The Scope for Using Proximal Soil Sensing by the Farmers of India

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Abstract: Knowledge about spatial distribution patterns of soil attributes is very much needed for site-specific soil nutrient management (SSSNM) under precision agriculture. High spatial heterogeneity exists in the agricultural soils of India due to various reasons. The present practice of assessing the spatial variability of the vast cultivated landscape of India by using traditional soil sampling and analysis is costly and time consuming. Hence, proximal soil sensing (PSS) is an attractive option to assess the plot-scale spatial variability pattern (SVP) of soil attributes for SSSNM. A PSS system, either in a fixed position or mounted on a vehicle (on-the-go), can be used to obtain measurements by having direct contact with soil. PSS measurements provide low-cost and high-density data pertaining to the SVPs of soil attributes. These data can be used to generate digital elevation and soil attribute variability maps at the field scale in a crop production environment. Based on the generated variability maps, locally available and economically feasible agricultural inputs can be applied using variable rate application strategies for sustainable cropping and enhanced farm profit. This overview presents the potential of adopting PSS in India and other developing countries. The scope, challenges, and probable solutions are also proposed. There is ample scope for adoption of PSS in India in view of diverse soil types, climatic conditions, cropping patterns, crop management practices, and ultimately, the ever-increasing demand for higher agricultural production. However, the successful adoption of the PSS technique in India will be dependent on the proper design and adoption of strategies which require adequate planning and analysis. There are several studies that have highlighted the usefulness of soil sensing technologies in Indian soils. There are also certain challenges and limitations associated with PSS in India, which could be addressed. The available proximal soil
sensing technologies will be of great help in improving the understanding of soil heterogeneity for adopting SSSNM in order to optimize crop production in India and other developing countries.

**Keywords:** soil sensors; site-specific nutrient management; precision farming; digital soil mapping; multiple soil classes

### 1. Introduction

Within the Indian agricultural context, cultivated areas of India consist of both rain-fed and irrigated agro-ecosystems. The average crop productivity of the country has remained low due to several factors including heterogeneous soil characteristics and improper water management. Moreover, India has major soil groups such as red, black, lateritic, alluvial, desert, forest, and hill soils with spatially variable soil physical, chemical, and biological properties. During the 1960s, plant growth of high yielding crop varieties was badly affected due to a deficiency of nitrogen (N). This was followed by a deficiency of both N and phosphorus (P) and, subsequently, zinc (Zn) deficiency became an important factor governing the success or failure of crops. Crops showed a positive response to potassium (K) application despite the medium to high K status of several Indian soils [1]. When crops were fertilized with N/NP, plants suffered from secondary and micronutrient deficiencies, as most of the high analysis fertilizers were devoid of secondary nutrients and micronutrients [2–4]. Adoption of intensive cropping practices with inadequate and imbalanced nutrient use, and use of lower amounts of organic manure have led to reductions in crop yields and total factor productivity (ratio of output to weighted average of inputs,) and the emergence of multi-nutrient deficiencies. The productivity was 17.9 kg of cereal grain/kg NPK applied during 1960–1970 and it was reduced to 6.3 kg of grain/kg NPK added during 1990–2000 [5]. This trend was also seen in the case of pulses and oilseeds. In Punjab, wheat yield showed a decline from 4850 kg/ha in 1996 to 4260 kg/ha in 2000. There is a wide gap between nutrients supplied and the uptake by crops. Replenishment of nutrients is not adequately followed in different soil/crop management systems; thus, subclinical or hidden deficiencies of several nutrients have been widely observed, resulting in a decline in the total factor productivity of applied nutrients. Some farmers who apply more than the recommended dose of NPK, still obtain reduced crop productivity due to hidden multiple micronutrient deficiencies, which is a matter of concern. Further, imbalanced or excess addition of fertilizer nutrients results in lowering of nutrient use efficiency and degradation of the soil and the environment [6,7].

Ensuring a proper supply of food and maintaining the sustainability of agricultural production systems are two important challenges for the world [8]. The developing countries such as India are experiencing added pressure due to scarcity of resources, land degradation, and an ever-growing population [9,10]. There is an urgent need for the introduction of new technologies and their adoption in Indian agriculture to meet the food grain production demand of 480 million tons by 2050, with proper management of biotic and abiotic stresses experienced by the crops. In the last several decades, there has been various changes in world agriculture. The developed countries have modernized their agricultural systems with advanced technologies for obtaining higher productivity. However, agriculture in India faces hurdles such as non- or less-adoption of advanced technologies and improper availability and use of inputs for agriculture.

The outer environment of agriculture-related developments in different countries of the world has changed because of the formation of a world trading system and the revolution in the information technology sector. This knowledge and information-based era provides opportunities to transform old farming practices to modern ones. Therefore, it is important to keep gain knowledge of the modern and advanced technologies used in agricultural practices of the developed countries and to find ways for their applications in Indian agriculture.
Recent agricultural production needs to be efficient to fulfill the ever-rising demand of quality agricultural produce in a sustainable manner that avoids soil and environment degradation [11,12]. The desired quantities of nutrients and water, which are the key inputs for agricultural production, are needed for best soil/crop management. The requirements of these inputs vary across the landscape due to variations in topography and soil types which ultimately influence crop environments. This requires proper identification and understanding of variations and applications of inputs as per local need. The efficiencies of production systems could be enhanced by accurate recognition and consideration of edaphic variation. On the one hand, variations in the physical, chemical, and biological soil properties are traditionally detected by soil sampling followed by laboratory analysis. This involves a huge cost to collect an adequate number of soil samples for accurate characterization to assess landscape variability. Low soil sampling density due to economic consideration is an important limitation. Moreover, a high-resolution soil-type map is one important tool that is not frequently available in developing countries such as India.

On the other hand, soil sensors provide cost- and time-effective quantitative data as compared with the conventional method of laboratory analysis [13]. These sensors, used in proximal soil sensing (PSS), are handy, wireless, intelligent, and having higher levels of accuracy and energy efficiency. A lot of research is being carried out in different parts of the world to develop proximal soil sensors and their applications. In the process of proximal soil sensing uses a sensor, either in contact or in close range (<2 m) of soil, for in situ estimation of surface or subsurface soil properties.

India is one of the biggest producers and consumers of fertilizers among the different countries of the world [14]. The higher fertilizer consumption in India may be due to large areas under cultivation coupled with the application of uniform doses of fertilizer irrespective of spatial variability of the soil in the same field. Therefore, it is of paramount importance to have a proper understanding of the spatial variability of soil nutrients and other associated properties in order to undertake site-specific soil nutrient management (SSSNM) with optimal fertilizer application. SSSNM results in higher economical production and a reduction in the negative environmental impact. Traditional soil management practices involve the use of soil surveys and sampling followed by laboratory analysis and the adoption of suitable management practices based on the soil test values of the collected samples. These practices will continue to help but they are expensive, time consuming, tedious, and some are qualitative in nature. There is a demand for good quality and inexpensive information through proximal soil sensing for site-specific soil management. This also requires laboratory analysis of some soil samples to calibrate proximal sensing data.

The first soil testing program was started in India under the Indo-U.S. Operational Agreement No. 4, on the Determination of Soil Fertility and Fertilizer Use, with the establishment of 16 soil testing laboratories in 1955–1956. Subsequently, several new soil-testing laboratories (including mobile soil testing vehicles) were established to cater to the needs of the farmers for soil testing services. At present, the country has 1218 static and 187 mobile soil testing laboratories, totaling 1405 laboratories with an analyzing capacity of 12.254 million samples per year (Fertilizer Statistics 2019–2020, FAI, New Delhi, India).

Assessment of the spatial variability of the vast cultivated landscape of India by traditional soil sampling and analysis is not possible. This means that PSS is a promising option for a country such as India to assess field-scale soil variability for implementing SSSNM strategies. The services of existing soil testing laboratories are essential for analysis of reference (sensor system calibration) samples. The aim of this review is to discuss field-scale soil heterogeneity, different PSS technologies used for assessing spatial variability of soils, sensor fusion, spatially differentiated crop management, and the scope for proximal soil sensing in India.

2. Soil Heterogeneity

Soil is a heterogenous mass and the soil properties vary widely from place to place. Factors such as parent material, climate, topography, flora and fauna, and time period
influence soil formation and also contribute towards soil variability. Jenny [15] depicted soil as a function of soil forming factors: soil = f (cl, o, r, p, t), where cl, o, r, p, and t represent climate, organism (both plants and animals), relief, parent material, and time, respectively. Similar soil types exist under prevailing similar sets of soil forming factors. Each soil forming factor plays a key role in certain environmental condition. On the one hand, soil in a region is mainly influenced by rainfall, climate, and vegetation distribution. On the other hand, soil in a smaller area is governed by the local distribution of vegetation, microclimate, parent material, and time. Soil surveyors consider that relief or topography and vegetation are indicators during a soil survey program for predicting soil boundaries and properties within a soil boundary. Recently, McBratney et al. [16] outlined the SCORPAN model that can quantitatively express the relations of soil and related environmental factors in a spatial context, which are helpful for digital soil mapping. Soil as soil class or soil attribute at a given time and space encompasses quantitative and empirical functions of seven covariates such as soil, climate, organism, relief, parent material, age, and spatial location, respectively.

Soil class or soil attribute = f (soil, climate, organism, relief, parent material, age, and spatial location).

Variable crop yield in a field is related to soil variability [16]. Therefore, it is important to understand the growing environments for better management of agricultural fields. As discussed above, interactions of the different soil forming factors result in variability of soil in different scales and in soil profile. A good example of this is seen in Figure 1 which shows the variability in soil organic carbon (SOC) in the top 0–15 cm soil depth across the Telangana state of India [17]. The researchers attributed this variability of SOC to the interactions of soil types, climatic conditions, and soil/crop management practices. Researchers in other parts of the world have also attributed SOC status to climatic conditions, type of vegetation, and soil/crop management histories [18,19]. SOC is relatively lower in dry and hot areas and higher in cool and/or wet areas. In addition, naturally occurring in-field variability of SOC is also significant. Soil management practices, including the addition of soil amendments such as fertilizer and lime, the addition of organic inputs, tillage, and crop rotations influence soil properties, and hence, soil heterogeneity [20]. Figure 2 shows another example of management-induced spatial variability of available sulphur (S) in surface soils of the northern state Uttarakhand of India [21]. The lower status of available S in the northern, western, and south-central portions of Uttarakhand is primarily because of soil/crop management practices. Available S status in soil is influenced by S immobilization and mineralization processes. Factors such as the presence of crop residues, S content in organic matter, soil pH, moisture content, microbial and enzymatic activity, and soil/crop management practices influence S immobilization and mineralization processes [22]. From a crop management point of view, field, as well as subfield scale, soil variability is important. Farm managers need to perform sampling properly for evaluating the variability of targeted soil properties by considering the important factors influencing soil variability.

The scale of spatial variability is different for various soil properties. It varies from very short distances, i.e., <1 m (for example, soil nitrate) to several meters and kilometers (for example, soil carbon). Mulla and McBratney [23] reported wide variations in the coefficient of variation (CV) and range values of semivariogram models (which indicate spatial structures of soil properties) of important soil properties of Australian soils. Table 1 lists the CV and range values of some important properties of acid soils in India [24–26]. Soil properties show weak to strong spatial dependency and low to high variability. The spatial dependency of soil properties has been analyzed through semivariogram analysis by estimating the nugget/sill (N/S) ratios of semivariograms (with N/S ratios of <0.25, from >0.25 to ≤0.75, and >0.75 for strong, moderate, and weak spatial dependency, respectively) [27]. The magnitudes of variability of soil properties were assessed from CV values (<10%, low; from 10 to 100%, moderate; and >100%, high) [28]. Studies pertaining to spatial variability of soil pH, electrical conductivity, available sulphur, and available micronutrients in some agriculturally important regions such as the Indo-Gangetic Plain and Narmada River basin
area of India reveal the wide variability of these properties (Table 2) [29,30]. The spatial variability of these soil properties has been attributed to soil types, prevailing climatic conditions, and adoption of various soil/crop management practices.

Figure 1. Spatial distribution of soil organic carbon (SOC) in 0–15 cm soil depth of Telangana, India (adopted from Shukla et al. [17]).

Figure 2. Spatial distribution of available sulphur (S) in 0–15 cm soil depth of Uttarakhand, India (adopted from Shukla et al. [21]).
Soil properties vary with space and time. Some soil properties are very dynamic in nature and keep changing rapidly with time. Whereas, some soil properties are relatively static. Examples of dynamic soil properties are soil temperature, soil moisture, soil solution, nutrient concentrations, soluble salt concentration, etc. Whereas, texture, soil colour, soil depth, and cation exchange capacity are examples of relatively static properties.

### 3. Proximal Soil Sensing

Farm managers need to understand and interpret soil physical, chemical, and biological parameters to properly understand the prevailing soil variability. This work is traditionally carried out by collecting soil samples and subsequently testing in a laboratory. This needs an accurate sampling strategy and appropriate methodologies and equipments. To understand the temporal and spatial variability of soil parameters, model-based soil sampling is useful. Geostatistical techniques are useful for analyzing soil variability, since it is possible to predict the values of soil parameters at unsampled locations using the values of soil parameters at sampled locations [31]. Dense soil sampling is not economically

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**Table 1.** Typical variability of soil properties in acid soils of India (EC, electrical conductivity) (compiled from Behera et al. [24,25]; Behera and Shukla [26]).

| Property                  | No of Samples | Range for Semivariogram Models (m) | Spatial Dependency | Coefficient of Variation (%) | Magnitude of Variability |
|---------------------------|---------------|------------------------------------|--------------------|------------------------------|--------------------------|
| Soil pH                   | 400           | 135–4509                           | Moderate           | 5–10                         | Low                      |
| Soil EC                   | 400           | 46–1337                            | Weak to strong     | 32–74                        | Moderate                 |
| Organic carbon content    | 400           | 323–11,936                         | Moderate to strong | 31–50                        | Moderate                 |
| Available potassium       | 400           | 160–2794                           | Moderate           | 45–100                       | Moderate                 |
| Exchangeable calcium      | 400           | 44–3359                            | Moderate to strong | 72–93                        | Moderate                 |
| Exchangeable magnesium    | 400           | 304–3586                           | Moderate to strong | 59–91                        | Moderate                 |
| Available zinc            | 400           | 2592–9078                          | Moderate to strong | 46–143                       | Moderate to high         |
| Available copper          | 400           | 3568–37,854                        | Weak to strong     | 39–71                        | Moderate                 |
| Available manganese       | 400           | 704–65,837                         | Weak to strong     | 51–121                       | Moderate to high         |
| Available iron            | 400           | 2692–5214                          | Moderate to strong | 26–70                        | Moderate                 |
| Total zinc                | 400           | 992–65,837                         | Moderate to strong | 32–44                        | Moderate                 |
| Total copper              | 400           | 3840–15,250                        | Moderate to strong | 33–71                        | Moderate                 |
| Total manganese           | 400           | 3513–24,809                        | Weak to strong     | 30–81                        | Moderate                 |
| Total iron                | 400           | 5845–65,837                        | Weak to strong     | 26–47                        | Moderate                 |

**Table 2.** Typical variability of soil properties in the agriculturally important Indo-Gangetic Plain and Narmada River basin area of India (M, moderate; S, strong; EC, electrical conductivity) (compiled from Shukla et al. [29]; Behera et al. [30]).

| Area            | No of Samples | Property       | Range for Semivariogram Models (m) | Spatial Dependency | Coefficient of Variation (%) | Magnitude of Variability |
|-----------------|---------------|----------------|------------------------------------|--------------------|------------------------------|--------------------------|
| Indo-Gangetic Plain | 55,101        | Soil pH        | 13,115                             | M                  | 12.6                         | M                        |
|                 |               | Soil EC        | 36,000                             | M                  | 74.6                         | M                        |
|                 |               | Soil organic carbon | 30,000                     | S                  | 40.8                         | M                        |
|                 |               | Available sulphur | 33,109                        | M                  | 85.7                         | M                        |
|                 |               | Available zinc  | 48,000                             | M                  | 57.2                         | M                        |
|                 |               | Available iron  | 54,000                             | M                  | 70.0                         | M                        |
|                 |               | Available manganese | 36,000                     | M                  | 70.3                         | M                        |
|                 |               | Available copper | 60,000                             | M                  | 68.0                         | M                        |

| Area            | No of Samples | Property       | Range for Semivariogram Models (m) | Spatial Dependency | Coefficient of Variation (%) | Magnitude of Variability |
|-----------------|---------------|----------------|------------------------------------|--------------------|------------------------------|--------------------------|
| Narmada river basin | 5984         | Soil pH        | 108,000                            | M                  | 11.01                        | M                        |
|                 |               | Soil EC        | 72,000                             | M                  | 48.39                        | M                        |
|                 |               | Soil organic carbon | 96,000                     | M                  | 55.13                        | M                        |
|                 |               | Available sulphur | 96,000                             | M                  | 65.94                        | M                        |
|                 |               | Available zinc  | 96,000                             | M                  | 71.21                        | M                        |
|                 |               | Available copper | 96,000                             | M                  | 72.81                        | M                        |
|                 |               | Available iron  | 96,000                             | M                  | 71.60                        | M                        |
|                 |               | Available manganese | 96,000                     | M                  | 74.97                        | M                        |
|                 |               | Available boron | 96,000                             | S                  | 57.51                        | M                        |
feasible under conventional sampling schemes, but it is needed for accurate capturing of soil variability. Therefore, both proximal and remote sensing techniques have been used to obtain dense spatial resolution which is economically affordable [32]. Proximal soil sensing is carried out by using a sensor close to the soil surface or in close contact with the soil. Whereas, the remote sensing technique involves obtaining data from sensors kept at >2 m away from a targeted object. Normally, the sensors are placed on an aerial platform or a satellite.

Proximal soil sensors are categorized by how they measure and operate, the source of their energy, and the inference used in the measurement of the target soil property. For instance, a proximal soil sensor is said to be invasive if during measurement there is sensor-to-soil contact, otherwise it is non-invasive. If measurements are invasive, then the sensors may be further described as in situ (i.e., the measurements are made within the soil) or ex situ (i.e., the measurements are made on excavated soil, e.g., measurements on soil cores). Proximal soil sensors may be described as being mobile, in which case they measure soil properties while moving or “on-the-go”, or they may be stationary, whereby measurements are made in a fixed position and possibly at different depths. A proximal soil sensor that produces its own energy from an artificial source for its measurements is said to be active. It is passive if it uses naturally occurring radiation from the sun or earth. If the measurement of the target soil property is based on a physical process, then the proximal soil sensor is said to be direct, but when the measurement is of a proxy and inference is with a pedo-transfer function, then the proximal soil sensor is indirect. For example, measurements with a resistivity proximal soil sensor that uses coulters inserted into the ground are invasive and in situ, the sensor uses an active source of energy. It has mobile operation and, depending on the soil property, inference might be either direct (e.g., electrical conductivity) or indirect (e.g., clay content). Measurements of an extracted soil core with a portable X-ray fluorescence proximal soil sensor can be, depending on the measurement setup, invasive and ex situ or non-invasive. The sensor uses an active source of energy, it has stationary operation, and inference can be either direct or indirect. Measurements with a $\gamma$-radiometer are non-invasive; they use a passive source (naturally occurring radioisotopes of Cs, K, U, and Th); operation is often mobile, although stationary measurements are also possible; and inference is mostly indirect.

High-density soil parameter maps can be obtained using proximal soil sensors while moving in the field, which is called on-the-go PSS. There are different types of on-the-go PSS systems. Many of the on-the-go PSS systems use either electrochemical, electrical and electromagnetic, mechanistic and optical, and radiometric sensors [33,34]. Electrochemical sensor contains ion-selective membranes which provide voltage output in response to the activity of some selected ions such as K, nitrate, and hydrogen (H). To measure the activity of targeted ions in soil by assessing the potential differences between reference and sensing part, glass or polymer membrane-based ion-selective electrodes or ion-selective field effect transistors are used. The electrical conductivity or resistivity or capacitance as affected by soil composition is measured by electrical and electromagnetic sensors [35]. Electrical conductivity at multiple soil depths can be sensed using more than two electrodes as the distance between two electrodes determines the effective depth of measurement. The mechanistic sensors are of three types, i.e., mechanical sensors (measure forces resulting from engagement of a tool with soil), acoustic sensors (measure sound due to interactions between a tool and soil), and pneumatic sensors (measure the resistance to air injected into the soil). Soil parameters such as compaction and texture are sensed by considering the movements of air and sound in soil, respectively, by using pneumatic and acoustic sensors. Gorthi et al. [36] evaluated a field-portable acoustic sensing device to measure soil moisture. Acoustic velocity in soils exhibited the impact of soil texture and compaction. A linear mixed-effect model showed an increase in the acoustic velocity with a decrease in gravimetric moisture content. The acoustic sensing device showed its potential for soil water content monitoring, leading to efficient irrigation planning. Soil mechanical strength can be sensed by mechanical sensors which work on the principle of vertical
cone penetrometer. Hemmat et al. [37] developed and field-tested an integrated sensor (instrumented disk coulter and penetrometer) for on-the-go measurement of soil mechanical resistance. With offset positioning of the sensors on the frame, the developed integrated sensor could map the mechanical resistance of soil profile to a depth of 30 cm. The optical and radiometric sensors measured the level of energy reflected or absorbed by the soil particles influenced by different soil parameters. Dhawale et al. [38] evaluated a prototype portable mid-IR spectrometer for direct measurements of soil reflectance and to model the spectra to predict sand, clay, and soil organic matter contents under a range of field, soil, and water conditions in four agricultural fields on the Macdonald campus research farm, Ste-Anne-de-Bellevue, QC, Canada. The results revealed that the portable spectrometer could be used to predict clay and sand contents of either wet or dry soil samples with a root mean square error of around 10%. Predictions of soil organic matter content resulted in root mean square error values that ranged between 0.76 and 2.24%. Andrade et al. [39] used X-ray fluorescence spectrometry and magnetic susceptibility for predicting soil texture in tropical soils of Brazil. The predictions produced acceptable accuracy in modeling and mapping clay and sand fractions, but were less effective to directly predict silt fraction. The sensors used in PSS respond to more than one soil parameters, but ideally, each sensor should respond to a single soil parameter. Therefore, separating the effects is a challenging process. It depends upon many factors specific to different regions. The commonly used on-the-go soil sensors and respective soil parameters that influence sensor signal are presented in Figure 3 [40]. Acceptable correlations were obtained between sensor outputs and targeted soil parameters when there was negligible interference from other soil parameters. PSS can provide high-density and low-cost information on soil spatial variability. The maps generated from PSS data could be superimposed with digital elevation maps for accurate delineation of areas in the field with significantly different crop production environments. They can also be used for identification of soil sampling sites. The establishment of soil management zones is possible by delineating homogenous areas based on sensor measurements [41]. The relationship between targeted soil properties (for example available nutrient in soil) with sensor measurement or with topography can be assessed through targeted soil sampling. If significant correlations are obtained, sensor measurements can be used for indirectly predicting a particular soil property and preparation of high-resolution maps.

The technology of PSS has been tested in several countries to predict and characterize different soil properties at different scales, to generate maps of soil resources, and to undertake appropriate decisions for land management [42,43]. For example, Rogovska et al. [44] developed “diamond-attenuated total internal reflectance (D-ATR) Fourier transform infrared (FTIR) spectroscopy” as a field mobile soil nitrate (NO$_3^-$) sensor and demonstrated its potential for quick estimation of NO$_3^-$ concentration on the move. PSS information can be coupled with weather forecasts and crop modeling information for optimum N management in crops using variable rate application technology [45].

Another important aspect of PSS is that crops act as effective sensors to indicate the quality of the prevailing local environmental conditions. Proximal sensing of reflectance from crop canopy can be used to understand the spatial distribution of crop performance in an area which ultimately could be explained by soil heterogeneity. The present research on precision agriculture envisages integration of different crops and soil sensing technologies for effective understanding of the spatial distribution patterns of soil parameters that significantly influence crop yields [46]. Subsequently, required agricultural inputs could be provided by following variable rate application technology as per local needs for better farm profitability and for a sustainable environment.
which should enhance crop production, since India has 49 million hectares of land with
possible by reducing the physical connections among the sensors. To ensure proper func-
production system. Zhang et al. [55] reported the usefulness of a portable farmland infor-
pH, whereas, apparent electrical conductivity sensors helped in differentiating the lime
properties [47]. A set of selected sensors could be used in a multi-sensor platform for better
use of multi-sensor platforms for PSS, there is a need for sensor fusion using wireless
sensor networking (WSN), which basically consists of a large number of multifunctional
sensor nodes with sensing, data processing, and communicating capacities. The usefulness
of WSN has been reported in crop and soil monitoring under precision agriculture [56,57].

Figure 3. On-the-go soil sensing systems (adopted from Adamchuk [40]).

4. Sensor Fusion

Sensors are transducers that alter signal output under the influence of external phe-
nomena, and also, more or less, under direct impact. However, in most cases, considering
the soil structure’s complexity, it is significantly impacted by side effects from different soil
properties. All the soil properties cannot be measured using a single sensor. Therefore, it
is very much important to select a suitable set of sensors for measurement of certain soil
properties [47]. A set of selected sensors could be used in a multi-sensor platform for better
performance and coverage of soil parameters. The use of a mobile multi-sensor platform
for measuring apparent electrical conductivity and pH together has been reported for the
development of lime requirement maps [48,49]. In this system, pH sensors measured soil
pH, whereas, apparent electrical conductivity sensors helped in differentiating the lime
needs based on electrical conductivity values, which were influenced by soil texture, even
at the same levels of pH. This system could be utilized for ameliorating acid soils in India
which should enhance crop production, since India has 49 million hectares of land with
acid soils [50]. Several more multi-sensor platforms such as simultaneous measurement of
soil K⁺, NO₃⁻, and Na⁺ [51,52], and soil capacitance, mechanical resistance, and optical
reflectance [53] have been designed and recommended for use. Taylor et al. [54] recorded
better fits of output from combined sensor systems for topsoil layers in a Scottish potato
production system. Zhang et al. [55] reported the usefulness of a portable farmland infor-
mation collection system having multiple sensors. Efficient functioning of the sensors was
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of WSN has been reported in crop and soil monitoring under precision agriculture [56,57].
5. Spatially-Differentiated Crop Management

As described earlier, soil heterogeneity is the combined effect of both natural and anthropogenic factors. The examples of prevailing spatial variabilities of soil parameters at different scales in agricultural soils of India were described earlier. This warrants the need for adoption of different crop management practices based on soil variability of the country. There are two types of variabilities of soil properties, i.e., dynamic (for example soil solution nutrient concentration) and static (soil texture). Therefore, it is very important to make judicious decisions for addressing the variabilities depending upon available resources and economic feasibility. Before undertaking the activities of addressing soil variabilities for spatially differentiated crop management, a farm manager needs to assess the type and degree of variability, area affected by the variability, economic feasibility, and the profits obtained from the adoption of SSSNM options. If the income from SSSNM is significantly higher than the cost incurred, then the farm manager should act to address the variability.

Addressing spatial variability in the field requires considerable involvement of money and time. The majority of Indian farmers do not have adequate financial sources for investing in sophisticated equipment to shift from conventional to smart agriculture. Further, there is a need to address issues such as educating farmers and the size of the agricultural field, etc. before transition. Farm managers need to understand and follow the steps including collection, storage and management, processing, analysis and interpretation of PSS data, and synthesis of information, followed by decisions for proper management prescriptions. Techniques such as machine learning and artificial intelligence play important roles in interpretation of PSS data to derive thematic soil maps and, ultimately, prescription maps for agricultural inputs and other field management practices [58–60]. Machine learning is a subset of artificial intelligence. Artificial intelligence includes machine learning and expert systems. Linear machine learning techniques such as partial least square (PLS) regression model, and nonlinear techniques such as random forest, artificial neural networks, least square support vector machines, support vector machine regression, and the cubist regression model have been used to interpret PSS data [61–63]. The extreme machine learning technique is also useful for this purpose [64].

Decisions related to crop management are of three types: strategic, tactical, and operational. The impacts of strategic, tactical, and operational decisions normally last for 10 years, 5 years, and 1 year, respectively [65]. The strategic decisions influence current, as well as future, land management decisions. Therefore, they need to be thought out adequately to implement strategic decisions to address variability. Tactical decisions are related to changes in crops or cropping systems, use of new equipment, management of data, etc. For example, farm managers may decide decisions to outsource the abovementioned activities to professional service providers. Operational decisions such as the purchase of agricultural inputs, use of labourers, and maintenance of farm equipments affect farm management for the coming year. Taking appropriate decisions helps in spatially differentiated crop management by enhancing farm efficiency and environmental sustainability. The management factors differ under various production systems. The important factors in irrigated agriculture are management of residue, water, soil compaction, and nutrient availability, whereas, drainage and soil erosion and nutrient availability affect rain-fed agricultural environment.

Farm managers need to perform qualitative assessments of the farm operations they intend to conduct for changes in management. The targeted problem must be identified and assessed before undertaking any decision for management. There are several variabilities, namely organic matter, soil acidity, salinity, weather, soil texture, topography, water infiltration, drainage, soil erosion, crop disease, insects, nutrient deficiency, crop cultivar, and weed infestation in crop growing environments that cause variability in yield; remedies for the variabilities are required. Factors such as nutrient deficiency, crop disease and insect infestation, and crop cultivars in Indian conditions need to be addressed first. It is very much important to remember that yield variability should be associated with soil heterogeneity. A uniform management approach may be adopted if there is no variability.
6. The Scope for Proximal Soil Sensing in India

There is ample scope for adoption of PSS in India in view of diverse soil types, climatic conditions, cropping patterns, crop management practices, and ultimately, the ever-increasing demand for higher agricultural production. Issues such as soil erosion, salinization/alkalization, soil acidity, low SOC levels, poor soil fertility, and soil pollution/contamination by toxic substances pose a threat to efficient management of the country’s soil resource for obtaining higher crop productivity [66]. In addition, poor crop productivity, low farm mechanization, and skewed use of farm inputs such as fertilizers, herbicides, and water are very common in Indian agriculture. In crop production, India occupies second, second, first, and second positions in the production of wheat, rice, pulses, and cotton, respectively, in the world scenario. However, the productivity of these crops varies from 38 (wheat) to 138 (pulses) in the world ranking [67,68]. The overall fertilizer consumption rate of India is less as compared with countries such as Egypt, China, Vietnam, and Netherlands. It has been reported that soil test-based application of adequate and balanced proportions of fertilizers (N, P, K, S, and micronutrients) resulted in enhanced crop productivity in several Indian states [69,70]. However, traditional soil sampling and subsequent analysis require huge cost involvement. Therefore, farm managers apply imbalanced and inadequate fertilizer without soil testing. Again, several Indian states have been using alarmingly high doses of pesticides and fertilizers. For example, Punjab state, occupying 1.5% of the geographical area, uses 7% of the NPK fertilizer and 60% of the herbicides consumed in the country [71,72]. Excess use of agri-inputs and over-exploitation of land resources in these areas pose unique problems, which are serious concerns for the policymakers and planners in India [67]. Therefore, adoption of proximal soil sensing technology in these states could do a lot to improve input use efficiency, crop productivity, and to reduce the negative impact on environment.

Similar to other countries, successful adoption of the PSS technique in India will depend on proper designing and adoption of strategies [13,73], which requires adequate planning and analysis. As listed below, there are three significant stages for introducing PSS in Indian agriculture, i.e., present, intermediate, and future stage. Implementation of the PSS technique in India would be a big exercise. However, it would be possible, as Yan et al. [74] detected the variability of soil moisture and soil salinity in coastal areas of China by integrating remote and proximal soil sensing information. The three stages are as follows:

1. The present stage involves establishing uniform soil and crop management practices, specialized institutions, and dedicated manpower, and creating awareness about the PSS concept by using different media.
2. This is followed by the intermediate stage which involves zone-wise PSS and delineation of soil/crop management zones across the country.
3. The future stage would involve fine grid sampling and calibration for the whole of India, and the adoption of SSSNM options.

Proximal soil sensors, such as electrical and electromagnetic sensors, have been used for on-the-go soil mapping of crop fields in India having different levels of soil salinity/alkalinity. Several researchers have correlated these maps with various soil parameters. Based on elevation and apparent electrical conductivity maps, the fields can be classified into different management zones and appropriate water and nutrient management strategies can be adopted for different crops. In addition, variable rate technology may be applied based on sensor readings for different input applications. Mapping can be done for both small and large plots. Preliminary studies conducted for mapping of electrical conductivity in some rain-fed lowland paddy fields of Chhattisgarh and Jharkhand revealed spatial variability of soil characteristics [75]. Narjary et al. [76] also prepared a digital soil map of
soil salinity of an experimental farm of the Central Soil Salinity Research Institute, Nain, Haryana, India with the data collected using an electromagnetic induction instrument. They carried out the mapping work using an EM38 instrument in vertical and horizontal modes on a grid survey, selecting 21 locations and collecting soil samples at four depth additions. Soil depth primarily influences variability. A more systematic definition of topsoil depth is needed to calibrate electrical conductivity measurements in each field. Spatial variable drought susceptibility may be related to apparent electrical conductivity maps which can be used for site-specific management in different fields.

Optical soil sensors can also be used for assessing soil organic matter content, texture, moisture, cation exchange capacity, soil NO$_3^-$ content, and pH in soil. Mechanical, acoustic, and pneumatic sensors can be used for assessing soil physical properties, especially in black, saline, and sodic soils of India, wherein field-scale spatial variability of soil physical properties affect crop growth. Electrochemical sensors with ion-selective electrodes (ISEs) and ion-selective field effect transistors (ISFETs) can be used for on-the-go mapping of H$^+$, K$^+$, NO$_3^-$, and sodium (Na$^+$) ions in different soil types in India. The method of on-the-go soil pH mapping for variable rate liming or liming based on delineated management zones will help in effective and economic management of acid soils which cover a significant portion of cultivated land in India. At the time of soil pH mapping, the capacity for obtaining high-resolution maps for soil K and nitrate levels could subsequently improve the potential of site-specific crop management for economic benefit and environmental sustainability. Further, this will help to reduce the overuse of fertilizers, enhance input use efficiency, and decrease the negative environmental impact, especially in states like Punjab and Haryana.

Various soil properties in different parts of the India have been mapped using different soil sensing approaches. A digital map of sand content in arid lands of western India was generated by Santra et al. [77] for use by different stakeholders. Legacy soil data after harmonization was used for generation of map. The terrain attributes and bioclimatic variables along with a soil map were used as covariates. Similarly, multi-depth and multi-property digital maps of important soil properties at a national scale were developed for India using legacy data [78]. Sreenivas et al. [79] also prepared digital maps of soil organic, as well as inorganic, carbon status of India. Several researchers have also reported on the use of various cost-effective optical sensors for predicting different soil properties. The status of soil N in agricultural soils [80] and different soil physico-chemical properties in Maharashtra state [81] of India were estimated by using visible and near-infrared reflectance (VNIR) spectroscopy. Srivastava et al. [82] also characterized salt-affected soils of Haryana state of India using VNIR spectroscopy. The mid infrared diffuse reflectance Fourier transform spectroscopy approach was used by Chakraborty et al. [83] to assess the lead (Pb) status in landfill/agricultural soils of India. Mukhopadhyay et al. [84] effectively used portable X-ray fluorescence (PXRF) spectrometry and NixPRO color sensor for characterizing landfill soils of Kolkata, India. The levels of SOC in eastern soils of India were aptly predicted by combining soil texture data with PXRF and NixPRO color sensor data. Additionally, there have been several other studies which highlighted the usefulness of soil sensing technologies in Indian soils.

7. Challenges and Probable Solutions for Adopting Proximal Soil Sensing in India

Limited trained experts and research activities pertaining to PSS in research institutes and state agricultural universities (SAU) of the country is one of the major challenges. This loophole can be plugged by imparting adequate training in the area of PSS to the soil scientists and agronomists of the Indian Council of Agricultural Research and SAUs. This can be achieved by establishing collaborations with organizations/institutions in United States of America, Europe, and Australia with expertise in PSS. There should be adequate funds allocated for conducting PSS research in the country. PSS can be expensive and complex and requires significant data processing for the farmers of the country. This problem could be solved by establishing advanced agricultural technology stations (AATS)
in different regions of the country. Initially, the experts in these AATs could undertake data processing and provide assistance to the progressive farmers using PSS. Subsequently, the progressive farmers could train the other farmers in the country. Once the benefits of PSS are realized, these services may be provided to the farmers on a custom hiring basis from the AATS. Adequate awareness needs to be created among the farmers and other stakeholders associated with agriculture in the country, about the direct and indirect benefits of PSS. This could be achieved by establishing demonstration units at AATS to visualize the benefits of PSS vis-à-vis farmers’ practices. However, different problematic issues associated with Indian soils may not be addressed with the current technological possibilities of PSS. For example, micronutrient management in Indian soils is a complex problem for Indian farmers; however, sensing soil micronutrients with current PSS systems is not clear. This issue could be addressed by developing and using different PSS systems befitting to the soil problems of India.

8. Conclusions

The techniques of proximal soil sensing could be used in India for evaluating static and dynamic variability of soil heterogeneity caused by natural and/or management-induced factors. Proper management of these variabilities can be carried out using the principles of production economics. The farm managers and crop growers of India need to have an adequate understanding about the different sources of soil heterogeneity. They must be able to make qualitative and quantitative assessments of soil spatial variability. Differentiated area management options may be adopted locally, if addressing soil heterogeneity is found profitable for economical and environmentally sustainable cultivation of crops. The available proximal soil sensing technologies in developed countries will be of great help for improving the understanding of soil heterogeneity and for adopting SSSNM in order to optimize crop production in developing countries including India.

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