29 Global Development in Soil Science Research: Agriculture Sensors and Technologies

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Abstract

The importance of soil resource to global food supply and climate change mitigation by carbon sequestration are the two most important factors for the constantly growing interest in global soil research. In view of its growing recognition as an important natural resource, the United Nations has declared 2015 as the "International Year of Soils" in the 68th Session of its General Assembly. With population increase, world hunger, water stress, and climate change, global crop production are continuously under stress to meet future demands. The global crop production will have to be doubled by 2050 to meet the population's projected demands. Thus, the pressure on soil resources is bound to increase and they need to be managed wisely. "If you can't measure it, you can't manage it." Assessing soil data is essential in monitoring soil attributes, evaluating changes related to soil quality, judging soil resources, and improving crop yields. The conventional soil analysis can provide accurate measurements for a limited number of samples due to the cost, time, and labor analysis, which leads to inadequate spatial field data and restricts the resolution of the prescription maps. The development of soil sensors and technologies can improve agricultural systems by providing a rapid, in situ, and innovative characterization and measurement of soil properties over current methods. In this chapter, we will explore the agriculture sensors and technologies used in precision agriculture, agribusiness and discuss how these tools can optimize crops and increase the world's capacity to feed future populations.

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Keywords

Soil resources · Soil sensors · Precision agriculture · Crop production · Soil mapping

Abbreviations

AI	Artificial Intelligence
Ca	Calcium
CEC	Cation exchange capacity
FDR	Frequency-domain reflectometry
GPS	Global positioning system
K	Potassium
Mg	Magnesium
N	Nitrogen
Na	Sodium
P	Phosphorus
SOC	Soil organic carbon
SOM	Soil organic matter
SWP	Soil water potential
TDR	Time-domain reflectometry
VFR	Variable fertilizer rate
Vis-NIR	Visible-Near infrared

29.1 Introduction

Agriculture feeds the globe. With population increase, world hunger, water stress, and climate change, global crop production is continuously under stress to meet future demands. As indicated by the researchers at the University of Minnesota, the global crop production will have to be doubled by 2050 to meet the population's projected demands (Ray et al. 2013). These researchers performed a study on the speculated crop production by 2050 using 2.5 million agricultural statistics. Their results showed that the global production of 4 key crops (rice, maize, wheat, and soybean) is below 2050 projected demands by 0.9–1.5% of the annual rate required to double global production by 2050 (Ray et al. 2013). Assessing soil data is essential in monitoring soil attributes, evaluating changes related to soil quality, judging soil resources, and improving crop yields. Soil data such as nutrients level, water content, compaction, pH, and salinity distribution are collected throughout the field by performing systematic soil sampling followed by laboratory analysis. However, these conventional tests can provide accurate measurements for a limited number of samples due to the cost, time, and labor analysis. This provides inadequate spatial field data and restricts the resolution of the prescription maps

(Dobermann et al. 2004). Hence, the development of soil sensors and technologies has the opportunity to improve agricultural systems through providing a rapid, in situ, and innovative characterization and measurement of soil properties over current methods. By deploying sensors and mapping soil properties, farmers can have a better understanding of their crops, reduce stresses on the environment, and make more precise decisions. This is where precision agriculture and farm automation technologies play great roles (Adamchuk et al. 2005; Hunt Jr and Daughtry 2018; Kanjilal et al. 2014). In this chapter, we will explore the agriculture sensors and technologies used in agribusiness and discuss how these tools can optimize crops and increase the world's capacity to feed future populations.

29.2 Precision Agriculture Overview

Precision agriculture is defined as a group of farmer practices done to achieve agricultural sustainability. These practices are based on the four Rs: right place, right time, right amount, and right application. Precision agriculture provides site-specific management of agriculture inputs to preserve the environment, enhance product quality, and increase crop yields. Sensors data have been used in precision agriculture to correct soil pH, generate fertilizer and watering recommendations, manage weed, control pests, and provide information on precise positioning, and other soil properties like compaction, air permeability, and temperature. Precision agriculture companies are attracting more farmers towards more flexible and faster startups that are capable of systematically maximizing crop yields.

29.2.1 Agricultural Sensors for Soil Chemical and Physical Properties

Several sensing technologies exist in precision agriculture to provide data that can help farmers in optimizing their crops and monitor different soil properties. Soil properties can be divided into two categories: chemical and physical. Soil chemical properties include pH, total carbon, total nitrogen (N), available phosphorus (P), sodium (Na), potassium (K), magnesium (Mg), calcium (Ca), heavy metal concentration, cation exchange capacity (CEC), and soil electrical conductivity (Brady et al. 2008). While soil physical properties include texture, color, porosity, density, air, and temperature (Brady et al. 2008).

29.2.1.1 Electrochemical Sensors

The physical nature and the chemical properties of soil determine its fertility. Soil fertility is crucial in determining the soil's ability to supply plant nutrients in enough amounts and proportion for plant growth. Crop production removes nutrients from the soil. Hence, sustainably reapplying plant nutrients is essential for optimum crop yield and environmental safety. Nutrients sensors are used to quantify the concentration of macronutrients and micronutrients in soils and monitor fertilizer application in soil accordingly. Electrochemical sensors are most commonly used to detect specific ions in soils. Electrochemical sensors function by relating electricity to chemical reactions and are broadly divided into three types: voltammetric, potentiometric, and conductometric (Veloso et al. 2012). They provide key information on soil pH, nutrients levels, heavy metal concentration, and electrical conductivity (Table 29.1).

29.2.1.2 Dielectric Sensors

Developments in soil moisture sensors have permitted real-time continuous soil water measurements. Soil moisture sensors can measure soil water data and be downloaded wirelessly within a certain radio range making the data acquisition easier for growers (Ganjegunte et al. 2012). Dielectric sensors are commonly used to measure the soil moisture content by measuring the electrical charge-storing capacity, referred to as dielectric constant, of the soil. Time-domain reflectometry (TDR), frequency-domain reflectometry (FDR), and capacitance (Table 29.1) are different kinds of dielectric soil moisture content sensors that are used directly in soil (Veldkamp and O'Brien 2000; Dean 1995; Ledieu et al. 1986). Soil water potential (SWP) is another basic parameter that describes the state of water in the soil. Soil water potential determines how water moves from the soil to the plant. SWP sensors function by measuring the dielectric permittivity of a solid matrix of porous ceramic discs and are used directly in soil (Malazian et al. 2011).

29.2.1.3 Mechanical Sensors

Soil compaction can be caused by the heavyweight of field equipment or by natural soil-forming processes, which causes soil particles to press together reducing pore space between them. This can cause soil degradation, increases root penetration resistance, and negatively affects crop production (Adamchuk et al. 2004). Mechanical sensors are used to measure soil compaction or mechanical resistance. These sensors evaluate soil compaction by measuring resistance forces resulting from cutting, breaking, and displacing of soil (Adamchuk and Rossel 2010). A standard vertical cone penetrometer is the most conventional method to measure soil resistance with depth at a given location, directly representing soil compaction (ASABE Standards 2006). Single-tip horizontal sensors are a different kind of mechanical sensors that are used to measure horizontal soil penetration resistance at specific depths. In addition to tip-based sensors, instrumented tine sensors are also used to measure the vertical distribution of soil compaction.

29.2.1.4 Acoustic and Pneumatic Sensors

Acoustic and pneumatic sensor measurements can be correlated to compaction; thus, they may be used as alternatives to mechanical sensors. Acoustic sensors are used to determine soil texture and structure by measuring the change in noise level as the tool interacts with the soil particles (Adamchuk and Rossel 2010). Microphone equipped soil shank and Microphone equipped horizontal cone penetrometer are two types of acoustic sensors that use frequencies to distinguish between different types of soil and detect compaction layers (Liu et al. 1993; Grift et al. 2005; Brady et al. 2008). Pneumatic sensors measure soil–air permeability, which is the pressure

Table 29.1 Summary of precision agricultural sensors for soil chemical and physical properties

Type of sensors	Functions	Examples of applications	References
Electrochemical	Detects specific ions in the soil	• Potentiometric ion-selective electrodes for N, K, Na, and pH • Cyclic voltammetry using carbon-based electrodes for P and iron minerals • Conductometric soil salinity/ electrical conductivity meter	Adamchuk et al. (2005), Memon et al. (2009), Zeitoun and Biswas (2020), Nagamori et al. (2007)
Dielectric	Measures dielectric constant in the soil to quantify soil moisture and SWP	• TDR for soil moisture content • FDR for soil moisture content • Capacitance for soil moisture content • Dielectric permittivity sensor for SWP	Ledieu et al. (1986), Veldkamp and O'Brien (2000), Dean (1995), Malazian et al. (2011)
Mechanical	Measures soil compaction or mechanical resistance	• Vertical cone penetrometer for soil compaction • Single-tip horizontal sensors for soil compaction • Instrumented tine sensors for soil compaction	ASABE Standards (2006), Adamchuk and Rossel (2010), Adamchuk and Rossel (2010)
Optical	Measures soil properties	• Vis-near infrared spectroscopy for soil erosion mapping, weed mapping, and SOC	Felton and McCloy (1992), Sepuru and Dube (2018)
Pneumatic	Measures air permeability of the soil	• air pressure transducer sensor for soil compaction	Clement and Stombaugh (2000)
Acoustic	Measure soil texture and structure	• Microphone equipped soil shank sensor for differentiating between soil types • Microphone equipped horizontal cone penetrometer sensor for soil compaction	Liu et al. (1993), Grift et al. (2005)

needed for air in a pore space to collapse into the soil at a given depth (Madhumitha et al. 2020). Air pressure transducer can be used to measure air pressure and flow to estimate soil compaction (Clement and Stombaugh 2000).

29.2.1.5 Optical Sensors

Optical sensors employ electromagnetic energy to characterize soil properties. They use various frequencies of light reflectance in visible (400–700 nm) (Viscarra Rossel et al. 2008), near-infrared (700–2500 nm), or/and mid-infrared (2500–25,000 nm) to perform soil analysis (Adamchuk and Rossel 2010). These sensors can be placed on vehicles or drones which can detect the level of energy absorbed, reflected, or transmitted by soil particles in real time. Optical sensors can gather multiple data with just a single scan, which provides an opportunity to determine many soil properties such as soil organic matter, soil texture, weed management, mineral composition, and particle size (Shonk et al. 1991; Sudduth and Hummel 1993, Shibusawa et al. 2001, Mouazen et al. 2005, Christy 2008, Sui et al. 2008).

29.3 Sensor Output Applied

Sensors data are implemented and processed in precision agriculture to provide site-specific management of agricultural inputs, improve product quality, increase crop yield, and increase crop production profitability while minimizing environmental effects. Precision farming takes advantage of these data in different ways. Due to the increasing costs of fertilizers production inputs of soil macronutrients (NPK) (Sinfield et al. 2009) and water eutrophication associated with N and P fertilizers losses (Stelzer and Lamberti 2001; Brady and Weil 1996), optimizing plant yield while minimizing consumption and application of fertilizers is highly encouraged in agricultural practices. **Variable fertilizer rate (VFR)** management of macronutrients (NPK) is one of the most promising strategies for precision agriculture to optimize fertilizers use and crop yields (Sawyer 1994).VFR application tools integrate different layers of spatial field data to develop application algorithms. Commonly, soil nutrients distribution throughout the field is estimated by performing systematic soil sampling followed by laboratory analysis. However, the high cost of soil sampling and laboratory analysis limits the resolution of the prescription maps and provides inadequate spatial field data (Dobermann et al. 2004). On-the-go mapping system provides a promising fast and cost-effective alternative that uses electrochemical sensors to quantify macronutrient levels.

Soil pH is a key component of crop productivity and nutrient availability in soil (Brady et al. 2008). On-the-go electrochemical soil pH sensors are used to provide spatial variability of pH in the agriculture field, **soil pH mapping** (Schirrmann et al. 2011). These data are used to make decisions on applying alkaline or acidic fertilizers to control the pH of the soil and manage the effects of extreme soil pH conditions.

Soil salinity is one of the major concerns in agriculture. It can cause soil erosion and negatively affect plant growth and yield. In the past few decades, **soil salinity**

mapping has been an active area of research particularly for agricultural soils (Abuelgasim and Ammad 2019). Electrical conductivity measurements are used to perform soil salinity mapping. These measurements are used to conduct the soil salinization performance index. To control and mitigate soil salinization, beneficial management practices are undertaken to reduce excess salt movement through appropriate soil water management (Government of Canada 2020).

Soil moisture and SWP data are used to conduct soil water retention curves used to calculate plant-available water and estimate crop water requirements to manage **irrigation scheduling** (Bittelli and Flury 2009). Irrigation scheduling is applied in agriculture to avoid over/under irrigation which provides a great potential to use water efficiently, reduce the amount of nutrients leaked into the groundwater, and promote water supply conservation practices (Ganjegunte et al. 2012). Soil water retention curves are also used in **hydrological models for flood and drought risks** to enhance hydrological processes like ponding, evapotranspiration, and interception (Collentine and Futter 2018; Burek et al. 2012).

Increased soil compaction has adverse effects on agriculture and the environment. It has shown to negatively impact soil structure, increase runoff and soil erosion, reduce crop production, and cause land degradation (Hemmat and Adamchuk 2008; Alaoui and Diserens 2018). **Soil compaction mapping** can help to pinout where exactly the soil compaction occurs and toidentify suitable mechanical, chemical, or biological recommendations to control soil compaction. Tip-based and tine-based mechanical sensors are two powerful sensors that are capable of mapping spatial and vertical variation in soil compaction (Hemmat and Adamchuk 2008).

Optical sensors data provide a good source of information for **soil weed mapping** to help create proper site-specific weed management programs. One of the commercially available optical weed sensors is called WeedSeeker, which was developed by Felton and McCloy (1992). It uses visible and NIR reflectance to differentiate between green plants (weeds) against a background of soil and dead plant materials (Wang et al. 2001). Most agricultural fields are spatially variable in weed infestation; however, herbicide applications assume that weeds are distributed uniformly (Wang et al. 2001). This causes excess herbicide use and major problems down the road, such as herbicide-resistant crops (Green 2012). Mapping out the distribution of weeds using optical sensors data is very powerful in site-specific management of herbicide inputs and improves the efficiency of herbicide application to weed-infested sites. Optical sensors data can also be used for **soil erosion mapping**. Soil erosion is a serious global problem that affects soil conditions and crop production (Teng et al. 2016). About 75 billion tons of fertile soil is lost globally from agriculture systems per year (Sepuru and Dube 2018). Spectral indices (based on soil reflectance) such as coloration index and brightness index can be used to characterize soil-surface state (El Jazouli et al. 2017). By mapping and evaluating soil erosion risks, soil scientists can undertake effective management practices in reducing soil erosion rates. Few examples of commercial optical sensors used in soil erosion mapping are ASTER, Landsat8, and Sentinel2 (Shoshany et al. 2013; Vrieling et al. 2008). Multispectral sensors data are also used in **soil organic carbon (SOC) mapping** which is essential in assessing the sustainability of soil cultivation and understanding the effects of agriculture practices on SOC level in soils (Žížala et al. 2019). **VFR** application tools also use optical surveys of plant health determined by fluorescence sensing to detect nutrient stresses (Liew et al. 2008).

29.4 Artificial Intelligence in Agriculture

With climate change and population increase, artificial intelligence (AI) is developing in the agriculture industry to improve and protect crop yield. In the last 5 years, AI startup companies (Table 29.2) in the agriculture sector have raised over $800 M (CBINSIGHTS 2017). Some of the major ways that AI is contributing to agriculture are farm automation robotics, driverless tractors, satellites, and drone high-quality imaging (Table 29.2).

Farm automation is a fairly new technology that makes farms more efficient by automating the crop production cycle (Kanjilal et al. 2014). Farms need a lot of labor. Farm automation can make farming faster and easier, leading to a moderate amount of labor and more agricultural growth. Robotics innovations towards automatic watering, robotic harvesters, and seeding robots are developed to perform farmer's mundane tasks addressing major issues like labor shortage and rising global population (Kanjilal et al. 2014). The integration of these technologies with the farm environment can provide safety, convenience, quality, and energy efficiency benefits. **Driverless tractors** use mobile on-the-go sensor platforms with a global positioning system (GPS) and radar to accurately and quickly sample and characterize soil properties in the field (Adamchuk et al. 2004). This is used in soil management practices to collect soil data for VFR management. **Drones technology** has opened a plethora of unprecedented data opportunities towards collecting data and information for entire fields. Drone technology can capture high-quality imaging that are processed by machine learning and computer vision algorithms. These can be used to monitor crops, scan fields, identify crops and their health and ripeness, provide real-time estimates of crops' needs for water, fertilizer, or pesticides, and collect necessary agricultural data (Puri et al. 2017). **Satellites** and drone images are

Table 29.2 Summary of artificial intelligence technologies used in agriculture

Type of technology	Functions/company	References
Drones	• Field data collection/SkySquirrel technologies, Sensurion, PrecisionHawk, GeoVisual	CBINSIGHTS (2017)
Robotics	• Farm automation for watering, harvesting, and seeding/ Harvest CROO robotics, Clearpath robotics, and abundant robotics • Driverless tractors for soil sampling and analysis/Case IH, New Holland, Resson, Farmbot, and Blue River Technology	CBINSIGHTS (2017)
Satellite imaging	• Crop health monitoring/FarmShots, OmniEarth, Orbital Insight, Descartes Labs • Predictive analytics / aWhere, ec2ec, and optimal	CBINSIGHTS (2017)

processed and analyzed using machine learning algorithms for crop health monitoring and predictive analytics. The algorithms can be utilized to classify soil data, detect diseases, pests, and plant nutrients need in farms. Predictive analytics uses machine learning models with satellites to predict weather conditions like wind speed, temperature, precipitation, and solar radiation. All are conditions that affect crop productivity (Zhang and Kovacs 2012).

29.5 Global Implication

Food demand is expected to increase anywhere between 59% and 98% by 2050 (Valin et al. 2014), which will have a significant effect on food security. This and other trends including climate change and urbanization make this issue more challenging. To reverse this situation, an enhanced application of agricultural technologies in research is required.

According to the Food and Agriculture Organization of the United Nations, from the 570 million global farms, 87% of them are operated by smallholder farms (Lowder et al. 2016). More than 80% of the food is grown on such farms for human consumption and livestock (Graeub et al. 2016). In China, the Ministry of Science and Technology planned the National Agricultural Science and Technology Project that plans to supply food to 1.6 billion people by the mid-twenty-first century by supporting research on agriculture science and technology such as implementing precision agricultural practices. (Maohua 2001). Precision agriculture technologies are believed to create less adverse environmental consequences by targeting inputs such as chemicals and fertilizers where needed and reducing the loss of nutrients from the excess application (Norton and Swinton 2000). A study in Germany conducted by Schmerler and Jurschik (1997) determined their nitrogen fertilizer savings by comparing site-specific fertilization to uniform fertilization on winter wheat and spring barley and found savings of 5–15% along with higher yields. Another study examined VFR technology on corn in Ontario, Canada, and found between 4 and 36% reduced nitrogen leaching (Thrikawala et al. 1999). Similarly, Saleem et al. (2014) also reported a 40% reduction in fertilizer application using VFR technology compared to a standard uniform rate method and also noticed a significant reduction in total phosphorus and inorganic nitrogen losses in surface runoff. They concluded that VFR application could potentially improve crop productivity and reduce production costs (Saleem et al. 2014). Hoskinson et al. (1999) found that application using VFR technology reduced fertilizer cost by 30 to 40% on wheat in Idaho, USA.

Precision agriculture has also shown promising results in pesticide reduction. It is estimated that over 26 million metric tons of pesticides are used worldwide, some that are shown to persist in the environment resulting in contamination in groundwater, surface water, air, and soil (Abit et al. 2018). Using site-specific management to control weeds could reduce herbicide use by up to 100% (Abit et al. 2018). A four-year study on site-specific weed control found reduced herbicide use of maize, sugar beets, and wheat in Germany (Gerhards II 1999). Timmermann et al. (2003) also conducted a four-year experiment in five fields of wheat, barley, sugar beet, and corn (in Bonn Germany), and found an overall reduction of insecticide savings by 54%. They also noticed a decrease in environmental damage, due to less water contamination from herbicides (Timmermann et al. 2003). Abit et al. (2018) also reported similar studies in site-specific weed control, which allowed herbicide savings of up to 20–44%. Also, precision agriculture has shown some promising results for water management. About 40% of the world's total food is cropped on irrigated lands, and in the USA alone about 80% of the nation's consumptive water is used for irrigated agriculture (Abit et al. 2018). Variable rate irrigation (VRI) is the site-specific management of water where individual parts of a field receive the appropriate amount to overcome water stress (Abit et al. 2018). Studies have shown that implementing VRI systems on agricultural land may reduce water use by 8–20% (Sadler et al. 2005). Furthermore, reducing water use can also reduce energy requirements by less pumping and therefore reduction in energy-related CO_2 emissions (Abit et al. 2018). For example, Hedley et al. (2010) found energy savings of 23–67 CO_2-eq ha^{-1} per yr. in dairy pasture, corn, and potato fields.

Adopting precision agriculture technologies depend upon many factors such as farm size and condition, affordability and expected profit from the technology, skill and knowledge of farmer, family structure and government policies. Further, the adaptation level varies with countries and their geographic regions (Say et al. 2018). The GDP of developing nations largely depend upon their agricultural sector (Jaiswal et al. 2019) and thus provide a great challenge to implement PA in these parts of the world. The yield monitoring and variable rate (irrigation and fertilizers) were most used method across developing nations in recent years. The auto guidance system for sowing, spraying, and harvesting is slowly getting popularized across Argentina, Brazil, India, South Africa, Turkey, and other developing nations. In summary, agricultural sensors and technologies provide significant potential for crop management and provide environmental benefits such as a decrease of greenhouse gas emissions and pollution caused by fertilizers and pesticides as well as water and energy reduction. Ensuring worldwide food security lies in scientific knowledge and technology. Developing agriculture precision techniques will help lead the way into modern agriculture practices, which will take on challenges such as food security worldwide.

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