Vol. 15, No. 2, pp. 181-202 (2015)
Journal of Agricultural Physics
ISSN 0973-032X
http://www.agrophysics.in

Review Article

Sensor System Technology for Soil Parameter Sensing in Precision Agriculture: A Review

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ABSTRACT

In recent times, online soil parameter measurement is extremely essential for site-specific applications using different controlled inputs in the agriculture farm areas. Especially for smart agriculture, online soil data acquisition, measurement and data processing are highly encouraging. As of now, research papers published are of traditional types and provide much detail about theoretical and laboratory experiments on various contact as well as non-contact sensing methodologies. But these literatures don‘t specify clear-cut applications and usefulness of specifications, particularly for soil parameter sensing in agriculture. In this paper, a detailed literature study of sensor system technologies on soil parameter sensing methodology as well as its implications and usefulness for precision agriculture have been discussed. Unique categorizations of sensing technologies have been carried out in this work with their potentials and limitations and soil parameter sensing methodology for agriculture. Six subcategories can be identified, which plays key roles. These are optical soil sensing, conductivity and permittivity type soil sensing, radiometry type soil sensing, strength based sensing, electrochemical sensing and lab-on-a-chip based soil sensing techniques. Finally, a comprehensive review of performance based comparative analysis is accomplished on different soil parameter sensors for the implementation of precision agriculture.

Key words: Precision Agriculture (PA), soil sensors, soil parameters.

Introduction

Sensor based soil analysis provides many advantages over conventional laboratory methods such as increased efficiency, collection of dense datasets which is helpful for better analysis, on-demand analysis and construction of agricultural prescription maps. Adamchuk *et al.* (2004) provided a comprehensive review of technologies used only for direct measurement of soil properties. This paper attempts to link between the physical principles of sensing methods and measurement of a soil property. In similar context, many researchers have evaluated sensing technologies for on-line detection of soil macronutrients e.g, nitrogen (N), phosphorus (P) and potassium (K), whereas some of them reviewed the sensing technologies for precision crop production which emphasis on crop and canopy mapping. The sensor based agriculture procedure plays a vital role in the implementation of precision agriculture, which is accomplished by accumulating real-time data on weather, quality of air, soil parameters, crop maturity, equipment and labor availability. Typically, agriculture can be used by accomplishing tasks

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like planting or harvesting against a predetermined schedule. But by utilizing precision agriculture, many predictions are possible that may minimize the planting, fertilizing and harvesting cost through enhanced efficiency all of which increase profits by conserving environment with all the benefit of the farmers. Precision agriculture is usually an environmentally friendly strategy, through which farmers can adjust the employment of inputs to reply to variable soil and crop conditions in a field. Using precision agriculture along with the involvement of ICT (Information and Communication Technology), data collection, processing and analysis can be performed in a control center, which can help farmers to look at the finest decisions for planting, fertilizing and harvesting crops. To accomplish this, new soil sensors and sensing mechanisms should be developed to characterize the soil permitting efficient site-specific soil management. The sensor based soil analysis provides several features over conventional laboratory methods as well as increased efficiency, number of dense datasets that would be ideal for better analysis, on-demand analysis and construction of prescription maps. This paper tries to link the physical principles of sensing methods and measurement of soil properties. Potentials and limitations of different sensing technologies are also discussed. Relationship between soil information collected using the sensors for site-specific applications of inputs are discussed, along with the most accurate method to measure soil parameters for implementation in precision agriculture. Finally a crop-wise soil nutrient requirement along with best suitable soil parameter sensing techniques to accomplish ICT based approach in precision agriculture is discussed.

Sensors for soil analysis in precision agriculture

The soil parameter measuring sensors can be grouped in seven major classes based on their operation and design concepts viz., electrical and electromagnetic, radiometric and optical, acoustic, mechanical, electrochemical and pneumatic soil sensors (Adamchuk *et al.*, 2004). The performance of these sensors varies due to different soil types, parent materials, soil and environmental factors like water content, soil temperature and environmental temperature, humidity, organic matter, topography, soil color. In many articles, following six distinct categories are suggested for soil parameter measurement methodologies. Soil parameter sensing using 1. optical principle (e.g. Spectroscopy); 2. electrical conductivity, resistivity and permittivity ([e.g. EC, TDR, FDR probe); 3. passive radiometry principle (e.g. Microwave and gamma ray); 4. strength based sensing (e.g. DST and TST); 5. electrochemical (e.g. ISE and ISFET); and 6. lab-on-a-chip methodology (Fig. 1).

The performance of all of the above sensors differs caused by different soil types, parent materials, soil and environmental factors like water content, soil temperature and environmental temperature, humidity, organic matter, topography, soil colour.

Sensors using optical principle

These sensors operate on the principle of acquiring reflected energy spectrum from soil samples. To generate a spectrum, radiation containing relevant frequencies in a particular range is directed to the sample. Depending on the constituents present in the soil, the radiation causes individual molecular bonds to vibrate, either by bending or stretching. These vibrations lead to absorption of light, to various degrees, with a specific energy quantum corresponding to the difference between two energy levels. As the energy quantum is directly related to frequency, the resulting absorption spectrum produces a characteristic shape that can be used for analytical purposes. In the visible range (400–780 nm), absorption bands related to soil colour are due to electron excitations, which assist in measurement of soil organic matter (SOM) and moisture (MC) content. However, in the NIR range (vis-NIR range is around 800-2500 nm), the overtones of OH and overtones and/or combinations of C-H + C-H, C-H + C-C, OH+ minerals, and N-H are important for the detection of SOM, MC, clay

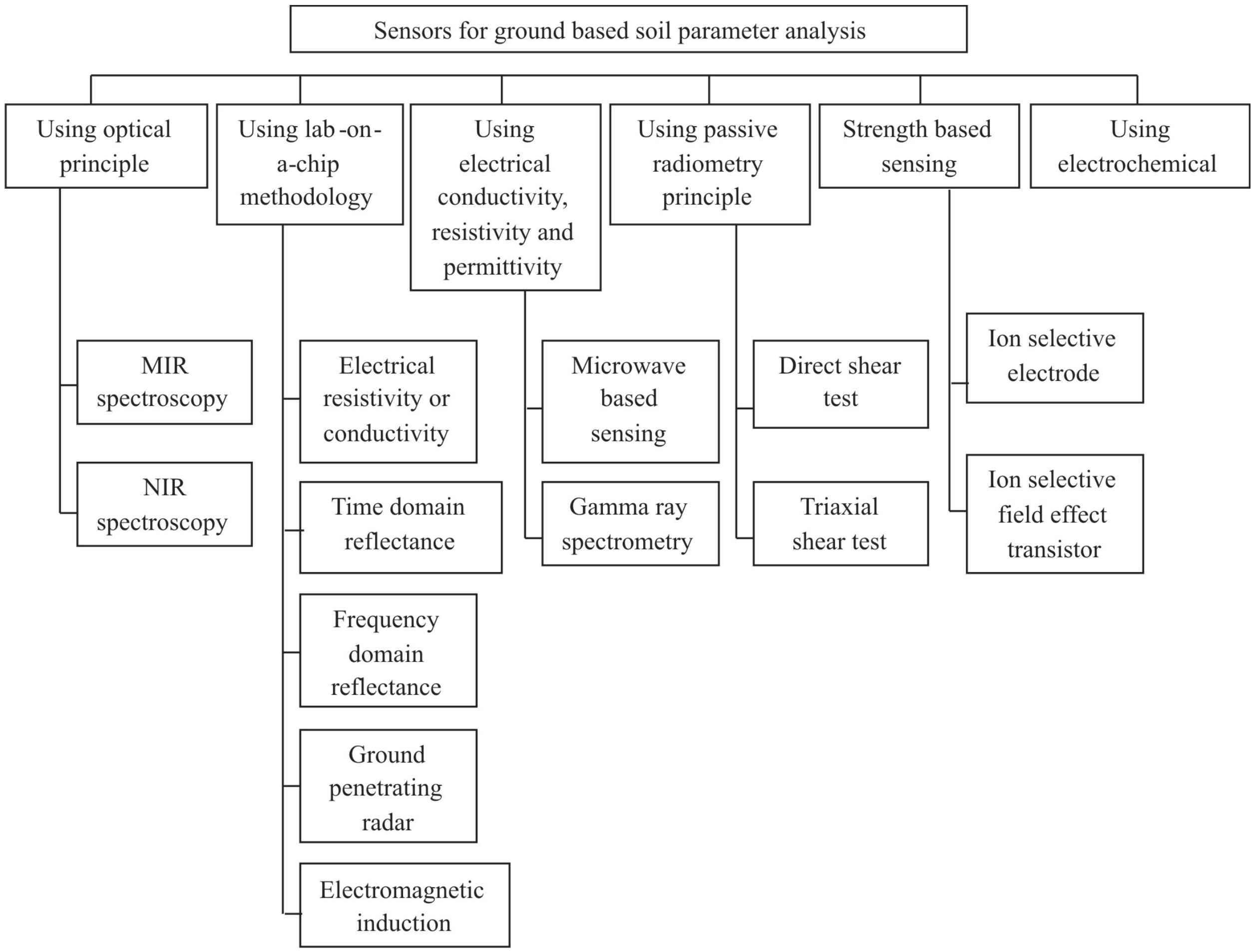

Fig. 1. Classification hierarchy of different soil sensors along with the subcategories

minerals, and nitrogen (Adamchuk *et al.*, 2004). Table 1 demonstrates a comprehensive account on the measurements of soil parameters using NIR spectroscopy in laboratory condition. The items studied with the measurement of soil parameters using NIR spectroscopy during *in-situ* condition is shown in Table 2. *In-situ* sensing devices are in contact with the object. A comparative study on MIR spectroscopy for measurement of soil parameters is given in table 3, and the measurement of soil parameters using NIR spectroscopy in online (Continuous sensing and sensing device can be mobile) condition is described in Table 4.

Xiaofei (2014) have developed a NIR-based portable detector of soil total N content that measures spectral data at 940, 1050, 1100, 1200, 1300, 1450, and 1550 nm. In this work, soil samples were collected from a farm in Beijing, China, and scanned using the detector to obtain their absorbance data under varying soil moisture and particle size. The detector used here is an InGaAs LED lamp house as its light source and consisted of an optical unit and a control unit. The absorbance correction and mixed calibration set method were proposed to correct the original spectral data and to eliminate the interference of soil moisture and particle size, respectively. An estimation model of soil total N content was established based on the corrected absorbance data at six wavelengths (940, 1050, 1100, 1200, 1300, and 1550 nm) using an algorithm of the back propagation neural network. These methods could efficiently eliminate the interference of soil moisture and particle size on predicting soil total N content. In a similar context, Horta *et al.* (2015)

Table 1. Summary of NIR spectroscopy measurement accuracy of soil parameters by laboratory visible and near infrared (vis–NIR) spectroscopy techniques

References	Soil properties	R^2	RPD	RMSEP	Reason for better accuracy	Accuracy
Reeves *et al* (2001); Slaughter *et al* (2001); Conforti (2015); Gomez *et al.* (2013); ChacónIznaga *et al.* (2014)	Organic Carbon	0.46–0.98	1.30–9.70	0.06–2.90 (%)	R2> 0.90, RPD > 3 and RMSEP < 7%	Excellent
Udelhoven *et al.* (2003), Krishnan *et al.* (1980), Cohen *et al.* (2005)	C_{inorg}	0.53–0.96	4.01–4.99	0.17–0.56 (%)	R2> 0.90, RPD > 3 and RMSEP < 7%	Excellent
Couteaux *et al.* (2003), Dalal *et al.* (1986), Guerrero *et al.* (2010), Vagen *et al.* (2006)	Total Nitrogen	0.04–0.99	0.34–6.80	0.0004–0.08 (%)	R2> 0.90, RPD > 3 and RMSEP < 7%	Excellent
Waiser *et al.* (2007), Ben-Dor and Banin (1995), Awiti *et al.* (2008), Chang *et al.* (2001)	Clay content	0.15–0.91	1.70–3.10	0.79–6.10 (%)	R2> 0.90, RPD > 3 and RMSEP < 7%	Excellent
Chang *et al.* (2001), Chang *et al.* (2005), Dalal and Henry (1986), Mouazen *et al.* (2006b), Slaughter (2001)	MC	0.84–0.98	2.36–5.26	0.50–4.88 (%)	R2> 0.90, RPD < 3 and RMSEP < 7%	Excellent
Cohen *et al.* (2005), Mouazen *et al.* (2006a), Shepherd and Walsh (2002), Stenberg [101], Conforti *et al.* (2015)	pH	0.50-0.97	0.57-2.39	0.04-1.43 (%)	R2> 0.90, RPD < 3 and RMSEP < 7%	Between Good and approximately quantitative prediction
Cohen *et al.* (2005), Mouazen *et al.* (2006a), Cozzolino*et al.* (2003), Zornoza *et al.* (2008)	Ca	0.07–0.95	0.60–2.75	0.66–52.90 (cmol kg^{-1})	R2> 0.90, RPD < 3 and RMSEP is more	Good
Awiti *et al.* (2008), Ben-Dor and Banin (1995), Chang *et al.* (2001), Mouazen *et al.* (2006a), Waiser *et al.* (2007), Lu *et al.* (2013), Conforti *et al.* (2015)	CEC	0.13–0.90	0.55–2.51	1.22–10.43 (cmol kg^{-1})	R^2 = 0.90, RPD < 3 and RMSEP is more	Good
Cozzolino *et al.* (2003), Groenigen *et al.* (2003), Udelhoven *et al.* (2003), Wetterlind *et al.* (2010)	Mg	0.53–0.91	0.48–2.54	0.03–38.36 (cmol kg^{-1})	R2≈ 0.90, RPD < 3 and RMSEP is more	Good

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References	Soil properties	R^2	RPD	RMSEP	Reason for better accuracy	Accuracy
Awiti *et al.* (2008), Ben-Dor and Banin (1995), Chang *et al.* (2001), Cozzolinoand Moron (2003)	Sand content	0.59–0.92	0.87–3.40	1.91–11.93 (%)	R2 varies rapidly, RPD is more than 2 and RMSEP > 7%	Approxi-mately quantitative
Awiti *et al.* (2008), Ben-Dor and Banin (1995), Chang *et al.* (2001), Cozzolino *et al.* (2003)	Silt content	0.41–0.84	1.09–3.07	1.79–9.51 (%)	R2< 0.90, RPD is nearly equal to 3 and RMSEP > 7%	Approxi-mately quantitative
Bogrekci and Lee (2005), Mouazen *et al.* (2010), Wetterlind *et al.* (101), Conforti *et al.* (2015), ChacónIznaga *et al.* (2014)	Total P	0.01–0.93	0.10–3.80	1.35–24.6 (100 mg kg^{-1})	R^2 varies rapidly, RPD is nearly 3 and RMSEP is more	Approxi-mately quantitative
Cozzolino and Moron (2003), Groenigen *et al.* (2003), Mouazen *et al.* (2006b), ChacónIznaga *et al.* (2014)	K	0.11–0.85	0.52–5.1	0.05–1.84 (cmol kg^{-1})	R^2 is less, RPD > 3 and RMSEP is quite ok	Approxi-mately quantitative
Chang *et al.* (2001), Mouazen *et al.* (2006a) Mouazen *et al.* (2010)					R^2 is very less, RPD is less and RMSEP is more	Distin-guishes between high and low

- Values of R^2, RMSEP, and RPD are based on the reference papers and those are not listed in this table.
- Classification of accuracy into excellent, good, approximately quantitative, distinguishes between high and low, not usable results are based on the maximum number of publications confirming an accurate category for a soil property. R^2, coefficient of determination; RMSEP, root mean square error of prediction; RPD, residual prediction deviation (SD/RMSEP); Excellent (RPD > 3.0 and R2> 0.90); Good (RPD = 2.5–3.0 and R2 = 0.82–0.90); Approximately quantitative (RPD = 2.0–2.5 and R2 = 0.66–0.81); Distinguishes between high and low (RPD = 1.5–2.0 and R2 = 0.50–0.65); and Not usable (RPD < 1.5 and R2< 0.5) (Chang *et al.*., 2001).
- The above data is collected from different research articles mentioned in the reference.

Table 2. Summary of NIR spectroscopy measurement accuracy of soil parameters by in situ visible and near infrared (vis–NIR) spectroscopy techniques

References	Soil properties	R^2	RMSEP	RPD	Accuracy
Fystro (2002), Udelhoven *et al.* (2003), Mouazen *et al.* (2010)	Organic Carbon	0.51–0.96	0.29–1.40 (%)	1.30–4.95	Between Good and approximately quantitative prediction
Chang *et al.* (2005), Fystro (2002), Mouazen *et al.* (2006a)	Total Nitrogen content	0.80–0.93	0.02–0.06 (%)	2.1–3.88	Good
Chang *et al.* (2005), Waiser *et al.* (2007), Bricklemyer and Brown (2010)	Clay content	0.76–0.83	5.25–6.1 (%)	1.45–2.36	Approximately quantitative

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References	Soil properties	R^2	RMSEP	RPD	Accuracy
Ben-Dor *et al.* (2008), Ben-Dor and Banin (1995), Slaughter *et al.* (2001)	MC	0.40–0.98	1.0–6.4 (%)	1.98–5.74	Excellent
Chang *et al.* (2005), Mouazen *et al.* (2006a), Mouazen *et al.* (2006b), Mouazen *et al.* (2007), Mouazen *et al.* (2010)	pH	0.66–0.74	0.39–0.72	1.55–2.14	Approximately quantitative
Chang *et al.* (2005), Udelhoven *et al.* (2003), Mouazen *et al.* (2006a), Mouazen *et al.* (2007), Mouazen *et al.* (2006a)	Ca	0.77–0.86	1.63–1.68 (cmol kg^{-1})	2.10–2.19	Approximately quantitative
Chang *et al.* (2005), Mouazen *et al.* (2006a), Mouazen *et al.* (2006b), Mouazen *et al.* (2007)	CEC	0.78–0.89	1.77–3.57 (cmol kg^{-1})	2.31–2.33	Approximately quantitative
Chang *et al.* (2005), Udelhoven *et al.* (2003), Mouazen *et al.* (2006a), Mouazen *et al.* (2006b), Mouazen *et al.* (2007)	Mg	0.49–0.84	0.30–0.30 (cmol kg^{-1})	1.39–1.56	Distinguish between high and low
Chang *et al.* (2005)	Sand content	0.49	12.44 (%)	0.87	Not usable results
Chang *et al.* (2005)	Silt content	0.13	6.04 (%)	0.80	Approximately quantitative
Bogrekci and Lee (2005), Maleki *et al.* (2006), Mouazen *et al.* (2007)	Total P	0.09–0.80	2.3–25 (mg 100 g^{-1})	1.45–2.24	Approximately quantitative
Udelhoven *et al.* (2003), Zornoza *et al.* (2008), Al-Asadi *et al.* (2014), Wetterlind *et al.* (2010)	K	0.33–0.87	0.21–3.90 (cmolc/kg^{-1})	1.21–2.80	Distinguishes between high and low
Mouazen *et al.* (2006a), Mouazen *et al.* (2006b), Mouazen *et al.* (2007), Mouazen *et al.* (2010), Zornoza *et al.* (2008)	Na	0.13–0.77	0.025–0.129 (cmolc/kg^{-1})	1.29–1.98	Not usable

- Values of R^2, RMSEP, and RPD are based on the reference papers and those are not listed in this table.
- Classification of accuracy into excellent, good, approximately quantitative, distinguishes between high and low, not usable results are based on the maximum number of publications confirming an accurate category for a soil property. R^2, coefficient of determination; RMSEP, root mean square error of prediction; RPD, residual prediction deviation (SD/RMSEP); Excellent, Good, Approximately quantitative, Distinguishes between high and low, and Not usable categories are as given in Table 1 (Chang *et al.*., 2001).
- The above data is collected from different research articles mentioned in the reference.

Table 3. Summary of MIR spectroscopy measurement accuracy of soil parameter analysis

Soil properties	R^2	RMSEP	References	Accuracy
Organic Carbon	0.92–0.99	0.32–2.42 (%)	McCarty *et al.* (2002), Madari *et al.* (2006), Bornemann *et al.* (2008), Reeves (2010)	Excellent
Total Nitrogen	0.86–0.99	0.023 (%)	Janik *et al.* (1998), Du and Zhou (2009), Minasny *et al.* (2009), Reeves *et al.* (2001)	Excellent
Clay content	0.67–0.99	1.54–8 (%)	Minasny *et al.* (2009), Madari *et al.* (2006), Taylor *et al.* (2006)	Excellent
pH	0.56–0.90	0.16–0.45	Janik *et al.* (1998), Reeves *et al.* (2001), Minasny *et al.* (2009), Taylor *et al.* (2006)	Good
Ca	0.38–0.96	18.7 (cmol/kg)	Janik *et al.* (1998), Minasny *et al.* (2009), Taylor *et al.* (2006)	Excellent
CEC	0.34–0.92	4.6 (cmol/kg)	Janik *et al.* (1998), Minasny *et al.* (2009), Taylor *et al.* (2006)	Good
Mg	0.76–0.94	18 (cmol/kg)	Janik *et al.* (1998), Minasny *et al.* (2009)	Excellent
Sand content	0.74–0.97	2.47–7.7 (%)	Janik *et al.* (1998),Madari *et al.* (2006), Taylor *et al.* (2006)	Excellent
Silt content	0.49–0.84	2.17–8.7 (%)	Janik *et al.* (1998), Madari *et al.* (2006)	Good
Total P	0.07–0.94	6.2–29.3 (mg 100 g-1)	Janik *et al.* (1998), Du and Zhou (2009), Reeves *et al.* (2001), Taylor *et al.* (2006)	Approximately quantitative
K	0.33–0.88	1.92–38.09 (mg/kg)	Janik *et al.* (1998)	Not usable
Na	0.31–0.72	0.6–1.1 (mg/kg)	Janik *et al.* (1998)	Not usable

Table 4. Summary of measurement accuracy of soil properties by on-line visible and near infrared (vis–NIR) spectroscopy

Spectrum type	Spectral range (nm)	Results	References	Accuracy
Single wavelength	660	SOM (R^2=0.70)	Shonk *et al.* (1991)	Average
vis–NIR spectrum	300–1700	MC, pH, SOM, and NO_3–N (R^2=0.68, 0.61, 0.64, and 0.19, respectively)	Shonk *et al.* (1991), Hummel *et al.* (2001)	Average
NIR spectrum	1603–2598	SOM and MC (R^2=0.79, 0.89, RPD= 2.17 and 2.86, respectively)	Hummel *et al.* (2001)	Good
NIR spectrum	900–1700	MC, TC, TN, pH (R^2=0.82, 0.87, 0.86, and 0.72, respectively)	Christy (2008)	Excellent
vis–NIR spectrum	300–1700	Similarity of OC, TC, MC, pH, P_{avl}, and P_{ext} maps	Mouazen *et al.* (2007)	Excellent
vis–NIR spectrum	350–2224	OC (SEP=0.34) and clay content (RPD=1.4, SEP=6.94%)	Bricklemyer and Brown (2010)	Average

have reviewed potentially cost-effective methods for measurement, sampling design, and assessment. Current tiered investigation approaches and sampling strategies can be improved by using new technologies such as proximal sensing. Design of sampling can be aided by on-the-go proximal soil sensing; and expedited by subsequent adaptive spatially optimal sampling and prediction procedures enabled by field spectroscopic methods and advanced geostatistics. Table 3 summarizes the need of soil parameter measurement with MIR spectroscopy. The table proves that OC (Organic Components) could possibly be measured and analyzed efficiently with MIR, with R^2 around 0.99. Less accurate results can be executed for total or organic N content. MIR enables the determination of soil texture, CEC, microelements that have a first-rate to excellent accuracy with a high quality accuracy of soil pH. Additionally, no list of using MIR for online measurement of soil properties continues to be published to date. A comparative study between NIR spectroscopy (laboratory, in-situ, online) based soil parameter analysis and MIR spectroscopy based soil parameter analysis is given in Table 5.

Table 5. Comparative study between laboratory vis-NIR spectroscopy, in situ vis-NIR spectroscopy and MIR spectroscopy based soil parameter measurement

Soil properties	In situ measurement accuracy (vis-NIR based)	Laboratory measurement accuracy (vis-NIR based)	On-line measurement accuracy (vis-NIR based)	Mid-Infrared (MIR) spectroscopy accuracy
Organic C	Between Good and approximately quantitative	Excellent	Between Good and approximately quantitative	Excellent
Total Nitrogen	Good	Excellent	Good	Excellent
Clay content	Approximately quantitative	Excellent	Between Good and approximately quantitative prediction	Excellent
MC	Excellent	Excellent	Between Good and approximately quantitative	-
pH	Approximately quantitative	Between Good and approximately quantitative	Between Good and approximately quantitative	Good
Ca	Approximately quantitative	Good	Between Good and approximately quantitative	Excellent
CEC	Approximately quantitative	Good	Good	Good
Mg	Distinguish between high and low	Good	Good	Excellent
Sand content	Not usable results	Approximately quantitative	Approximately quantitative	Excellent
Silt content	Approximately quantitative	Approximately quantitative	Approximately quantitative	Good
Total P	Approximately quantitative	Approximately quantitative	Approximately quantitative	Approximately quantitative
K	Distinguish between high and low	Distinguish between high and low	Distinguish between high and low	Not usable
Na	Not usable	Not usable	Not usable	Not usable

Sensors using electrical conductivity, resistivity and permittivity

There are numerous principles on this category of sensors to acquire soil parameters directly or indirectly by utilizing electrical conductivity, resistivity and permittivity principles. The sensors participate in these kinds are derived from below mentioned measurement procedures:

1. Electrical Conductivity (EC) based soil sensor
2. Time Domain Reflectance (TDR) based soil sensor
3. Frequency Domain Reflectance (FDR) based soil sensor
4. Ground Penetrating Radar (GPR) based soil sensor
5. Electromagnetic Induction (EMI) based soil sensor
6. Coaxial Impedance Dielectric Reflectometry Sensors

Electrical Conductivity (EC) based soil sensor

Electrical conductivity (EC) of soil is a way of measuring the level of salt content in the soil (salinity level of the soil). This is also an important parameter for measuring soil health. This has effects on crop yields, crop suitability, plant nutrient availability as well as activity of soil microorganisms. These have effects on key soil processes, which include emission of greenhouse gases such as nitrogen oxides, methane, and carbon dioxide. More amount of salt content may slow the plant growth process by influencing the soil-water balance. EC sensing can also be done using contact-based methods, which is based on the flow of current towards the soil with the contact electrodes and also the difference in voltage used to calibrate the conductivity value. Even though EC does not offer a direct measurement of salt compounds, it can also be correlated with the concentrations of nitrates, potassium, sodium, chloride, sulfate, and ammonia. For several non-saline soils, determination of EC can be a convenient as well as an affordable way to estimate the amount of N content available for better plant growth. That is certainly a negative aspect of accomplishing this, which might cause error during the measurement. Amakor *et al.* (2014) compared four saturated paste-related methods of estimating salinity with respect to specific soil management goals. Comparison of the methods across six soil depths and three textural groups demonstrates that estimates of salinity are significantly influenced by the method, depth of sampling, and soil texture. Whereas electrical conductivity in saturated paste extracts (ECe) and direct measurement of EC in soil pastes (ECcup) estimates differed significantly from each other and from those of the other methods, EC based on electromagnetic induction (ECH25ECe) and EC in diluted saturated paste extracts (ECed) estimates were similar. In addition, high correlations between estimates of salinity by ECH25ECe and ECe indicate their similarity and suggest the suitability of the ECH25ECe method as a reference parameter for monitoring salinity. Márquez Molina *et al.* (2014) have identified the spatial distribution of bulk electrical conductivity (ECb) of non-saturated variability association with variability of nitrates and bio available phosphorous, water content, topography and electrical conductivity (EC) of saturated paste extract. The analysis of the impact was done at two pens with different time of confinement of the animals (Pen1 and Pen 2, with 16 months and 7 years of animal occupation, respectively). Some of the key references of measurement methods are indexed in Table 6. An ER type soil probe for direct data acquisition using any DAQ instrument is displayed in Fig. 2.

Time Domain Reflectance (TDR) based soil sensor

The TDR probe is generally employed to characterize and locate faults in metallic cables. This principle may also be used for soil MC measurement with good accuracy. A TDR transmits short rise time pulse throughout the conductor. The resulting reflected pulse that's measured within the output/input towards TDR is plotted just like a function of energy. Because the

Table 6. List of some of the ER or EC probes

References	Sensor model	Specifications	Dimensions	Availability
Caproco Inc.[1]	Electrical Resistance Soil Probe	Element Type Normal Sensitivity, High Sensitivity Interfaces with the Caproco ER Analyzer	Length: 12.0 cm Weight: 10 g	Commercially available
Campbell Sci Inc.[1]	229-L Water Matric Potential Sensor 253-L Soil Matric Potential Block	Measurement Range: -10 kPa to -2500 kPa Resolution: ~1 kPa at matric potentials < -100 kPa	Diameter: 1.5 cm (0.6 in.) Length: 6.0 cm (2.4 in.) Weight: 10 g (0.35 oz) Cable Weight: ~23 g m^{-1})	Commercially available
Vegetronix Inc.[3]	VH400 Soil Moisture Sensor Probes	Power consumption: < 7mA, Supply Voltage: 3.3V to 20 VDC, Power on to Output stable:400 ms, Output Impedance: 10K ohms, Operational Temperature: -40ºC to 85ºC, Accuracy at 25°C: 2% Output: 0 to 3V related to moisture content, Shell Color: Red	Width: 7.09mm Length: 93.76mm	Commercially available
Murata *et al.* (2014)	Toyohashi University of Technology, Toyohashi, Aichi 441-8580, Japan	Temperature range: 15 °C to 33 °C Error: +5% to –10% Calibration: R2=0.9965 AC operating frequency: 10KHz	5.6 cm in length 0.8 cm wide 1.3 cm height	Developed by Toyohashi University

[1]Caproco specializes in the custom design, fabrication and servicing of Internal Corrosion Monitoring and Control Systems. http://www.caproco.com/indexnoflash.htm

[2]Measurement & Control Products for Long-term Monitoring.https://www.campbellsci.com

[3]Vegetronix specializes in innovative agricultural electronic systems, which include low cost soil moisture sensor probes, data acquisition systems, irrigation controllers, grow lights and controller, and water saving flow control devices, and SDI-12 protocol translators. http://www.vegetronix.com

Fig. 2. Soil Electrical Resistivity (ER) or Electrical Conductivity (EC) probe near a plant for installation

speed of signal propagation is actually comparatively constant for the transmission medium and time is frequently read as a function of the cable's length. If two metal rods are set up soil, the reflected pulse is generally a function in the soil dielectric constant which is a function of the soil moisture content. Increased water content slows down the pulse reflectance time. The TDR is actually insensitive to salinity provided that the salinity level is low enough, even when a good waveform is returned. As the salinity levels increase, the signal reflection from TDR ends of the rods inside TDR probe is lost (amplitude is

Fig. 3. Time Domain Reflectance (TDR) probe for soil MC measurement

less). Such things happen because of conduction around the signal when using the saline soil pertaining to the rods. The amount of conduction increases because the soil wets.

Arsoy *et al*. (2013) has focused on development of a methodology using Artificial Neural Network (ANN) for enhanced determination of soil water content based on dielectric permittivity measurement via TDR. Within this study, the dielectric permittivity obtained with the TDR measurement, the bulk dry density, the specific gravity and the fines content were selected as the input parameters for an ANN model. The performance of the ANN model has been compared with some of the existing calibration models. The average RMSE of the ANN-based approach was 0.009 and 0.007 $cm^3\ cm^{-3}$ with 8 and 11 nodes, respectively, while the same value was in a range of 0.019 to 0.033 $cm^3\ cm^{-3}$ for the existing calibration models and 0.015 to 0.018 $cm^3\ cm^{-3}$ for the best-fitted calibration models when all soil classes considered together. Figure 3 shows a TDR probe is installed in a land and connection cable is used for data acquisition. Some of the key references of measurement methods are indexed in Table 7.

Frequency Domain Reflectance (FDR) based soil sensor

There are many soil probes available today who uses the Frequency Domain Reflectometry (FDR) methodology. This kind of measurement uses an oscillator to propagate an electromagnetic signal via a metal electrode or any other wave guide. Here the difference between output wave and the return wave frequency is measured to analyze soil moisture. The FDR probes are accurate but must be calibrated properly to calculate soil moisture content. It also provides a quicker response time as compared to TDR probes and can be linked into a standard data logger to gather readings. The soil moisture content incorporates a linear relationship with the logged fringe-capacitance. Al-Asadi and Mouazen (2014) have collected 1013 soil samples from England and Wales, from 32 arable and grassland fields with different soil types were measured with a vis-NIR spectrophotometer (LabSpec®Pro Near Infrared Analyzer, Analytical Spectral Devices, Inc., USA) after in situ measurement with a ThetaProbe FDR (Delta-T Device Ltd.). Two calibration methods of the vis-NIRS were tested, namely, partial least squares regression (PLSR) and artificial neural network (ANN). The ThetaProbe calibration was performed with traditional methods and ANN. ANN analyses were based on a single-variable input or multiple-variable input (data fusion). During ANN – data fusion analysis, vis-NIRS spectra and ThetaProbe output voltage (V) were fused in one matrix with or without laboratory measured texture fractions and organic matter content (OM). A detailed comparison between TDR and FDR probe is described in table 8. A general construction of FDR is shown in Fig. 4.

Ground Penetrating Radar (GPR) based soil sensor

The GPR is a geophysical technique which utilizes electromagnetic energy with central frequencies generally between 50 and 1200 MHz to generate the subsurface soil parameter map. The GPR ground wave data can be used for accurate estimation of soil water content of the shallow soil at a finer resolution. The transmitted electromagnetic ground wave energy passes directly with the soil by the receiving antenna, which has a velocity dependant on the dielectric permittivity in the soil. Electromagnetic energy

Table 7. Some of the available TDR probe based soil sensors

References	Sensor model	Specifications	Dimensions
IMKO Micromodultechnik GmbH [1]	HD2 meter and PICO64 probe	Power supply: 7V..24V-DC Power consumption: 100mA @ 12V/DC during 2..3sec. of measuring Moisture measuring range: 0..100% volumetric water content	Size: 155 x Ø63mm Rod length: standard: 160mm Rod diameter: 6mm
Spectrum Technologies Inc.[2]	FieldScout TDR 300 Soil Moisture Meter	Measurement Units: Percent volumetric water content Resolution: 0.1% volumetric water content Accuracy: ±3.0% volumetric water content with electrical conductivity < 2 mS/cm Range: 0% to saturation (Saturation typically around 50% volumetric water) Battery/Life: 4 AAA alkaline batteries; approximately 12-month battery life Data Logger: 3,250 measurements without GPS; 1,350 with GPS/DGPS	Two 1.5 inch (3.8 cm) Rods Two 3 inch (7.5 cm) Rods
Campbell Sci Inc.[3]	TDR100	Pulse generator output: 250 mV into 50Ω Output impedance: 50 Ù ±1% Time response of combined pulse generator and sampling circuit: d” 300 ps Pulse length: 14 ìs Timing resolution: 12.2 ps Waveform sampling: 20 to 2048 waveform values over chosen length	23.6 x 5.9 x 12.6 cm (9.3 x 2.3 x 5.0 in)

[1] IMKO Micromodultechnik GmbH offers high-tech moisture measurement products as reliable, high-quality, state-of-the-art alternatives by offering high-precision readings, high reliability, ease of use and rapid results online and offline. http://imko.de/en/products

[2] Spectrum Technologies manufactures and distributes affordable, leading-edge measurement information technology to the agricultural market throughout the world. Founded in 1987 by Mike Thurow, Spectrum Technologies is headquartered in Aurora, IL. http://www.specmeters.com/

[3]Measurement & Control Products for Long-term Monitoring.https://www.campbellsci.com

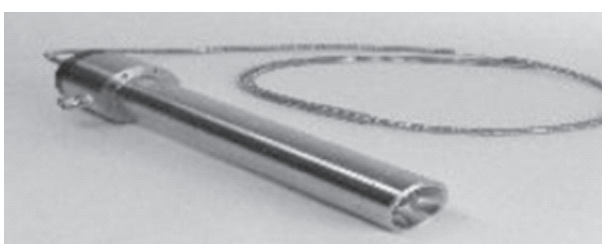

Fig. 4. Frequency domain reflectance (FDR) probe for soil MC measurement

propagates from a transmitting antenna, and is also modified by subsurface contrasts in dielectric permittivity (k) and magnetic permeability (m). As most of the soil has negligible variation in magnetic permeability, k provides the most important aspect of the recorded GPR response. A number of the electromagnetic energy passes from a transmitting to receiving antenna with the air, and is known as the airwaves. Area of the transmitted energy, referred to as ground wave, propagates through the soil across the ground-air interaction towards receiving antenna, and section of the transmitted energy is reflected from the subsurface in contrasts to dielectric permittivity.

Tosti *et al.* (2013) has studied different ground-penetrating radar (GPR) methods and techniques used to investigate the clay content in sub-asphalt compacted soils. Experimental layout provided the use of typical road materials, employed for road bearing course construction. Three types of soils classified by the American Association of State Highway and Transportation Officials (AASHTO) as A1, A2, and A3 were used and adequately compacted in electrically and hydraulically isolated test boxes. Percentages of bentonite clay were gradually added, ranging from

Table 8. A Comparative study between TDR and FDR probe for soil moisture content (MC) measurement

Sensor Type	Testing Methodology	R^2	Required Size for good accuracy	References
TDR	Laboratory	0.80-0.99	0.20-0.70m (More than 0.7m provides better accuracy)	Wagner *et al.* (2011), Dalton *et al.* (1984), Heimovaara (1993), Stangl *et al.* (2009), Young *et al.* (1997)
	In-situ	0.84-0.99		Calamita *et al.* (2012), Topp *et al.* (1985), Dasberg and Dalton (1985), Wu *et al.* (1997)
	On-line	0.90-0.9		Thomsen *et al.* (2007), Evett (2003)
FDR	Laboratory	0.90-0.99	Diameter 2 mm, separation distance 13 mm, lengths 1 or 2 or 3 cm.	Jagdhuber *et al.* (2015)
	In-situ	0.90-0.98		Hamed *et al.* (2006)
	On-line	0.90-0.98		Sun *et al.* (2006), Whalley *et al.* (1992)

2% to 25% by weight. Analyses were carried out for each clay content using two different GPR instruments. Benedetto (2010) proposed a new technique that avoids several disadvantages of existing techniques. In this study, ground-coupled Ground Penetrating Radar (GPR) techniques are used for non-destructively monitor the volumetric water content. The signal is processed in the frequency domain; this method is based on Rayleigh scattering according to the Fresnel theory. The scattering produces a non-linear frequency modulation of the electromagnetic signal, where the modulation is a function of the water content. To test the proposed method, five different types of soil were wetted in a laboratory under controlled conditions and the samples were analyzed using GPR. The GPR data were processed in the frequency domain, demonstrating a correlation between the shift of the frequency spectrum of the radar signal and the moisture content.

Electromagnetic Induction (EMI) based soil sensor

Electromagnetic induction (EMI) based conductivity measurement technique is a non-invasive and non-destructive sampling method. No probes are required to use EMI, and measurements can be done quickly and inexpensively. In the EMI sensing approach, a transmitter coil at or above the soil surface is energized through an alternating current, setting up a primary, time-varying flux in soil. This magnetic flux induces small currents from the soil, which generate a secondary magnetic flux. A receiver coil responds to the primary and secondary magnetic fields. By operating at 'low induction numbers', the ratio between the primary and secondary fields become a linear function of conductivity. At field and landscape scales, ECa maps have the potential to provide higher degrees of resolution and better distinction of soil types than soil maps prepared with traditional tools. Saey *et al.* (2015) have evaluated different inversion procedures of EMI data and studied their effectiveness to characterize the depth of the interface between two contrasting soil layers, as well as their respective conductivities. A 1D-laterally constrained inversion procedure was compared with a non-constrained, robust 1D-inversion procedure. Both procedures make use of a low induction number (LIN) -approximated depth response curves and provided similar results, although the calibration with soil data was essential to attribute absolute values of the inverted data. In the similar context, Lardo *et al.* (2012) have observed the relations of the apparent electrical conductivity (ECa) of soil and also measured using a Profiler GSSI EMP-400 with soil abiotic and biotic parameters as volumetric water content, pH, electrical conductivity, coarse elements, density, biomass of different earthworm ecological categories (anecics and endogeics). Trials were carried out in nine commercial vineyards in Languedoc-Roussillon (France) cultivated according to different soil management technologies: grass cover, chemical weeding and tillage. Earthworms were measured. Strong relationships between the abundance and biomass of anecic and endogeic earthworms and ECa values were found, particularly in grass covered and chemically weeded plots. This result is supported by the high determination coefficients found (R^2 from 0.53 to 0.94).

Coaxial Impedance Dielectric Reflectometry (CIDR) Sensors

Soil probes which use the Coaxial Impedance Dielectric Reflectometry technique of soil moisture measurement employ an oscillator to build an electromagnetic signal that is propagated throughout the unit (usually by metal tines/other waveguide) and in the soil. Part of this signal is reflected back by the soil, and the sensor will measure the amplitude of the reflected signal plus the incident signal in volts. Precisely these raw voltages are used in the mathematical numerical solution to Maxwell's equations to first calculate the impedance, then both real and the imaginary dielectric permittivity which is used to accurately estimate soil water content. The Stevens Hydra Probe is the only commercially available sensor to use the Coaxial Impedance Dielectric Reflectometry method along with complex computations in soil measurement, resulting in the Hydra Probe's high measurement accuracy. The soil measurement computations are performed by a microcontroller inside the Hydra Probe, making it easy to use as the probe can output results in standard engineering units.

Soil parameter sensing using the passive radiometry principle

Passive radiometry sensing, is simply regarding the radio-physical techniques ideal for remote observations inside environment. It is usually determined by measurements using the natural radio waves of objects. Mladenova *et al.* (2013) have attempted to provide a more thorough understanding of the fundamental differences between the algorithms and how these differences affect their performance in terms of a range of soil moisture provided. The comparative overview presented in the paper is based on the operating versions of the source codes of the individual algorithms. Analysis has indicated that the differences between algorithms lie in the specific parameterizations and assumptions of each algorithm. The comparative overview of the theoretical basis of the approaches is linked to differences found in the soil moisture retrievals, leading to suggestions for improvements and increased reliability in these algorithms. Gamma-ray spectrometry or radiometry has evolved over several decades and widely used in many agricultural applications line exploration of soil minerals as well as environmental and geological mapping. Escorihuela *et al.* (2010) has analyzed brightness temperature, soil moisture and temperature measurements acquired over a bare soil during the SMOSREX experiment. A more detailed profile of surface soil moisture was obtained with a soil heat and water flows mechanistic model. It was found that (1) the soil moisture sampling depth depends on soil moisture conditions, (2) the effective soil moisture sampling depth is shallower than provided by widely used field moisture sensors, and (3) the soil moisture sampling depth has an impact on the calibration of soil roughness model parameters. In the similar context, Rautiainen *et al.* (2014) has presented a novel algorithm for detecting seasonal soil freezing processes using L-band microwave radiometry. L-band is the optimal choice of frequency for the monitoring of soil freezing, due to the inherent high contrast of the microwave signature between the frozen and thawed states of the soil medium. Dual-polarized observations of L-band brightness temperature at a range of observation angles were collected from tower-based instruments, and evaluated against ancillary information on soil and snow properties over four winter seasons.

Strength based soil parameter sensing

Soil strength always changes with time under the influence of climate changes, soil management and plant growth. Hence the unit of strength is the same as stress (Pa in SI unit system). It is a measure of the soil resistance to deformation by continuous displacement of its individual soil particles. The shear strength parameters of a soil are determined in the lab primarily with two types of tests like DST and TST.

i. Direct Shear Test (DST)

- It is quick and Inexpensive.
- The disadvantage is that it neglects the soil on a specified plane, which is probably not the weakest one.

ii. Triaxial Shear Test (TST)

- Specimens are exposed to (approximately) uniform stresses and strains.
- The overall stress-strain-strength behavior can be examined.
- Various combinations of cell pressure and axial stress can also be employed.

Amšiejus *et al.* (2014) have performed experimental tests by the common type of direct shear apparatus which shows that normal stress on the shear plane of soil sample is not equal to the vertical component of distributed external load applied to the top of soil sample. Performed measurements cleared that only 65–85% of total vertical load is transmitted to the sample shear plane. Thus, determining of the soil shear strength depends on shear apparatus construction, *i.e.* on the actual magnitude of vertical load transmitted to the shear plane. The paper presents an analysis of shear strength parameters of sand determined by two different constructions of direct shear apparatuses with the movable lower shear ring. Cetin and Gökoðlu *et al.* (2013) have discovered that in the consolidated undrained tests, failure occurs at higher levels of strain than previously believed, while in the consolidated drained tests, failure occurs at much lower levels of strain than previously believed.

Soil parameter sensing using electrochemical principle

Routine laboratory analysis of assorted nutrients is time consuming, and it cannot be performed directly in the field. Several electrochemical sensors were developed that can offer quick information regarding nutrient status and pH valuation in the soil. An electrochemical sensor consists of an ion selective membrane, which will selectively respond to the target ion, plus a transducer, that transforms the reactions into detectable electrical signals. Ion Selective Electrode (ISE) and Ion Selective Field Effect Transistor (ISFET) are two types of normally used potentiometric electrochemical sensors for soil nutrient analysis. Birrell and Hummel (2001) have developed an integrated multi-sensor soil analysis system. Ion-selective field effect transistor (ISFET) technology was coupled with flow injection analysis (FIA) to produce a real-time soil analysis system. Testing of the ISFET/ FIA system for soil analysis was carried out in two stages: (1) using manually extracted samples, and (2) the soil to be analyzed was placed in the automated soil extraction system, and the extracted solution fed directly into the FIA system. The sensor was successful in measuring soil nitrates in soil solutions (r^2>0.9). The rapid response of the system allowed a sample to be analyzed in 1.25 s only, which is satisfactory for real-time soil sensing. Lehmann and Grisel (2014) has presented a multisensor probe containing four ISFET (Ion Sensitive Field Effect Transistor) sensing elements aiming at real time monitoring of nutrients in soil. A miniature solid-state reference electrode is integrated with the probe, which renders the probe resistant against prolonged periods of drying. The sensing elements inside the probe are selective towards K^+, NO_3^-, $H_2PO_4^-$ as well as pH.

Soil parameter sensing using Lab-on-a-chip methodology

Some emerging advanced techniques, including Micro-Electro-Mechanical System (MEMS), Micro-fluidics and Lab on the valve (LOV) are already attempting for electrochemical detection in biological, chemical and medical fields and still provide new ideas and good opportunities for electrochemical sensors from fabrication to measurement. Up to now, most soil nutrient detection methods are only able to measure one target ion by using conventional electrochemical measurement caused by an ion selective membrane, in principle, only selectively answering and adjusting one target ion. Electrochemical sensors may be integrated onto one chip as a sensor array which is a feasible approach of multi-targets simultaneous detection. However, all the membranes developed for soil NPK detection would not reply to only one specific ion, but additionally along with other interfering ions present in the analyst. One main challenge faced could be the reliability of the sensor array. This can be achieved by avoiding the interferences from other ions while using the sensor array for simultaneous detection.

Jackson *et al.* (2008) has studied the feasibility of using inexpensive wireless nanotechnology based devices for the field measurement of soil temperature and moisture. The developed MEMS based temperature and moisture sensors are composed of micromachined MEMS cantilever beams equipped with a water sensitive nano-polymer and an on-chip piezoresistive temperature sensor. The sensor is based on a shear stress principle, which the microsensor chip combines a proprietary polymer sensing element and Wheatstone Bridge piezoresistor circuit to deliver two DC output voltages that are linearly proportional to moisture and temperature. In the similar context, Smolka (2014) has developed a soil nutrient sensor system for the combined measurement of NO_3, NH_4, K and PO_4 in the field. For the measurement, a soil sample is suspended in a universal extraction liquid. After filtration, the amount of dissolved nutrients is measured in this liquid. In this way, only a single extraction procedure followed by a single measurement is required, minimizing the work for the generation of nutrient concentration maps and depth profiles. The sensor data is processed in a software system together with crop growth models and weather data to calculate the required amount of fertilizers. A mixing and dosing unit at the field coupled to any standard irrigation system will allow for automated fertilization. Zhang *et al.* (2014) has developed a real-time monitoring of water and fertilizer concentration using spectroscopy and optical fiber technology. On the specific, a calorimetric can be set in the smart pipeline of all-in-one water injection fertilize, then process analysis was carried out on the composition of NPK by UV-VIS spectroscopy, can get the actual concentration of the solution under test.

Ramanujan (2013) has developed a microfluidic water sensor within a fingertip-sized silicon chip that is a hundred times more sensitive than current devices. In soil or when inserted into a plant stem, the chip is fitted with wires that can be hooked up to a card for wireless data transmission or is compatible with existing data-loggers. Chips may be left in place for years, though they may break in freezing temperatures. Such inexpensive and accurate sensors can be strategically spaced in plants and soil for accurate measurements in agricultural fields.

Comparative study on different soil parameter sensing devices

There are several types of soil nutrient sensing devices available. Some of them are under research-development stage and others are commercially available. A comparative analysis of different types of soil sensors based on soil parameters and suitability for specific analysis applications are resented in Table 9.

Conclusions

The application of different soil sensors for precision agriculture is discussed effectively. Much detailed comparative analysis of kinds of many sensors are essential for the soil parameter measurement systems. It is observed that very few works have been done on compact lab-on-a-chip type soil parameter sensing methodology. Soil moisture measurement using lab-on-a-chip is only reported till date with highest accuracy. Other soil parameters can also be measured using similar lab-on-a-chip method with better accuracy which needs more research for the implementation of precision agriculture. The vis-NIR spectroscopy based soil parameter sensing can be used to analyze nearly all necessary soil parameters, although the accuracy of measurement may differ according to sensor arrangements. The efficient and effective implementation of different sensor system technologies on soil parameter sensing

Table 9. Comparison between several soil sensors and their measurement accuracy

Soil Parameters	Reflectance based soil sensors [NIR-Near IR Spectroscopy, MIR-Mid IR Spectroscopy]		Conductivity, resistivity, and permittivity based soil sensors [EC-Electrical Conductivity, TDR—Time Domain Reflectance, FDR-Frequency Domain Reflectance, GPR- Ground Penetrating Radar, EMI-Electro-Magnetic Induction]						Passive radio-metric based soil sensors	Strength based soil sensors [DST-Direct Shear Test, TST-Triaxial Shear Test]		Electrochemical based soil sensors [ISE-Ion Selective Electrode, ISFET-Ion Selective Field Effect Transistor]		Tensio-meter based soil moisture sensor	Lab-on-a-Chip based soil parameter sensor
	NIR	MIR	EC	TDR	FDR	GPR	EMI	CIDR		DST	TST	ISE	ISFET		
Org. C	Good	Excl	NUR	NUR	NUR	NRR	NRR	NRR	NRR	NRR	NRR	NRR	NRR	NRR	Excl
Total N	Good	Excl	NUR	NUR	NUR	NRR	NRR	NRR	NRR	NRR	NRR	ApQu	ApQu	NRR	Excl
Clay	Good	Excl	NUR	NUR	NUR	NRR	NRR	NRR	NRR	NRR	NRR	NRR	NRR	NRR	NRR
MC	Good	-	Good	Excl	Excl	Good	Good	Good	Good	NRR	NRR	NRR	NRR	Good	Excl
pH	Good	Good	NUR	Good	NUR	Good	Good	NRR	NRR	NRR	NRR	ApQu	ApQu	NRR	Excl
Ca	Good	Excl	NUR	NUR	NUR	NRR	NRR	NRR	NRR	NRR	NRR	NRR	NRR	NRR	Excl
CEC	Good	Good	NUR	NUR	NUR	NRR	NRR	NRR	NRR	NRR	NRR	NRR	NRR	NRR	Excl
Mg	Good	Excl	NUR	NUR	NUR	NRR	NRR	NRR	NRR	NRR	NRR	NRR	NRR	NRR	Excl
Sand	ApQu	Excl	NUR	NUR	NUR	NRR	NRR	NRR	NRR	NRR	NRR	NRR	NRR	NRR	NRR
Silt	ApQu	Good	NUR	NUR	NUR	NRR	NRR	NRR	NRR	NRR	NRR	NRR	NRR	NRR	NRR
Total P	ApQu	ApQu	NUR	NUR	NUR	NRR	NRR	NRR	NRR	NRR	NRR	ApQu	NRR	NRR	Excl
K	DHL	NUR	NUR	NUR	NUR	NRR	NRR	NRR	NRR	NRR	NRR	ApQu	ApQu	NRR	Excl
Na	NUR	NUR	NUR	NUR	NUR	NRR	NRR	NRR	NRR	NRR	NRR	NRR	NRR	NRR	NRR
SC	NRR	NRR	NRR	Good	Good	Good	Good	NRR	NRR	Good	Excl	NRR	NRR	NRR	NRR
EC	Good	Good	Good	Excl	Excl	Good	Good	NRR	Good	NRR	NRR	NRR	NRR	NRR	Excl

Excl-Excellent result, Good - Between Good and approximately quantitative prediction, ApQu- Approximately quantitative, DHL- Distinguishes between high and low, NUR-Not Usable Result, NRR-No Result Reported methodology will generate an enormous effect on land productivity, farmer‘s income and to develop a competent agricultural management system.

Acknowledgement

Authors thank to All India Council for Technical Education (AICTE), New Delhi, India to provide project grants under Career Award for Young Teachers (CAYT) scheme 2013-2014 and also continue research work in the implementation of the precision agriculture mechanism.

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Received: October 12, 2015; Accepted: December 10, 2015