no data aggregation is done. At the farm level, data is aggregated from different fields within the farm. At regional level, data collected from the farmers can be combined for effective to get regional insights These data collected at the regional level can be combined to national level decision making and can also be used in analysis of the future trends [19, 169].

3.8 Soil Mapping

Soil mapping holds high promise in the area of digital agriculture for production of high quality high resolution soil maps. Through soil mapping impact of different physical, chemical, biological phenomena on the crop and yield can be assessed [112]. The production potential of the soil can be correlated with plant growth and seeding can be adjusted accordingly. Effects of fertilizer can be assessed using soil maps to make adjustments to inputs accordingly. The loss of nitrogen can be controlled to improve yield. Some basic components of the soil mapping are soil texture (percentage of clay, slit, and sand) mapping, salinity, soil organic matter mapping (OM), curvature, slope, tomography, and TWI.

Currently, electrical conductivity, optical, topography, gamma, and electromechanical sensors are being used for soil mapping [61, 63]. The soil salinity and texture sensors work by measuring the in situ electrical conductivity of the soil and are based on the ability of soil to conduct electricity. The clay soils have the higher conductivity because of the presence of significant amount of the fine clay particles. On the other hand sandy and silty soils have particles in large size. Therefore, their ability conduct electricity is low as compared clay soils. The measurements electrical conductivity measurement differences are used to map soil texture. The electromagnetic induction and soil contact are popular EC methods. In soil contact EC measurement method, sensors work in contact with the soil using EM wave, whereas MI sensors work on the principle of induction. Both methods have comparable results.

Soil texture mapping using EC has many advantages: 1) crop growth is directly related to the soil texture water holding capability of soils also depends on soil texture. Clay and silty soils have higher water holding capacity as compared to the sandy soil because of the number of the pores and pore size difference [49]. The root depth and other soil properties such as cation exchange capacity (CEC) also depend on the soil texture. Soil mapping is also used to characterize the soil response to the applied herbicides. Soil animal population, transport of nutrients, and buffering capacity are soil factors vital for crop production and growth. The major application of soil maps generated through soil sampling is in demarcation of soils in different zones, variable rate seeding and sowing rates, assessment and management of nitrogen, and yield maps. These maps combined with output of other soil sensing mechanisms lead to creation of comprehensive real-time decision making tool.

Moreover, the soil EC can also be calibrated with soil type with laser diffraction mechanisms. It also guides soil sensor location, and density in the soil for sensor guided irrigation management in the field thus leading to optimum operation. In the regions with high soil variability soil maps are proven useful in development of seeding plans [16].

Organic carbon and matter sensing can be carried out using optical reflectance [209] to distinguish between organic matter and carbon. An agricultural field with darker color soil texture has higher amounts of organic matter as compared to lighter color textured soils. This phenomena is caused by the absorption and bonding of light with CH and OH molecules of the soil which leads to darker colored soils in with at presence of higher organic level and high soil water content. In soil maps these areas also appear darker. However, the current ability of these soil mapping systems is milted up to top inch of organic matter. On the other hand organic matter layers can be 2–3 inch deep in some soils. Therefore, development of optical soil sensing techniques with ability to generate layered soil maps below 2–3 inches is very essential. Because soil organic matter improves soil aggregation, helps in mineralization of N, P, and S, expedite the nutrient exchange process, reduce the top soil crusting process, and prolongs the soil water content retention in soil, and reduces soil compaction and bulk density. Given this important nature of the organic matter, the OM soil maps can be used as good indicator of the soil health and increase OM understanding. These can also aid in nitrogen management, and variable rate seeding. These can also be related to other soil parameters, EC, and nitrogen soil models for informed decision making.

The results from multitude of available soil mapping approaches discussed in this section can be used powerful with fused sensor data using multiple soil layers. These multi-layer soil maps are important to understand and get insights about what the change, what caused it, and what is the best course of action to deal with it [17]. In precision farming, existing challenges in adoption of soil mapping approaches and resulting maps are limited motivation to use them because lack of high precision maps. Moreover, in practice, fixed application of lime, K, and p is carried out, and relationship of the insights gained from the yield is not very strong. Now with the availability of high precision maps the inputs are indirectly dependent on the soil texture and growers are customizing there application of fertilizer based on the maps that leads to improvement in crop yield as well. Creating these soil maps is becoming more convenient with improved technology and ubiquitous connectivity. With the success of variable seeding and fertilizer application, there is need for high precision soil maps to inform these variable technologies.

3.9 Digital Agriculture Education

There are many climate and production differences (e.g., crops, water availability, irrigation practices terrain) between the different regions of the world. This contrast leads to differences crop yield, return on investment for the same crop in different regions. Therefore, precision farming education and curriculum should be designed accordingly [151].

3.9.1 Curriculum Development

For precision agriculture curriculum, the leonine courses should be available to growers, policy makers, farm managers, and workers in order to provide training on latest developments. These training sessions can also be conducted on campus in evening and on Saturdays to attract larger agricultural community. Government funding can help to start these initiatives to train and certify digital agriculture workforce. Universities in consultation with the industry partners and Ag companies can develop course plans for students. Availability of internships in this area will aid in creation of skilled workers for jobs. For farm mangers, one such sequence of courses can combine latest developments in irrigation management, food sciences, with advanced precision agricultural technology. Other major digital agriculture areas needing attention are integrated management of pests, training in safety, and use of connected heavy machinery and equipment. Although many community colleges in USA are offering training in these areas but with the rapid developments and advances in technology the institution of higher education should assume the role of training the next generation of students to adopt digital agricultural careers. Universities can not only conduct research but also transfer it to the community through start-ups and partnering with industry.

These connections can help students to learn the current needs of industry, the direction in which market is proceeding, and current precision agricultural use-case. These partnerships will also help to build focused faculty research groups and labs, and will make huge advancements in the field through integration of ideas. The existence of novel challenges and right opportunities will increase the motivation to work together to find solutions and technology transfer. The industry board from precision agriculture company will help shape the overall curriculum learning objectives through technology updates, discussions, and feedback. Through classroom integration curriculum can be enriched with examples, industry based capstone design projects. Through this hands-on training student will learn better about new developments in the area. Internships in digital agricultural companies though meaningful projects will also contribute to digital agriculture workforce development and create new employment opportunities at all level for students, industry, and academia. Overall, these university-industry partners can together solve many challenges in the area of silage and grain covers, underslab gas barriers, fumigation, building enclosures and landfill covers.

The precision agriculture curriculum should be viewed as multidisciplinary tree have branches in agronomy, computer science and electrical engineering, sensor technology and sensing approaches, biological sciences and engineering with one shared goal of increasing crop yield though reducing input cost, better management and informed decision, and sustainable agriculture practices. The propose of the digital agriculture curriculum should be able to develop global leaders for solving great changes in the area with a common commitment to future of digital agriculture. It will benefit farm mangers, software developers, agronomists, engineers and technicians, and educators. It requires dedicated efforts by providing more resources, reducing adoption barriers to precision agriculture technologies, and investing in industry academia partnerships.

3.9.2 Work Roles in Digital Agriculture

The precision agriculture work roles are described below:

- An applicator is the field worker who works to apply fertilizer and pesticides by using the related equipment.
- An agronomist specializes in soil and crop management, and provide recommendation to the farmers.
- A precision equipment technician is expert in digital agriculture equipment installation, trouble shooting, repair and maintenance on the field.
- A precision sales specialist deals with sale and support of digital agriculture equipment and software. In this role, a precision sales specialist can also provide services remotely.
- A data manager collects and analyses data from customers, farms, and agriculture businesses.

3.10 Energy Harvesting

For sustainable underground soil sensing and field communications operation, it is highly desirable to transfer wireless power to subsurface radios and sensors. In the agriculture field, ideally, the lifetime all sensing equipment should be greater than 5 years [78]. With the recent developments and improvements in technology and through development of energy efficient sensor materials, the energy requirements for these sensors are decreasing rapidly. However, underground radios still require power to communicate through the soil to aboveground receivers. There are many intermittent energy harvesting resources available on the field for precision agriculture that includes solar, vibration, bacteria as fuel cells, thermal, underground living plants. However, the literature is scarce on underground wireless RF power transfer. The maintenance, repair, removal of sensors for battery replacement, and re-installation of underground equipment is costly and access to field equipment are sometimes not only difficult and also causes disturbance to soil and plants. The extended lifetime of digital equipment is very important adoption of the technology in precision agriculture.

In the digital agriculture, these underground devices can be powered in many different ways. The first method is based on wireless power transfer and is based on EM induction and magnetic resonance [68], and radiation.

Through RF power transfer energy can be transferred from source to the subsurface equipment using the wireless electromagnetic waves. These waves exhibit less deterioration and attenuation as compared to resonance and induction based approaches. Therefore, it can be used for long distance (up to few meters) energy transfer [31]. The normal power consumption of underground devices is few milliwatts. Since, underground digital agricultural devices can operate with low power using duty cycling. In duty cycling, the sensors and radio are activated only when sensing data and communication is required. In a large farm, the sleep time can vary from few hours to days depending on the growing season, climate, and irrigation needs. For remaining time the nodes remain in the sleep mode. Therefore, even few micro-watts power is sufficient for sustainable operation in the agricultural fields [91, 213].

Wireless RF power transfer requires external sources. The power beacons can be developed and utilized for this purpose. However, in the field it is hard to have fixed aboveground energy sources as power beacons permanently dedicated to power the sensors and radios. However, these sources can be mounted on pick-up trucks and farm equipment such as tractors. Moreover, the UAVs can be used to install these external power source combined with other data collection and sensing equipment for concurrent information and power transfer. Novel methods need to be developed for external energy transfer. The power transfer through the soil should be investigated. The ideal depth of sensors and distance between different nodes can be modeled by understanding the deterioration of signals in the soil. A detailed survey of power transfer in over-the-air wireless communications and networks has been given in [104, 105]. External power sources can be designed based on a single antenna approach where energy can be transferred to single node only. However, recently, the idea of using multi-antenna approaches has attracted the attention of the research community, where the beamforming can be used to direct energy to multiple nodes by using the beamforming.

3.10.1 In Situ Energy Harvesting Methods

This interaction with the external power sources can be avoided with the development of in situ energy harvesting methods. The second method is based on energy harvesting from different sources. The piezoelectric technology has the capability to convert the vibration energy into the power. It can be modeled through circuit and mechanical methods (mass, spring, and damper) [89, 216]. However, this technique required to correct vibration frequency in order for power generation. The operation of diverse equipment and traffic leads to generation of different frequencies in the field. Therefore, either the multiple vibration sensors tuned to different frequencies, or one sensor with broadband spectrum sensing capability is needed [66, 123]. In [89], the applications of vibration energy harvesting has been investigated in a corn field. Through the use of piezoelectric energy harvesting technology, where these devices are buried in the field at low depths, has been used to harness the vibration field sources (e.g., the seeders, farm machinery, and harvester, combine and other agricultural equipment). This empirical analysis has shown the viability of this technique for digital agriculture. However, the provision of prolonged sustainable energy to underground sensors is still challenging because this method is not sufficient to provide power to multitude of devices underground. The burial depth of the equipment is one major issue because at deeper depths attenuation is higher in the soil. To overcome challenges in the area of energy harvesting in the field, more insights into the vibration propagation in soil are needed. There is also need for development of new protocols and platforms for subsurface power transfer. The link layer protocols for optimal frequency section and sensor placement should be developed. An in-depth validation of these approaches is required at the field level with consideration of models, non-linear efficiency, power consumption of circuits. It should also be combined with novel channel estimations methods in underground communications.

3.10.2 Wireless Subsurface Power Transfer

Generally, agriculture fields do not have enough ambient RF energy (stray EM waves) that can be harvested for self-sustainable operation. Another method is based on the use of energy harvesting for received data communications signals. It is done either through time sharing approach, where some slots are allocated to information transfer and alternative time slots are assigned to RF energy sensors. Other approach is based on frequency sharing, where frequency of the information signal is shared with the RF energy harvester. Beam splitting is another method for distribution of energy via energy scheduling approach. These co-channel data and power transfer approaches have been investigated in [31, 32, 135]. However, it leads to information communication performance degradation and required designing new equipment which increase the cost of deployment hence increasing the challenges in digital agriculture adoption.

There is also need of medium access protocol (MAC [52]) for RF energy transfer techniques to work for multiple users in wireless underground network [115]. A rectenna is a type of energy harvesting antenna which is used for collection and rectification of the EM waves [136]. Many technologies are available to manufacture a rectenna for use in digital agriculture applications. These include CMOS, tunnel, Schottky and spin diodes, and active rectification. These rectennas also required matching circuits to match the input impedance of the rectifier to the impedance of the antenna for maximum energy harvesting. Design of such antennas has been explored in [47], that can be tailored for underground RF energy transfer applications. Some field experiments using these antennas in bridge settings are done in [47, 79]. Further investigation of possible distance up to which RF power can be transferred should be investigated as power transfer efficiency is dependent on the distance. There is also need of development of energy beamforming with adaptive steering towards any underground and aboveground nodes. Because with the advancement and adoption of precision agriculture practices, a multitude of sensors will be deployed across the field. The use of multiple antennas in the aboveground power source can be used to achieve very narrow-width beams with capability to carry more power as compared to traditional single antenna transmission. For beamforming with beam steering capability to work, there is need of accurate channel estimation of underground channel between transmitter-receiver pairs to obtain the channel gains. The wireless underground channel impulse response can be utilized for this purpose [160].

Additionally, the traditional receiver guided [207, 215] and up-link phase estimation approaches can be used. To reduce the equipment complexity and to conserve energy there is need of development low complexity channel estimation schemes based on the receive power only (e.g., one bit feedback algorithm) [214]. Moreover, in agricultural Internet of Things (Ag-IoT), an energy neutral operation [175] is desirable to avoid the saved energy from being depleted and also to attain high efficiency of energy transfer and harvesting schemes. Duty cycling of the underground can be utilized as well to conserve energy. This depends on many factors such as requirement of frequency sensing operation, distance from the external power sources, crop, fertilizer inputs, and weather [170, 204]. Duty cycling can be activated based on some threshold of power going below some level and system should also have the ability to automatically make changes on the sleep and wake-up duration based on the changes in these field factors. Moreover, the nodes running out of power should be capable of requesting energy on urgent basis. Further research is also needed to assess the number of external power sources needed based on the fixed sensor density in a typical agricultural field and should also be able to accommodate mobile sensors.

Recently, magnetic near field inductive power transfer approach has been proposed for magnetic induction based wireless underground sensor networks [91]. There are many standards available for magnetic near field inductive power transfer. However, its range is limited to distances less than 1m.

Far field wireless power transfer (WPT) can be used for long energy transfer. There are many advantages of long-range wireless power transfer approach in the underground sensing and communications in digital agriculture.

- Physical contact with devices and wired connection can be completely removed
- Mobility can be achieved in energy transfer as an external power sources can charge many devices in the field
- On-demand and reliable delivery can be insured all conditions in contrast to other sources of power which are weather or farm activity dependent

A concurrent wireless and power wireless network can be effectively used to transmit data and power in full-duplex settings. First case is aboveground to underground energy transfer in which solar energy harvested from the aboveground nodes can be transferred to underground nodes. In the second case of underground to aboveground energy transfer, the energy harvested by the underground nodes from the vibration and bacterial sources acting as fuel cells can be transmitted to aboveground nodes. Therefore, both this bi-directional energy transfer will lead to more reliable and sustainable operation for longer periods of time anywhere and anytime.

3.10.3 Solar Power

Solar power transfer through aboveground nodes can also be used in the agriculture fields in the sun belt area to transfer power to underground nodes. The harvested solar energy can be steered to different underground nodes using the soil moisture adaptive beamforming with phased antenna arrays [154]. The Solar Power Radio Integrated Transmitter (SPRITZ) can be developed combined with solar cells that provide the DC power.

3.10.4 Energy Harvesting Challenges

The design underground energy transfer in digital agriculture should address following major issues:

- Transfer range for fully functional underground energy transfer network, underground-to-underground power transfer range should be 35m, which is the current communication range for the same wireless channel. However, for the transfer link where there are sources available aboveground the energy transfer range of 100m is desirable to cover a standard 300x300m agricultural field.
- Multipath Support. Energy transfer technique should be able to function where direct line of sight is not available. During plant growth in the growing season, many reflections from soil-air interface and multipath can exist which can pose critical challenges to effective energy transfer.
- Efficiency: Highly effective approaches are needed for through-the-soil power transfer. Because of complex permittivity of the soil high attenuation of wireless signals carrying data and power can reduce the efficiency of these approaches. High RF to DC conversion efficiency of devices is also vital for efficient energy harvesting.
- Mobility. Since multitude of farm machinery and pickup trucks can function in the field, hence, mobility power transfer will enhance the efficiency as compared to the fixed external power sources in the field.
- Accessibility: The under wirelesses power transfer approaches should be resistant to the changing crop pattern, weather, irrigation conditions. Ubiquitous accessibility will ensure reliable power supply in the wake of changing environmental conditions.
- Standards for in-field power should be developed so that all existing and new digital agricultural devices can be compatible and function in the transfer network.
- Energy consumption storage. There is also need of development of new methods to store energy at the underground nodes and reducing energy through development novel adaptive duty cycling approaches.

- Frequency spectrum. Types of uniform power and data transfer in digital agriculture should be used to effectively utilize the underground frequency spectrum (less than 1 GHz) within the bounds of existing delay spread and coherence bandwidth.

3.10.5 Combined Power and Data Transfer in Digital Agriculture

The different types of uniform power and data transfer in digital agriculture are discussed in the following:

- Concurrent transfer of data and power. The same channel is used for power and data transfer. The power sensor can be integrated in the receiver nodes (co-located) or two separate devices can be used this type of transfer.
- Uni-directional data and uni-directional power, one line is used for transfer of power (from transmitter to receiver) and other link is used for data (from receiver to transmitter)
- Time-shared approach, channel is shared between data and energy by using the time sharing approach depending on the need of the energy and information transfer

3.11 The Ag-IoT Systems

The academic and commercial IOUT systems are given in Tables 3.1 and 3.2, whereas their classification is shown in Fig. 3.8.

Table 3.1 The academic IOUT systems [202]

Architecture	Sensors	Comm. Tech.	Node density
Automated irrigation system [65]	DS1822 (temperature) VH400 (soil moisture)	OTA, ZigBee (ISM)	One node per indoor bed
Soil scout [192]	TMP122 (temperature) EC-5 (soil moisture)	UG, custom (ISM)	Eleven scouts on field and a control node
Remote sensing and irrigation sys. [90]	TMP107 (temperature) CS616 (soil moisture) CR10 data logger	OTA, bluetooth (ISM)	Five field sensing, one weather station

(continued)

Table 3.1 (continued)

Architecture	Sensors	Comm. Tech.	Node density
Autonomous precision agriculture [42]	Watermark 200SS-15 (soil moisture) data logger	UG, custom (ISM)	Up to 20 nodes per field
SoilNet [25]	ECHO TE (soil moisture) EC20 TE (soil conductivity)	OTA, ZigBee (ISM)	150 nodes covering 27 ha
MOLES [187]	Magnetic induction communications	Magnetic induction	Indoor testbed
Irrigation nodes in vineyards [200]	Yield NDVI	Variable rate irrigation	140 irrigation nodes per field
Sensor network for irrigation scheduling [38, 167]	Capacitance (soil moisture) watermark soil moisture sensors	OTA	6 nodes per acre
Cornell's digital agriculture [33]	E-Synch, touch-sensitive soft robots vineyard mapping technology, RTK	OTA	Field dependent
Plant water status network [139]	Crop water stress index (CWSI) modified water stress index (MCWSI)	OTA	Two management zone—two treatments in each zone
Real-time leaf temperature monitor system [98]	Leaf temperature ambient temperature relative humidity and incident solar radiation	OTA	Soil and plant water status monitors,
Thoreau [220]	Temperature, soil moisture electric conductivity and water potential,	OTA	Based on Sigfox,
FarmBeats [196]	Temperature, soil moisture Orthomosaic and pH,	OTA	Field size of 100 acres
Video-surveillance and data-monitoring WUSN [55]	Agriculture data monitoring Motion detection, Camera sensor	OTA	In the order of several kilometers
Purdue university's digital agriculture initiative [134]	Adaptive weather tower PhenoRover sensor vehicle	OTA	Field dependent
Pervasive wireless sensor network [210]	Soil moisture, camera	OTA	Field dependent
Pilot sensor network [96]	Sensirion SHT75	OTA	100 nodes in a field
SoilBED [46]	Contamination detection	UG	Cross-well radar

Table 3.2 The commercial IOUT systems [202]

Architecture	Sensors	Comm. tech.	Node density
IRROmesh [84]	200TS (temperature)	OTA, custom (ISM)	Up to 20 nodes network mesh
	Watermark 200SS-15 (soil moisture)	OTA, cellular	
Field connect [88]	Leaf wetness	OTA, proprietary	Up to eight nodes per gateway
	Temperature probe	OTA, cellular	
	Pyranometer	OTA, satellite	
	Rain gauge		
	Weather station		
SapIP wireless mesh network [43]	Plant water use	OTA	Up to 25 SapIP nodes with 2 sap flow sensors each
	Measure plant stress		
	Soil moisture profile		
	Weather and ET		
Automated irrigation advisor [195]	Tule actual ET sensor	OTA	Field dependent
Internet of agriculture-biosense [24]	Machinery auto-steering and automation	OTA	Field dependent—Real-time irrigation decision making
	EC probe & XRF scanner		
	Electrical conductivity map		
	NDVI map		
	Yield map		
	Remote sensing		
	Nano and micro-electronic sensors		
	Big data, and Internet of Things		
EZ-farm [77]	Water usage	OTA	IBM bluemix and IBM IoT foundation
	Big data, and Internet of Things		
	Terrain, soil, weather		
	Genetics		
	Satellite info		
	Sales		

(continued)

Table 3.2 (continued)

Architecture	Sensors	Comm. tech.	Node density
Internet of food and farm (IoF2020) [82]	Soil moisture	OTA	Field dependent
	Soil temperature		
	Electrical conductivity and leaf wetness		
Cropx soil monitoring system [34]	Soil moisture	OTA	Filed dependant
	Soil temperature and EC		
Plug & sense smart agriculture [128]	Temperature and humidity sensing	OTA	Field dependent
	Rainfall, wind speed and direction		
	Atmospheric pressure		
	Soil water content, and leaf wetness		
Grain monitor-temputech [191]	Grain temperature and humidity	OTA	Multiple depths in grain elevator
365FarmNet [1]	Mobile device visualization tool for IOUT data	OTA	Field dependent
SeNet [166]	Sensing and control architecture	OTA	Field dependent
PrecisionHawk [130]	Drones for sensing	OTA	Field dependent
	Field map generation		
HereLab [69]	Soil moisture	OTA	Field dependent
	Drip line PSI and rain		
IntelliFarms [80]	YieldFax	OTA	Field dependent
	Biological		
	BinManager		
IoT sensor platform [83]	IoT/M2M sensors	OTA	Field dependent
Symphony link [185]	Long range communications	OTA	Field dependent

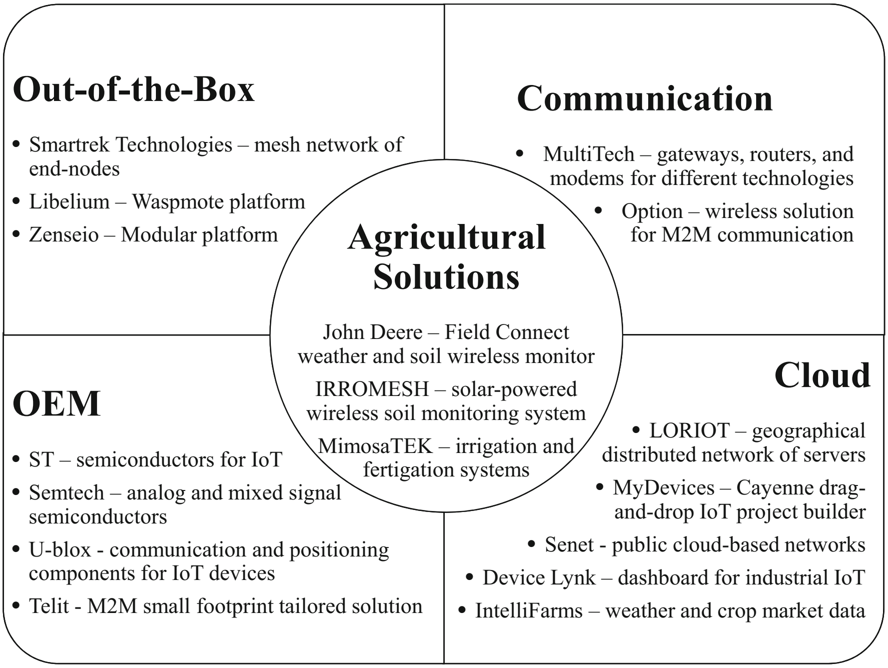

Fig. 3.8 The classification of commercial IOUT solutions [202]

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