Site-specific seeding using multi-sensor and data fusion techniques: A review

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Contents

1. Introduction 2
2. Principles of site-specific seeding 4
   2.1 Map-based site-specific seeding 5
   2.2 Sensor-based site-specific seeding 5
3. Key field quality indicators for defining site-specific productivity potential 6
   3.1 Soil quality indicators 7
   3.2 Soil quality indexes 9
   3.3 Crop quality indicators 15
4. Soil and crop sensing technologies 19
   4.1 Proximal soil sensing 19
   4.2 Crop sensing 29
   4.3 Multi-sensor and data fusion 33
5. Site-specific recommendation 43
   5.1 Site-specific seeding rate recommendation 43
   5.2 Site-specific sowing depth recommendation 46
6. Implementation of map-based site-specific seeding 51
7. Economics of site-specific seeding 52
8. Integration, research gaps and future prospects 54
   8.1 Research and technology gaps 54
   8.2 Discussions and future prospects 55
9. Conclusions 61
Acknowledgment 63
References 63
Further reading 82

Abstract

Site-specific seeding (SSS) is a precision agricultural (PA) practice aiming at optimizing seeding rate and depth, depending on the within field variability in soil fertility and yield potential. Unlike other site-specific applications, SSS was not adopted sufficiently by

Advances in Agronomy
ISSN 0065-2113
https://doi.org/10.1016/bs.agron.2019.08.001

farmers due to some technological and practical challenges that need to be overcome. Success of site-specific application strongly depends on the accuracy of measurement of key parameters in the system, modeling and delineation of management zone maps, accurate recommendations and finally the right choice of variable rate (VR) technologies and their integrations. The current study reviews available principles and technologies for both map-based and senor-based SSS. It covers the background of crop and soil quality indicators (SQI), various soil and crop sensor technologies and recommendation approaches of map-based and sensor-based SSS applications. It also discusses the potential of socio-economic benefits of SSS against uniform seeding. The current review proposes prospective future technology synthesis for implementation of SSS in practice. A multi-sensor data fusion system, integrating proper sensor combinations, is suggested as an essential approach for putting SSS into practice.

1. Introduction

Agricultural soils are highly variable both spatially and temporally. Some soil properties change largely over time [e.g., moisture content (MC), nutrients], whereas others changes over space (e.g., texture), or both (e.g., MC and nutrients). Spatiotemporal heterogeneity of agricultural soils affects crop production and yield (Jones et al., 1989; Kravchenko and Bullock, 2000; Spomer and Piest, 1982; Stone et al., 1985). The degree of soil variability differs from field to field, according to different affecting factors such as terrain attributes, inherited soil variability and agricultural practices. Nevertheless, traditional farming practices adopt a uniform seeding rate (USR), irrespective to the within field variations. Most frequently, USR does not match the within field variability, where suboptimal or supra-optimal seed rates are applied at different parts of the field. Consequently, improper seeding rates will most probably lead to improper plant populations. It will either raise the above-ground (i.e., solar radiation inception) and below-ground (i.e., nutritional) inter plant competition or fail to reach the highest crop yield (Jiang et al., 2013). Inappropriate plant populations density necessitates improper inter cultural input applications such as fertilizers, manure and crop protection products. Over application of agrochemicals also can negatively affect the soil biota, disturb aquatic ecosystems and pollute environment largely (Esau et al., 2014a,b). Non-optimal input allocation may raise production costs and reduce overall economic return (Chattha et al., 2014). Therefore, ultimate fate of this USR practice is to acknowledge poor production outcomes, which can drive food security toward endanger for ever-growing population in coming future.

The terms site-specific or variable rate (VR) applications in precision agriculture (PA) are commonly known as analogous to each other. Site-specific approach means variable application of input resources, e.g., seeds, fertilizers, tillage, water for irrigation and crop protection products within a field. Optimal input rates are made for optimum production at each within-field location aiming at reducing resource inputs and labor costs, maximizing farm productivity and reducing environmental risk due to over application of agricultural inputs (Khanal et al., 2017). Site-specific seeding (SSS) refers to both variable seed densities and sowing depth. Isbell (2005) defined SSS as a PA practice to help farmers tailoring their seeding rates to address field variability thereby increasing utilization efficiency. SSS ensures optimal number of plant density for a particular part of a field by placing right number of seeds regarding to the yield potential of a specific region of field. As a result, SSS can maximize overall production by managing within field variabilities and farm resources. It has great potentiality to produce extra profit margin through three different ways, i.e., (i) increase yield by the same amount of seeds, (ii) applying smaller amount of seeds for similar yield and (iii) maximizing yield for the smallest amount of seeds. Site-specific seeding is an environmental friendly approach that entertains optimal plant populations and ensures the optimal application of the other agricultural inputs like fertilizers, manure, insecticides and pesticides (Holmes, 2017). According to the Alabama Precision Extension, SSS reduces overall seed costs and maximize yield (Isbell, 2005). Nevertheless, practicing variable plant populations within fields is an old concept and the availability of GPS technology has given a new era to re-introduce this promising idea (Robert et al., 1999).

High resolution sensing and mapping of soil quality and crop growth variation is crucial to implement SSS successfully, aiming at maximizing crop production and minimizing resource input and cost. Within field variability is a complex phenomenon of multiple biotic and abiotic factors (Clay et al., 2009; Van Roekel and Coulter, 2011) that influence soil fertility and crop growth and thus affect overall production. Analyses with multiple factors could essentially represent soil fertility better than individual factor. Soil nitrogen (N), potassium (K), phosphorus (P), magnesium (Mg), electrical conductivity (EC), cation exchange capacity (CEC), acidity (pH), soil organic matter (SOM) and organic carbon (OC) are considered as the most significant properties affecting soil fertility and crop productivity (Ehsani et al., 2005; Qi et al., 2018; Vasiliniuc and Patriche, 2011; Whetton et al., 2017a). To measure soil and crop properties, a large number of sensors are available under both in research or commercially. These include but not limited to electrical, magnetic, electromagnetic, electrochemical, mechanical, optical and radiometric techniques (Adamchuk et al., 2004; Sudduth et al., 1997). Each sensing technology has been used to measure a single property or multiple soil properties. Moreover, one sensor can hardly measure all soil related yield potential factors alone, which calls a need for multi-sensor data fusion approach (Kuang et al., 2012; Tabll et al., 2017). A proper modeling technique can extract information from sensor signal and laboratory reference measurement. Few of proposed modeling tools can model linear and others can potentially model nonlinear complex relationships with some specific pros and cons depending on the application scenario (Nawar and Mouazen, 2017a). Geographic information system (GIS) along with geo-statistical analysis followed by modeling enable mapping within field soil and crop variabilities with highly accurate geo-reference kinematic global positioning system (RTK-GPS). Depending on the homogeneity of soil quality map, a field can be divided into homogeneous management zones (MZs), with each having different soil fertility and yield potential. It is hypothesized that each MZ should be assigned unique seed rate and sowing depth as individual MZ has specific yield potential (Nawar et al., 2017).

Although relatively large number of sensing, modeling and control technologies have been practicing randomly in PA (Lee et al., 2010; Zhang et al., 2002), very few has been reported for SSS (Daberkow and McBride, 2000). Initially SSS was presented as an uneconomic means of PA practice due to technological impairment and higher cost of sensors and control instruments. Low economic potential of SSS is the main factor to slow adoption (Say et al., 2018). Among all the available and potential technologies, it is essential to select and integrate most scientifically sound and economically viable technologies to improve the implementation and adoption of SSS and accelerate the technology extension. To our best knowledge, no review article has attempted to cover all the respective spectra of practicing SSS. Therefore, this paper is an integrative review on the-up-to-date PA technologies and principles for implementing SSS. It will also discuss the economics and environmental potentials, highlighting prospective technology synthesis for practical implementation of site specific seeding.

2. Principles of site-specific seeding

There are two fundamental approaches of SSS: (i) map-based and (ii) sensor-based systems (Grisso et al., 2011). In the map-based approach, the sensing and sampling of soil and crop, modeling and mapping, and development of SSS recommendations are made in advance before the actual field application, whereas in sensor-based SSS, these different steps are done in real-time using advanced algorithms, hardware and software technologies. The following sections discuss these two approaches in details.

2.1 Map-based site-specific seeding

Map-based SSS concerns the adjustment of the application rate according to previously developed and uploaded prescription map in the virtual terminal of the precision seeding machine. Appropriate sensing and differential global positioning system (DGPS) technology are essential to measure required soil and/or crop properties and other important attributes. GIS and geo-statistical analysis enable mapping the measured attributes. Based on the fertility status of different parts of the field, the field is split up into few smaller zones. These zones are commonly known as management zones (MZs). Each MZ is assigned a certain seeding rate aiming at creating an application map (AM) or a control map. Once an AM is generated, it is converted into machine compatible shape file and finally uploaded into the virtual terminal (Taylor et al., 2006). During field operation, variable seeding rate (VSR) controller delivers seed rate regarding to the optimal rate and respective location as prescribed in AM. The most positive aspect of this map-based system is that it allows sufficient time lag between sensing and VR application, to facilitate proper data processing for improving overall application accuracy. Recommendations are made at office in consultation with farmer, agronomist and experts. Predefined recommendations allow for "look ahead" system, which improves controller responses and smoothens the VSR in transition. In this principle, points location on the application map and corresponding field points should be well synchronized by a proper geo-referencing system (Grisso et al., 2011). Conversely, point synchronization feature makes this system highly sensitive to an error associated with miss placement of seeds. Map-based systems are not suitable for sharp variability in soil conditions attributed to weather circumstances. Therefore, systems that overcome the limitations of the map-based approach are necessary for future smart farming.

2.2 Sensor-based site-specific seeding

In sensor-based SSS high-resolution data collected with advanced sensor technologies is needed in real time. This continuous stream of sensor data is transferred successively into information and recommendations to be implemented by a proper controller, all applied in real-time (Grisso et al., 2011). Sensor-based seeding is seen to overcome the limitations of map-based approach. Since it does not require a DGPS and AM, it is free from error regarding locations of sampling points, position of the applicator and map interpolation issues. It is not sensitive to the sharp variation in soil conditions due to weather circumstances. However, a lag time is a common issue for the implementation of sensor-based application. If the distance between sensor and actuator is not large enough corresponding to the actual lag time, it may place the required seed rate far from the corresponding sensing point. Therefore, the design of sensing and controlling unit is highly critical and sometimes problems may arise due to poor system design. Moreover, integrating an automatic sensing, modeling and controlling systems is a complex job indeed. Several studies are available about sensor based site-specific applications for other agricultural inputs than seed. The VR fertilizer application (Chattha et al., 2014; Maleki and Zamiran, 2009; Maleki et al., 2008; Mouazen and Kuang, 2016), and pesticide [Chlorpyriphos (CPP)] spot applications (Esau et al., 2014a,b) can be highlighted as examples of sensor based site-specific applications. It is unexpected but true, that this review failed to find any study concerning the sensor based SSS application to date. Therefore, SSS has a great scope to adopt similar principles like other sensor-based site-specific applications. Future research should focus on developing and evaluating of sensor-based SSS under various soil quality, crops, locations and weathers conditions.

3. Key field quality indicators for defining site-specific productivity potential

The SSS mainly deals with two-core questions, i.e., (i) how much seeds should be allocated and (ii) which seed densities should be applied and at which depth. However, answering these two particular questions seem to be relatively complex. Allocating the correct rate of seeding and depth should be made according to productivity potential of a particular zone of a field. Mapping soil and crop quality indicators related to yield potential is essential for successful application of SSS. The assessment of soil quality is done through soil quality indexes (SQI) that are calculated as a function of individual or of fusion of several quality indicators (e.g., organic matter, N, P, K, pH, clay content). Crop quality is widely measured in terms of vegetation indexes (VIs), which calculated from measured reflectance spectra from crop canopy. Defining and quantifying of both SQI and crop VI could affect the successful implementation of SSS largely. Therefore, this section focuses on identifying the key soil quality indicators, SQIs and VIs essential for assessing the soil and crop quality and associated yield potential.

3.1 Soil quality indicators

There is a great debate about the terminology "soil quality" and "soil fertility," and previously researchers discriminated soil quality from soil fertility. Gheorghi (1932) mentioned this discrimination as the philosophical ideology rather than soil quality status. Soil fertility is described as soil's ability to provide essential plant nutrients (Watson et al., 2006) and water in adequate amounts and proportions for plant growth and reproduction to result in sustained and consistent yields of high quality. Soil quality is the ability of soil to perform its various functions for biological productivity, ensure ecosystems services, maintain environmental sustainability and promote plant and animal habitat (Doran et al., 1994). Since the functions are immeasurable directly, appropriate physical, chemical and biological parameters are selected as proxy for the different soil functions (Karlen et al., 2004). An important condition for a soil property to be considered as a soil quality indicator is that it should show sensitivity to any changes occurring within the soil function in discussion. Other favorable features of soil quality indicators include (i) a positive correlation with ecosystem services, (ii) easily measurable, (iii) sensitive to management, and (iv) whenever possible, to be a factor of an earlier available dataset (Andrews et al., 2004).

Scientists have been attempting to characterize the soil quality indicators (Vasiliniuc and Patriche, 2011) and quantifying their importance for crop yield (Whetton et al., 2017a). It is hardly possible to evaluate soil functionality based on little or individual soil property responsible for regulating crop yield (Nolin et al., 2001; Ward and Cox, 2001), as crop yield variation is affected by a number of biotic and abiotic factors (Shanahan et al., 2004; Van Roekel and Coulter, 2011; Viscarra Rossel and Behrens, 2010). Soil generally supplies a large amount of macronutrients along with trace amount of micronutrients except H, O, and C since plants draw most of them from air and water. The plant available soil nutrients are highly variable, due to complex nature of soil nutrient dynamics, which are strongly influenced by root–soil interactions. Plants can uptake only a limited portion of total amount of nutrients for their growth and development depending on the chemical formulation of soil minerals and interaction with other influencing parameters. For instance, about 30–70% of the total phosphorus (P) content in agricultural soils is organically bound and this percentage can be as high as 80–95% for grassland, peat and forest soils (Li et al., 2014a,b). The soil P availability is also influenced by the frequent presence the Fe, Al, and Ca ions, since the Fe and Al are key parameters to P fixation. Soil inherent acidity (i.e., pH) does critically regulate the P fixation and pH value between 6.0 and 7.5 is considered as an ideal acidity for soil P to be available to the plants (Pierzynski et al., 1994). In addition, availability of nutrients are highly dependent on soil physical properties such the soil texture, soil organic matter (SOM), soil moisture content (MC), electrical conductivity (EC) and temperature. In-field soil microclimate varies with the variation of soil texture, color, soil depth, clay content largely in temporal scale (Liu and Luo, 2011; Zheng et al., 1993). Some of the soil variations are strengthened due to the agricultural practices such as land preparation (tillage) and agro-chemical (fertilizer, manure and CPP) applications (Carvalho et al., 2003; Keesstra et al., 2016; Montzka et al., 2011). For instance, tillage can manipulate soil physical and hydraulic properties like water holding capacity, plant available water, hydraulic conductivity, soil bulk density (BD) and particle size distribution (González et al., 2015; Mohammadshirazi et al., 2017; Pires et al., 2017; Pöhlitz et al., 2018). These properties have direct interactions with plant available nutrients dynamics and soil-plant-water relationships (Bogunovic et al., 2018; Breland and Hansen, 1996; Gomez et al., 2002; Lipiec and Stepniewski, 1995; Mouazen and Ramon, 2006; Rosolem et al., 2002; Tracy and Zhang, 2008). Physical soil properties also have direct links with topographic attributes such as elevation, slope, aspect of slope, and profile and plane curvature (Franzen et al., 2002). All of these mentioned chemical and physical properties and topographic attributes are highly inter-linked and changing one characteristic influences the change of other characteristics (Ceddia et al., 2009; Paulus et al., 2010; Wilson and Gallant, 2000). This interlinked changing property creates a complex context of identifying soil quality indicators to address in-field soil quality variation. Bünemann et al. (2018) reviewed 65 scientific studies about soil quality assessment approaches. They identified a total of 27 soil parameters that were frequently considered as quality indicators. Mostly reported indicators were organic carbon (OC), pH and available P, whose frequency was higher than 70%. Including top three indicators, 50% of studies considered two more indicators only, namely, BD and water storage. This indicates that in total five indicators showed frequency higher than 50%. Only 10 out of 27 indicators were reported repeatedly (frequency >30%), whereas other parameters showed lower frequency (<30%). Among three categorical soil properties, chemical properties were largely considered than physical and biological properties. There was no biological property in the top 10 frequently recommended indicator's list.

3.2 Soil quality indexes

Soil quality index is a measurable soil parameter that affects the capacity of a soil to perform a specific function (Karlen et al., 2006). The most common method for calculating SQI was described by Andrews et al. (2004) and later several scientists followed this methodology for different locations and management goals (e.g., Askari and Holden, 2015). It comprises of three successive steps: (i) selecting key quality indicators, (ii) assigning appropriate scores and weight for each indicator, and (iii) integrating different indicators into one index value. Key indicators may ranges from soil physical, chemical and biological attributes forming a large data matrix called total data set (TDS). Selecting a proper indicator set is crucial for SQI calculation, and the most relevant soil quality indicators should be specified based on the management goals. One frequently used method is the selecting the minimum dataset (MDS) out of TDS by means of principal component analysis (PCA) (Andrews et al., 2002; Armenise et al., 2013).

Experts' opinion can also help in the selection of the right set of quality indicator. After selecting a MDS, the next step involves the transformation of each MDS indicator value into scores using scoring curves. Scoring curves are generally known as logic statement or algorithm. Algorithms may vary from linear to nonlinear types (Andrews et al., 2002). The weight factors are obtained from the PCA results. In the case of uncorrelated indicators in principal components (PCs), weighting factors were equal to the percentage of total variance explained by specific PC standardized to unity. For correlated indicators, the percentage of the total variance explained by the PC is divided among these and then standardized to unity (Masto et al., 2008). Finally, SQI is calculated by summing up these additive and/or weighted indicators. The higher the SQI the higher is the soil quality for a certain soil function (Mukashema, 2007). Usually, SQI values are normalized within a particular range say 1–10 (Andrews et al., 2004; Armecin and Cosico, 2010; Mukashema, 2007).

Table 1 summarized several studies about SQIs, corresponding to different soil functions, management goals, quality indicators and key facts and utilization. Productivity management goals are linked with some soil functions

Table 1 Summary of soil quality indicators and indexes with their respective management goal and supporting soil functions.

Fertility index name	Index model/logical conditions	Soil class	Prospective management goal	Focused soil functions	Key soil quality indicators (contribution ranking, %)	Key notes	Key references
Synthetic indicator of soil (SISF)	$SISF(\%) = \{VETL(\%) + PGI(\%)\} \div 2$ where, $VETL(\%) = \{BSI(\%) + CSI(\%)\} \div 2$ BSI, Biological synthetic indicator CSI, Chemical synthetic indicator	NA	Productivity, Environmental protection	Nutrient cycling, Biodiversity and habitat, Filtering and buffering	TC, ext. OC, Humic acid, TN, organic P, pH	SISF is one of the indicators significant for agronomic point of view.	Gheorghi (1932)
Biological index of soil fertility (F)	$F = \sqrt{(M^2 + H^2 + T^2)}$ where, M, enzyme activity H, SOM content T, sorption capacity (SC) of soil	Sandy	Environmental protection	Biodiversity and habitat	SOM, SC	Soil fertility index evaluated for maize ($r = 0.878$) and potatoes ($r = 0.879$).	Myśków et al. (1994)
Overall soil quality index (Index)	Index = f(y nutrient + y water + y rooting) where, y, is the weighting function for each function	Silt loam	All goals	Water relations, nutrient relations, Rooting relations	AGG, OC, porosity, crop residue, OC, water storage porosity, Bray P, exh. K, pH BD, pH, OC, air porosity	Index was evaluated for assessing the soil fertility change due to tillage operation over 8 years period.	Hussain et al. (1999)
Soil fertility index (SFI)	$SFI = pH + SOM + P + K + Ca + Mg - Al$	Diverse	Productivity	Nutrient cycling	pH, SOM, P, K, Ca, Mg, Al	Drawbacks of this index about the unclear definition of unit assignment to the parameter used, i.e., Ca, Mg, K, Al is in Meq 100/g, P in ppm, and SOM is in percentage.	Moran et al. (2000)
Soil evaluation factor (SEF)	$SFE = [Ca + Mg + K - \log(1 + Al)] * SOM + 5$	Humid tropical	Productivity	Nutrient cycling	Ca, Mg, K, Al, SOM	SEF showed significant positive correlations with soil OC, CEC, N, P, K.	Lu et al. (2002)

<table>
<tr><td>Soil quality indicator (SQI)</td><td>$SQI = \left(\frac{\sum_{i=1}^{n} S_i}{n}\right) \times 10$
S, score value for each indicator feature
n, number of indicator</td><td>NA</td><td>Productivity, environmental protection, waste management</td><td>Nutrient cycling, Resistance and resilience, Water relations</td><td>PMN, pH, P, AGG, BD, TOC, AWC, SAR, EC</td><td>SQI determined by integrating the scores into an index value and evaluated for four different case studies. Step wise regression showed that the scored indicators usually had R^2 similar or greater than those of the observed indicator values.</td><td>Andrews et al. (2004); Armecin and Cosico (2010)</td></tr>
<tr><td>Soil fertility index (SFI)</td><td>$SFI = \left(\frac{\sum_{i=1}^{n} S_{ci}}{N}\right) * 10$
$S_{ci} = C_j * p_c$
$p_c = \frac{1}{n_c}$
where,
Pc, probability of the class c
nc, the number class
Sci, score given to each class
N, number of indicators</td><td>Diverse</td><td>Productivity</td><td>Nutrient cycling</td><td>pH, OC, Al, P, K, Ca, Mg</td><td>SFI vary from 0 to 1, which means from extremely low fertile soil to very high fertile soil. Each MSFI (minimum soil fertility indicator) was assigned a score equivalent to its probability of falling in very high fertile soil (i.e., SFI = 1) by using the threshold and soil property classes.</td><td>Mukashema (2007)</td></tr>
<tr><td>General Indicator of Soil Quality (GISQ)</td><td>$GISQ = 1.51SI_{OM} + 1.13SI_P + 1.11SI_F + 1.10SI_M + 0.35SI_C$
$SI_{(OM,P,F,M,C)}$ are the sub-indicators of organic matter, physical, fauna, morphological, chemical variables
$SI_i = \sum_{i=1}^{n} w_i v_i$
SI, sub-indicators
Vi, variable values
Wi, respective weights</td><td>Diverse</td><td>All goals</td><td>All functions</td><td>Multiples</td><td>GISQ showed better performance at locally but their methodology for SQI calculation can work everywhere.</td><td>Velasquez et al. (2007)</td></tr>
<tr><td>Soil fertility index for sugarcane (SFI-SC) production</td><td><table><tr><td>Index</td><td>Clay, g/kg</td><td>CEC, mmol/kg</td><td>Bsat, %</td><td>SOM, g/kg</td></tr><tr><td>High fertile</td><td>>350</td><td>>150</td><td>>70</td><td>>25</td></tr><tr><td>Fertile</td><td>150–350</td><td>50–150</td><td>50–70</td><td>15–25</td></tr><tr><td>Least fertile</td><td><150</td><td><50</td><td><50</td><td><15</td></tr></table></td><td>Oxisols, Entisols, Alfisols, Ultisols, Inceptisols (Soil Survey Staff, 1999)</td><td>NA</td><td>NA</td><td>Clay [78], CEC [32], Bsat [8], SOM [36]</td><td>Soil properties showed significant contributions to the fertility index than terrain attributes. SFI-SC showed a fair agreement with green vegetation index (Spearman correlation, 0.45).</td><td>Viscarra Rossel et al. (2010)</td></tr>
</table>

Continued

Table 1 Summary of soil quality indicators and indexes with their respective management goal and supporting soil functions.—cont'd

Fertility index name	Index model/logical conditions	Soil class	Prospective management goal	Focused soil functions	Key soil quality indicators (contribution ranking, %)	Key notes	Key references
Soil quality index (SQI)	$SQI = \sum_{i=1}^{n} W_i \times S_i$ where, s_i, scores of individual indicator w_i, corresponding weight factor	Fluvisol, silty clay loam	Productivity	Nutrient cycling, water relations	Clay, SOM, Exh. K, PAW, avl. P	Correlation between SQI and crop yield (wheat and sugar beets) was not significant that make sense to consider better MDS including other indicators. The author also suppose this SQI could be applicable at regional scale.	Armenise et al. (2013)
Integrated fertility quality index (IFQI)	$IFQI = \sum_{i-1}^{n} W_i * I_i$ where, Wi, weight coefficient of the ith fertility quality parameter Ii, score of the Ith parameter N, number of parameters The score is determined according to standards scoring function (SSF) (Hussain et al., 1999) for all indicators except pH $f(x) = \begin{cases} 0.1 & x \le x_1 \\ \frac{0.9(x_1 - x_1)}{x_2 - x_1} + 0.1 & x_1 \le x \le x_2 \\ 1.0 & x \ge x_2 \end{cases}$ Specially for soil pH this SSF is: $f(x) = \begin{cases} 0.1 & x < x_1, x \ge x_4 \\ \frac{0.9(x - x_1)}{(x_2 - x_1)} + 0.1 & x_1 \le x \le x_2 \\ 1.0 & x_2 \le x \le x_3 \\ \frac{0.9(x - x_3)}{(x_4 - x_3)} + 0.1 & x_3 \le x \le x_4 \end{cases}$ where X, monitoring value of parameter X_1, x_2, x_3, x_4, influence of each parameter on crop growth (Qi et al., 2011; Wang and Gong, 1998)	Diverse	Productivity, environmental protection	Nutrient cycling, filtering and buffering	OC, TN, TP, TK, AP, AK	IFQI was evaluated to assess the change of soil fertility over the 20 years period due to application of fertilizer. Fertility index performed differently for different cropping rotations and across the fertilizer treatments.	Shang et al. (2014)

Soil quality index (SQI)	$SQI_A = \sum_{i=n}^{n} \frac{S_i}{n}$ $SQI_W = \sum_{i=n}^{n} W_i S_i$ $S_{NL} = \frac{a}{1+\left(\frac{x}{x_o}\right)^b}$ $S_L = \left(\frac{x-l}{h-l}\right)$ $S_L = 1 - \left(\frac{x-l}{h-l}\right)$ where A and W, additive and weighted additive scoring cases, respectively S_i, score of each indicators (linear or non-linear) S_L, linear score S_{NL}, non-linear score W_i, weight value of each indicator n, number of indicators a, maximum score, equal 1 x, measured value of indicators x_0, mean value of indicators b, slope of equation, equal (±) 2.5 l, minimum value of indicator h, maximum value of indicator	Typical brown earths and luvisols	Productivity, Environmental protection	Nutrient cycling, physical stability and support, resistance and resilience	TN, CN ratio, Mg, ASD, BD, PR, SR	This research compared their proposed SQI against visual evaluation of soil structure (VESS) practiced by Askari et al. (2013). SQI effectively could represent the influence of tillage on soil quality.	Askari and Holden (2015)
Soil quality index (SQI)	$SQI_{AP} = \left(\frac{\sum_{i=1}^{n} S_i}{7}\right)$ where, SQI_{AP}, soil quality index for arable land Si, non-linear scores for seven indicators	Typical brown earths and typical luvisols (Arable)	Productivity, environmental protection	Nutrient cycling, physical stability and support, resistance and resilience	BD, Mg, CN ratio, TN, SR, ASD	Vis-NIR was found effective to calculate SQI with excellent accuracy under grassland (RPD = 3.04, $R^2 = 0.92$, RMSE = 0.03) and arable (RPD = 2.78, $R^2 = 0.89$, RMSE = 0.04) management.	Askari et al. (2015)
	$SQI_{GP} = (0.557 * G_1) + (0.262 * G_2) + (0.181 * G_3)$ where, SQI_{GP}, soil quality index for grassland G_1, G_2, G_3 are non-linear scores for OC, BD and CN ratio	Typical surface-water gleys and stagnic luvisols (Grassland)	Productivity	Nutrient cycling, physical stability and support, resistance and resilience	OC, BD, CN ratio		

Continued

Table 1 Summary of soil quality indicators and indexes with their respective management goal and supporting soil functions.—cont'd

Fertility index name	Index model/logical conditions	Soil class	Prospective management goal	Focused soil functions	Key soil quality indicators (contribution ranking, %)	Key notes	Key references
Soil quality index (SQI)	$SQI(\%) = \left(\frac{y_i}{y_{total}}\right) \times 100$ where, Sum of soil attribut index, $y_i = m_1x + m_2x\ldots + e$ m_1, m_2, ….corresponding regression coefficients for "x" indicators y_{total}, combined soil attribute indices obtained from regression	Diverse	Productivity, environmental protection	Nutrient cycling, physical stability and support, resistance and resilience, water relations	BD, CN ratio, OC, TN, AWC, pH, EC	SQI based yield prediction showed good accuracy ($R^2 = 0.74$) for maize and ($R^2 = 0.89$) for soybean.	De Paul Obade and Lal (2016)

AGG, Macro-aggregate stability; *ASD*, aggregated size distribution; *PMN*, Potential Mineralizable Nitrogen; *PR*, penetration resistance; *SR*, soil respiration.
Prospective management goals and focused soil functions are based on Andrews et al. (2004) approximately.

such as nutrient cycling, water relations, physical stability and support, resistance and resilience. Some of SQIs are relevant to a specific management goal (Lu et al., 2002; Moran et al., 2000; Mukashema, 2007), whereas others incorporate more than one management goals (Andrews et al., 2004; Armecin and Cosico, 2010; Gheorghi, 1932). When the management objective is productivity, summation of score-based derived SQI (Armenise et al., 2013) is frequently suggested. Although a wide range of quality indicators are reported for SQI determination, these are measured by traditional laboratory analysis. Exception is also rarely reported for quality indicators measured with advanced sensor technology, e.g., visible and near infrared (vis-NIR) spectroscopy for SQI calculation and also for direct prediction of soil quality indicators (Askari et al., 2015).

Based on the above-provided information, it can be assumed that, top 13 most frequently reported indicators should be used to calculate SQI while the management goal is crop productivity. Fig. 1 illustrates the cross identification of soil quality indicators satisfying three different reference contexts: (i) quality indicators listed in Table 1 related to crop productivity, (ii) frequency of recommended soil quality indicators reviewed by Bünemann et al. (2018) and (iii) most crop influential soil quality indicators reported by several studies*. These identified soil quality indicators yield a ranked list of indicators shown in Table 2, which are assumed to be sufficient to support soil functions (e.g., nutrient cycling, water relations, physical stability and support, resistance and resilience) satisfying the crop productivity management goal (Andrews et al., 2004).

Practically speaking, soil quality indicators can be measured by: (i) the traditional methods of laboratory analyses (Wienhold et al., 2004), (ii) the Munsell soil color chart (Gobin et al., 2000) or (iii) proximal and remote sensing tools (Kuang et al., 2012; Mulla, 2013). However, the implementation of SSS requires high spatial resolution data that can be collected by category (iii), e.g., proximal and remote sensing tools. The optimal sensor technology or combination of sensor technologies to measure the MDS for the top key soil quality indicators for SSS need to be determined.

3.3 Crop quality indicators

Crop quality indicators can be used as the measure of crop health and yield potentiality. Crop canopy and it's geometric characteristics are the key indicators of crop growth and productivity (Lee and Ehsani, 2009). Multiple studies reported the use of canopy information as potential indicators to

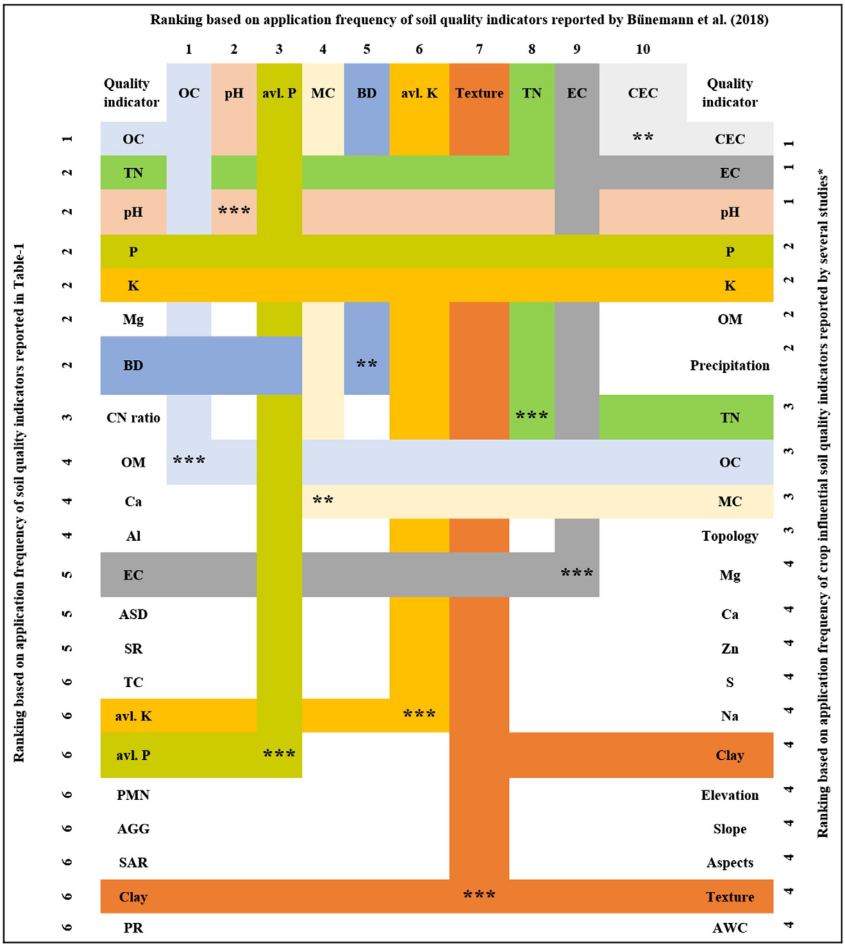

Fig. 1 Cross identification of soil quality indicators for crop productivity management based on three different reference scales. *Heege (2013a,b), Kravchenko et al. (2003), Kravchenko and Bullock (2000), Licht (2015a,b), Miao et al. (2006), Vasiliniuc and Patriche (2011), Whetton et al. (2017a). **Indicates those quality indicators supported by two reference scales. This group also includes Mg, Ca and SOM. ***Indicates those quality indicators supported by three reference scales. *AGG*, macro-aggregate stability; *ASD*, aggregated size distribution; *AWC*, available water capacity; *BD*, bulk density; *CEC*, cation exchange capacity; *CN ratio*, carbon and nitrogen ratio; *EC*, electrical conductivity; *MC*, moisture content; *OC*, organic carbon; *PMN*, potentially mineralizable nitrogen; *PR*, penetration resistance; *SAR*, sodium absorption ratio; *SOM*, soil organic matter; *SR*, soil respiration; *TC*, total carbon; *TN*, total nitrogen.

Table 2 Ranking of identified key soil quality indicators for productivity management goal.

Sl. No.	Soil property	Rank (Ranking score[a])	Supporting soil function(s)
1	pH	1 (100)	Nutrient cycling, Physical stability and support, Water relations
2	Avl. P	2 (90)	Nutrient cycling
3	Avl. K	2 (90)	Nutrient cycling
4	TN	2 (90)	Nutrient cycling
5	Texture	2 (90)	Physical stability and support
6	OC	2 (80)	Resistance and resilience
7	EC	2 (80)	Water relations
8	CEC	2 (80)	Nutrient cycling
9	MC	3 (70)	Water relations
10	BD	3 (70)	Physical stability and support, Water relations
11	SOM	4 (60)	Resistance and resilience
12	Mg	4 (60)	Nutrient cycling
13	Ca	5 (50)	Nutrient cycling

[a]Ranking score (0–100). Higher the score means higher the contribution.
BD, bulk density; *Ca*, calcium; *CEC*, cation exchange capacity; *EC*, electrical conductivity; *MC*, moisture content; *Mg*, magnesium; *OC*, organic carbon; *SOM*, soil organic matter; *TN*, total nitrogen.

predict crop yield (Villalobos et al., 2006; Zaman et al., 2006) and biomass production (Ehlert et al., 2008). Canopy dimensions including crop height, width and volume were widely considered to develop variable rate recommendation (Rüegg et al., 1999; Viret et al., 2007). Assessment of overall crop growth and health condition cannot be done directly by measuring crop morphological attributes. Early detection of crop biotic and abiotic stresses is also essential to reduce yield losses and increase profitability. Therefore, a group of vegetation indexes (VIs) are being repeatedly reported for monitoring crop quality and predicting crop yield (Marino and Alvino, 2014). Vegetation indices are mathematical combinations of several spectral bands mainly the red, green and infrared wavelengths, and they are designed to find functional relationships between crop characteristics and sensing observations (Wiegand et al., 1989). Some of the most commonly used VIs are presented in the Table 3, although >100 VIs have been reported

Table 3 Mostly known reflectance based vegetation indexes (VIs) used for assessing the crop canopy quality and their mathematical formulation.

Reflectance vegetation indexes

Vegetation indexes name	Mathematical formulation	Key reference
Normalized Difference Vegetation index (NDVI)	$\frac{\text{NIR}-\text{Red}}{\text{NIR}+\text{Red}}$	Sellers (1985)
Green Normalized Difference Vegetation index (GNDVI)	$\frac{\text{NIR}-\text{Green}}{\text{NIR}+\text{Green}}$	Ma et al. (1996)
Red Ratio of Vegetation index (RVI)	$\frac{\text{NIR}}{\text{Red}}$	Birth and McVey (1968)
Green Ratio of Vegetation index (GVI)	$\frac{\text{NIR}}{\text{Green}}$	Birth and McVey (1968)
Chlorophyll Vegetation Index (CVI)	$\frac{\text{NIR}}{\text{Green}} \times \frac{\text{Red}}{\text{Green}}$	Vincini et al. (2008)
Soil Adjusted Vegetation Index (SAVI)	$\frac{\text{NIR}-\text{Red}}{\text{NIR}+\text{Red}+\text{L}}$	Huete (1988)
Optimized Soil Adjusted Vegetation Index (OSAVI)	$\frac{\text{NIR}-\text{Red}}{\text{NIR}+\text{Red}+0.16}$	Rondeaux et al. (1996)
Red Edge Normalized Difference Vegetation index (RENDVI)	$\frac{\text{NIR}-\text{RedEdge}}{\text{NIR}+\text{RedEdge}}$	Gitelson and Merzlyak (1994)
Canopy Chlorophyll Content Index (CCCI)	$\frac{\text{RENDVI}-\text{RENDVImin}}{\text{RENDVImax}-\text{RENDVImin}}$	Barnes et al. (2000)
Ratio of RENDVI and NDVI	$\frac{\text{RENDVI}}{\text{NDVI}}$	Varco et al. (2013)
Red Edge Index (REI)	$\frac{\text{NIR}}{\text{RedEdge}}$	Vogelmann et al. (1993)
Chlorophyll Index (CI)	$\frac{\text{NIR}}{\text{Red}} - 1$	Gitelson et al. (2003)

Adopted from Padilla, F.M., Gallardo, M., Peña-Fleitas, M.T., De Souza, R., Thompson, R.B., 2018. Proximal optical sensors for nitrogen management of vegetable crops: a review. Sensors. 18, https://doi.org/10.3390/s18072083.

(Bannari et al., 1995; Ollinger, 2011; Xue and Su, 2017) for different applications. One should be wise to choose an optimal VI and/or their combinations for accurate estimation of crop yield (Chlingaryan et al., 2018). The VIs must be measured directly from the crop canopy although some other specific vegetation indexes differentiate crop vegetation from the soil surface, for example, the soil adjusted vegetation index (SAVI) (Huete, 1988). Among all VIs, the normalized difference vegetation index (NDVI) (Sellers, 1985) is probably the most widely reported and used vegetation index (Padilla et al., 2018). The NDVI showed a strong correlation ($R^2 = 0.85$) with leaf area index (LAI) (Sankaran et al., 2015), which is defined as the total leaf area per unit of ground area (Watson, 1937). It is considered as an important factor for explaining various physiological processes in crop such as evapotranspiration, photosynthesis, and crop yield (Price and Bausch, 1995). During the initial crop growth stage, low LAI and soil light scattering make spectral measurement difficult to isolate crop vegetation from soil (Huete, 1988). Later in crop season, high LAI can cause some VI measurements insensitive to the crop responses. However, the NDVI can be used as a proxy to calculate LAI (Pontailler et al., 2003) and yield prediction (Pantazi et al., 2016). The use of NDVI and SAVI for potato yield prediction showed moderate to good prediction accuracy ($R^2 = 0.39$ to 0.65). The prediction accuracy of VI varied among different sensing devices (Al-Gaadi et al., 2016) or crop sensors. A good choice of crop sensor should consider the crop growth stage, real application conditions and sensing period.

4. Soil and crop sensing technologies

High-resolution soil and crop data is the prerequisite for evaluating the spatial and temporal variability of a field to implement site-specific applications including seed rate. Sensing technologies are proven for mapping different source of variations at different geographic scales. They outperform the traditional soil and crop sampling and chemical analyses of being fast, cost effective and provide high resolution spatial representation (Adamchuk and Viscarra Rossel, 2010). Though a wide range of proximal soil sensing technologies have been reported (Adamchuk et al., 2004), the current review refers to proximal sensing (PS) and remote sensing (RS) technologies relevant to SSS. One more sensing approach designated as multi-sensor data-fusion is also discussed. A proper choice of a particular PS or RS technology depends on several factors including sensor cost, spatiotemporal coverage and resolution (in case of RS in particular), spectral range (e.g., optical), and intended application (Mulla, 2012). The use of RS to measure soil quality indicators has limited applicability to measure few millimeters of top soil and requires bare soil surface (Whetton et al., 2017a).

4.1 Proximal soil sensing

Proximal soil sensing (PSS) is the ground-based sensing tools to detect respective signals with or without direct contact with the objects, while residing within a sensing distance ranging from few centimeters to few meters (i.e., 2m) (Viscarra Rossel et al., 2011). PSS is fast, cost-effective, portable, and environmental friendly tools for measuring wide range of soil physical, chemical and biological properties. In order to map soil fertility characteristics, researchers have built numerous PSS platforms (Adamchuk et al., 2004; Hummel et al., 1996; Sudduth et al., 1997) using different sensing techniques, e.g., electromagnetic induction (EMI), electrical resistivity, ground-penetrating radar (GPR), passive gamma ray spectrometry, diffuse reflectance spectroscopy in the visible–near-infrared (vis–NIR) and mid-infrared (mid-IR) range (Stenberg et al., 2010), electrochemical sensors, e.g., ion-sensitive field effect transistors (ISFETs) and ion-selective electrodes (ISEs) (Adamchuk et al., 2005; Viscarra Rossel et al., 2005) and X-ray fluorescence spectroscopy. Adamchuk et al. (2004) classified PSS into six categories depending on the measurement concepts: (i) electrical and electromagnetic, (ii) optical and radiometric, (iii) mechanical, (iv) acoustic, (v) pneumatic and (vi) electrochemical. Later, Kuang et al. (2012) suggested five categorical soil sensors based on the measurement conditions such as (i) reflectance, (ii) conductivity, resistivity, permittivity, (iii) passive radiometric, (iv) strength and (v) electrochemical based soil sensors. Initially, electric and electromagnetic soil sensors were widely used for PA applications (Adamchuk et al., 2004). Afterward, other soil sensors were brought into application, bearing in mind that a right choice of soil sensor should depend on several factors such as soil property to be measured, mode of application (in situ, on-line or laboratory), actual field conditions (e.g., MC), sensor performance, among others. According to the SQIs determined above, two widely used proximal soil sensors that are potentially linked with implementation of SSS will be discussed, namely, EMI and vis-NIR spectroscopy.

4.1.1 Electromagnetic induction

Electromagnetic induction (EMI) is a non-contact, non-invasive, active sensor, whose working principle is the Faraday's law. It consists of a primary coil (transmitter) and a secondary coil (receiver) installed on both ends of a nonconductive bar, or double coils in more recent versions. McNeill (1980) explained the working principle of EMI devices in that the supply of alternating current excites the transmitter coil to induce an alternating magnetic field in the soil volume called primary magnetic field. This magnetic field generates small eddy currents in the soil while the soil matrix induces a weak secondary magnetic field corresponding to the eddy currents. Afterward, the receiver coil measures the secondary magnetic field, whose intensity is directly linked with the apparent electrical conductivity (ECa) of soil.

The magnitude and phase of the secondary magnetic field in the receiver coil differs from the primary magnetic field due to soil properties, spacing and orientation of transmitter and receiver coils (Hendrickx and Kachanoski, 2002). The exploration depth of the EMI signal depends also on the relative spacing between transmitter and receiver coils, instrument orientation and working frequency (McNeill, 1980). Soil ECa is the integrated contribution of soil physical and chemical properties and conductivity due to dissolved electrolytes in soil water and conductive minerals. Except metal objects, the soil conductivity is primarily electrolytes, as most of the soil and rock minerals are poor electrical conductors, formed by rocks and minerals (clay) (McNeill, 1980). The conductivity is proportional to the number of ions dissolved in the soil solution. In addition to electrolytes, soil physical properties including porosity and pore size distribution, moisture filled macro pores, and temperature of pore-water greatly affect soil ECa. Since a number of factors affects the ECa, it is difficult to identify the individual causal effect on soil ECa. Therefore, the majority of EMI applications in PA were aimed at mapping within field variability and to delineate MZs that can be used for site-specific soil and crop management (Corwin and Lesch, 2003).

Several authors used EMI to map soil salinity (Hendrickx et al., 1992; Williams and Baker, 1982), soil texture classes (e.g., James et al., 2003), including top soil clay content and depth of clay layers (e.g., Williams and Hoey, 1987; Stadler et al., 2015) and MC (e.g., Sheets and Hendrickx, 1995; Sun et al., 2011). Soil ECa can be used as a proxy of quantifying soil heterogeneity effect on crop yield (Stadler et al., 2015). The most relevant reviews about applications of EMI based ECa survey data for mapping various soil properties are summarized in Table 4. Most commonly used EMI device is EM38 found among all the literatures although other EMI devices are available such as EM31, EM34/3, GEM300, CMDminiexp and DUALEM.

4.1.2 Visible near infrared (vis-NIR) diffuse reflectance spectroscopy

Near infrared (NIR) spectroscopy's working principle relays on the internal vibrations of covalent bonds of soil molecules (C–H, O–H, N–H) due to applying external excitation, such as a light source. Stenberg et al. (2010) described the fundamentals of reflectance spectroscopy for soil analysis as when radiation is directed to a sample soil, individual molecular bonds vibrate by either bending or stretching, depending on the constituent present in soil. These vibrations lead to absorption of light, to various degrees, with a specific energy quantum corresponding to the difference between

Table 4 Potentiality and performance of electromagnetic induction (EMI) for the measurement of soil physical and chemical properties.

Soil properties	EMI device used	Performance (R^2)	Key references
Soil water content	EM38 & EM31, VERIS3100, GEM300, CMD-MiniExplorer	0.37–0.99	Brevik et al. (2006), Hezarjaribi and Sourell (2007), Hossain et al. (2010), Huth and Poulton (2007), Khakural et al. (1998), Mueller et al. (2003), Reedy and Scanlon (2003), Sheets and Hendrickx (1995), Stadler et al. (2015), Tromp-van Meerveld and McDonnell (2009)
Available N	EM38	*	Eigenberg et al. (2002)
OC	VERIS3100, EM38	*0.52–0.80	Banton et al. (1997), Martinez et al. (2009), Vitharana et al. (2008a,b)
Soil pH	EM31, EM38	*0.49–0.91	Dunn and Beecher (2007), Van Meirvenne et al. (2013), Vitharana et al. (2008a,b)
$CaCO_3$	EM38	0.80	Vitharana et al. (2008a,b)
Exc. Ca & Mg		0.87	McBride et al. (1990)
CEC	EM31 EM38	0.17–0.71	Rodrigues et al. (2015), Triantafilis et al. (2009)
Soil texture	EM38, DUALEM-21S, VERIS3100, CMD-MiniExplorer	0.67–0.98	Heil and Schmidhalter (2012), James et al. (2003), Stadler et al. (2015)
Clay content	EM38, EM34/3, CMD-MiniExplorer	*0.02–0.92, **2.83%	Cockx et al. (2009), Harvey and Morgan (2009), Mueller et al. (2003), Rodrigues et al. (2015), Sommer et al. (2003), Stadler et al. (2015), Williams and Hoey (1987)

*Significant ($P < 0.05$); **Root means square error (RMSE); *CEC*, cation exchange capacity; *EMI*, electromagnetic induction; *OC*, soil organic carbon; *N*, nitrogen.

two energy levels. As the energy quantum directly relates to the frequency, the resulting absorption spectrum is of a characteristic shape that can be used for further analytical purposes. The frequencies at which light is absorbed appear as a reduced signal of reflected radiation and are displayed in % reflectance (R), which can then be transformed to apparent absorbance (log(1/R)) (Chang et al., 2001). The wavelength at which the absorption takes place (i.e., energy quantum size) depends also on the chemical matrix and environmental factors such as neighboring functional groups and temperature, allowing for the detection of a range of molecules, which may contain the same type of molecular bonds.

Soil reflectance spectrum of NIR is complex and contains diversified but rich information of chemical and physical composition (Workman and Shenk, 2004). Broadening and overlapping bands cause vis-NIR spectra to contain fewer absorption peaks than the MIR spectra and can be more challenging to interpret. Nevertheless, this region contains useful information on organic and inorganic materials in the soil. Absorptions in the visible region (400–780 nm) primarily indicate the presence of minerals in soil that contain iron (e.g., hematite, goethite) (Mortimore et al., 2004; Sherman and Waite, 1985). Likewise, SOM can show broad absorption bands in the visible range that are dominated by chromophores and the darkness of SOM. Absorptions in the NIR region (780–2500 nm) are associated with overtones of OH, SO_4, and CO_3 groups, and combinations of fundamental vibrations that take place in the MIR range (Clark, 1999). Clay minerals can also have absorption in the NIR region due to metal-OH bend plus O–H stretch combinations (Viscarra Rossel et al., 2006a,b). Water has a strong influence on vis–NIR spectra of soils, with dominant absorption bands of water around 950, 1450 and 1950 nm, in the third, second and first overtones of OH absorptions. Vis-NIR spectroscopy can measure several soil properties simultaneously with adverse but appreciable prediction accuracy. Literatures reported successful application for soil MC, pH, OC, TN, TP, TK, CEC, and clay content measurement. Generally, fewer literatures found on measuring soil physical properties like bulk density (Cho and Sudduth, 2015) or soil classification (Mouazen et al., 2005).

At the beginning of application of the vis-NIR spectroscopy technique for soil analysis, multiple linear regression (MLR) analysis was most used. However, today there are different linear and nonlinear modeling tools to transfer the vis-NIR spectral data into qualitative and quantitative information. These include among others partial least squares regression (PLSR), and machine learning tools, such as artificial neural networks (ANN), random forest (RF), cubist and support vector machine (SVM) (Nawar and Mouazen, 2017a). Neither machine-learning algorithm nor linear regression is best performing for all properties since the prediction performance strongly depends on the data structure, variability and size of the calibration and validation sets. Irrespective to the calibration algorithms, the prediction output is usually validated and compared by means of root means squared error of prediction (RMSEP), coefficient of determination (R^2) and residual prediction deviation (RPD) (Kuang et al., 2015; Mouazen et al., 2010; Nawar and Mouazen, 2017b). It is common practice to use more than one performance index at a time for reliable model selection and evaluation. The best performing models are those of the highest R^2 and RPD and lowest RMSEP.

Vis-NIRS has been reported for laboratory and field applications. Among field applications, on-line vis-NIR sensing platforms offer high-resolution data on soil (e.g., Mouazen, 2006) (Table 5). Although on-line field measurement has some good features, literature found few researches under this category, due to problems associated with noise, sensor-to-soil distance variation and debris (Mouazen et al., 2007). Almost all studies showed higher accuracy for laboratory measurement than corresponding field studies, particularly concerning the on-line measurement mode (Kuang et al., 2012). For instance, Marín-González et al. (2013) reported larger R^2 values for laboratory measurement of pH, CEC, Ca_{exc} and Mg_{exc} of 0.86, 0.68, 0.86 and 0.66, respectively, compared with the on-line measurement of 0.78, 0.62, 0.61, 0.67, respectively. Higher RPD of 2.69, 1.77, 2.19 and 1.72, respectively, were reported for the laboratory measurement, compared to the on-line results of 2.14, 1.61, 1.30 and 1.49, respectively. Soil properties with direct spectral responses (MC, OC, TN, and clay) in the NIR range can be measured with higher confidence under both the field and laboratory conditions (Mouazen et al., 2007; Nawar and Mouazen, 2017b, 2018), compared to properties having indirect spectral responses (e.g., Mg, P, K, pH, Fe, Cu, Mn, Zn) (Marín-González et al., 2013; Malley and Williams, 1997). Literature demonstrates that there is a lack of studies on on-line measurement of soil micronutrients.

Vis-NIR showed the highest and consistent performance results ((R^2) > 0.84, (RPD) > 2.36) in measuring soil MC, compared to the other properties both those having direct spectral and indirect spectral responses. Properties having indirect spectral responses are measured with NIR spectroscopy due to the covariation with the soil properties having direct spectral responses (Stenberg et al., 2010). For example, soil pH showed stronger covariation with clay mineralogy and MC. Kuang et al. (2012) reported successful measurement of soil CEC, pH, exchangeable Ca and Mg using NIR spectroscopy although prediction performances were relatively lower than for the directly responsive properties. The current review points out two key prospects for the future use of vis-NIR spectroscopy: (i) future research should focus on minimizing measurement accuracy related gaps between field and laboratory measurement modes and (ii) there is need for an on-line measurement of soil micronutrients. Since the proven evidence of vis-NIR capable to measure diversified soil quality indicators under laboratory and on-line field condition, it can be concluded that the vis-NIR is the best proximal sensing candidate for SSS.

Table 5 Summary of the use of visible and near infrared (vis-NIR) spectroscopy for measuring soil properties.

Soil properties	Spectral response behavior	Laboratory measurement performance[a]			Key references	On-line (field) measurement performance[a]			Key references
		R^2	RPD	RMSE[b], %		R^2	RPD	RMSE[b], %	
Chemical properties									
TN	direct	0.04–0.99	0.34–6.80	0.0004–0.08	Coûteaux et al. (2003), Cozzolino et al. (2013), Dalal and Henry (1986), Guerrero et al. (2010), He and Song (2006), Kuang and Mouazen (2011), Vågen et al. (2006)	0.86–0.98	5.58–6.57	0.01–0.10	Christy (2008), Nawar and Mouazen (2017a,b)
TP	indirect	0.01–0.93	0.10–3.80	1.35–24.6 (100 mg/kg)	Bogrekci and Lee (2005), Cozzolino et al. (2013), He and Song (2006), Moron and Cozzolino (2007), Mouazen et al. (2010), Kuang (2016), Niederberger et al. (2015), Pinheiro et al. (2017), Stenberg et al. (2010), Wetterlind et al. (2010)	0.60	1.5	6.0 (mg/kg)	Kuang (2016)
Avl. P	Indirect	0.68–0.95	1.70–4.54	0.01–19.79 (100 mg/kg)	Bogrekci and Lee (2005), Cohen et al. (2005), Ludwig et al. (2002), Qiao and Zhang (2012)	0.69, 0.86	1.80	1.345, 8.67	Lei and Rong-biao (2016), Mouazen et al. (2007)
Ext. P	Indirect	0.32–0.77	0.40–2.07	1.70–3.89 (100 mg/kg)	Chang et al. (2001), Cohen et al. (2005), De Oliveira et al. (2015), Udelhoven et al. (2003)	0.64–0.77	1.72–2.89	8.87 (mg/kg), 11.523	Mouazen et al. (2007), Shaddad et al. (2013)
TK	Indirect	0.11–0.85	0.52–5.13	0.05–1.84 (cmol/kg)	Cozzolino et al. (2013), Cozzolino and Moron (2003), He and Song (2006), Mouazen et al. (2006a,b), Qiao and Zhang (2012), Tekin et al. (2016), Van Groenigen et al. (2003)	0.64–0.78	1.68	13.42, 0.13	Lei and Rong-biao (2016), Tekin et al. (2016)

Continued

Table 5 Summary of the use of visible and near infrared (vis-NIR) spectroscopy for measuring soil properties.—cont'd

Soil properties	Spectral response behavior	Laboratory measurement performance[a]				On-line (field) measurement performance[a]			
		R^2	RPD	RMSE[b], %	Key references	R^2	RPD	RMSE[b], %	Key references
OC	direct	0.46–0.98	1.30–9.70	0.06–2.90	Chang et al. (2001), Cozzolino et al. (2013), Dalal and Henry (1986), Kuang and Mouazen (2011), Nawar and Mouazen (2018), Pinheiro et al. (2017), Shepherd and Walsh (2002), Viscarra Rossel and Behrens (2010)	0.71–0.86	1.93–2.33	0.34–2.01	Bricklemyer and Brown (2010), Cho and Sudduth (2015), Kuang et al. (2015), Mouazen et al. (2007), Nawar and Mouazen (2018), Yang et al. (2012)
In-OC	Indirect	0.53–0.96	4.01–4.99	0.17–0.56	Brown et al. (2006), Cohen et al. (2005), Fontán et al. (2010), Krishnan et al. (1980), Yang et al. (2012)	0.31	1.24		Yang et al. (2012)
TC	Indirect	0.56–0.90	1.83–3.96	0.16–0.90	Kuang and Mouazen (2011), Mouazen et al. (2007)	0.73–0.98	1.92–7.54	0.01–0.268	Mouazen et al. (2007), Nawar and Mouazen (2017a,b)
Ca	Indirect	0.07–0.95	0.60–2.75	0.66–52.90 (cmol/kg)	Cohen et al. (2005), Cozzolino and Moron (2003), Mouazen and Ramon (2006), Pinheiro et al. (2017)	0.80	2.17	0.66	Van Groenigen et al. (2003)
Exc. Ca	Indirect	0.86	2.19	4.43	Marín-González et al. (2013)	0.61	1.30	7.11	Marín-González et al. (2013)
Mg	Indirect	0.53–0.91	0.48–2.54	0.03–38.36 (cmol/kg)	Chang et al. (2001), Cozzolino and Moron (2003), Pinheiro et al. (2017), Tekin et al. (2016), Udelhoven et al. (2003), Van Groenigen et al. (2003), Wetterlind et al. (2010)	0.60	1.56	2.19	Tekin et al. (2016)
Exc. Mg	Indirect	0.66–0.82	1.72–2.27	0.29–0.69	Marín-González et al. (2013), Van Groenigen et al. (2003)	0.67	1.49	0.34	Marín-González et al. (2013)
S	Indirect	0.92	2.19	2.1	Cozzolino et al. (2013)	–	–	–	–
Fe	Indirect	0.64–0.97	1.35–3.30	3.7–23.60 (mg/kg)	Cohen et al. (2005), Malley and Williams (1997), Moron and Cozzolino (2003), Yarce and Rojas (2012)	–	–	–	–

Mn	Indirect	0.65–0.92	1.79–3.66	56.4–190 (mg/kg)	Chang et al. (2001), Malley and Williams (1997), Moron and Cozzolino (2003), Yarce and Rojas (2012)	–	–	–	–
Zn	Indirect	0.44–0.95	1.07–3.80	1.4–299 (mg/kg)	Cohen et al. (2005), Kooistra et al. (2001), Malley and Williams (1997), Viscarra Rossel et al. (2006b), Yarce and Rojas (2012)	–	–	–	–
Cu	Indirect	0.25–0.84	0.92–4.00	0.8–6.01 (mg/kg)	Chang et al. (2001), Malley and Williams (1997), Siebielec and McCarty (2004), Wu et al. (2007), Yarce and Rojas (2012)	–	–	–	–
pH	Indirect	0.50–0.97	0.57–2.69	0.04–1.43	Cohen et al. (2005), He and Song (2006), Marín-González et al. (2013), Mouazen et al. (2006a,b), Pinheiro et al. (2017), Viscarra Rossel and Behrens (2010), Shepherd and Walsh (2002)	0.61–0.84	2.08–2.34	0.12–0.215	Christy (2008), Hummel et al. (2001), Kuang et al. (2015), Marín-González et al. (2013), Mouazen et al. (2007), Shibusawa et al. (2001)
CEC	Indirect	0.13–0.90	0.55–2.51	1.22–10.43 (cmol/kg)	Awiti et al. (2008) Chang et al. (2001), Marín-González et al. (2013), Mouazen et al. (2006a,b), Pinheiro et al. (2017)	0.62	1.61	–	Marín-González et al. (2013)
SOM	Indirect	0.69–0.96	1.79–2.08	0.058–1.09	He and Song (2006), Hong et al. (2018), Qiao and Zhang (2012)	0.64–0.85	2.17–2.63	0.19–0.36	Hummel et al. (2001), Nawar et al. (2016), Shibusawa et al. (2001), Shonk et al. (1991)
Na	Indirect	0.09–0.68	0.92–1.94	2.3–25 (cmol/kg)	Chang et al. (2001), Mouazen et al. (2006a, b), Mouazen et al. (2010), Tekin et al. (2016)	0.78	1.57	0.04	Tekin et al. (2016)
Al	Indirect	0.61–0.68	0.5–1.97	0.88–506.7 (mg/kg)	Cohen et al. (2005), Pinheiro et al. (2017), Siebielec and McCarty (2004)	–	–	–	–

Continued

Table 5 Summary of the use of visible and near infrared (vis-NIR) spectroscopy for measuring soil properties.—cont'd

Soil properties	Spectral response behavior	Laboratory measurement performance[a]			Key references	On-line (field) measurement performance[a]			Key references
		R^2	RPD	RMSE[b], %		R^2	RPD	RMSE[b], %	
Soil physical properties									
Clay content	Direct	0.15–0.96	1.70–4.94	0.79–6.10	Awiti et al. (2008), Ben-Dor and Banin (1995), Brown (2007), Chang et al. (2001), Conforti et al. (2015), Curcio et al. (2013), Gholizadeh et al. (2014), Pinheiro et al. (2017), Quraishi and Mouazen (2013)	0.72–0.90	1.40–3.15	0.96–6.94	Bricklemyer and Brown (2010), Kuang et al. (2015), Nawar et al. (2016)
Sand content	Indirect	0.59–0.92	0.87–3.40	1.91–11.93	Awiti et al. (2008), Ben-Dor and Banin (1995), Chang et al. (2001), Conforti et al. (2015), Cozzolino and Moron (2003), Curcio et al. (2013), Gholizadeh et al. (2014), Pinheiro et al. (2017)	0.38–0.61	1.26–1.41	3.37–4.0	Cho and Sudduth (2015)
Silt content	Indirect	0.36–0.84	1.09–3.07	1.79–9.51	Awiti et al. (2008), Ben-Dor and Banin (1995), Chang et al. (2001), Conforti et al. (2015), Cozzolino and Moron (2003), Curcio et al. (2013), Gholizadeh et al. (2014), Pinheiro et al. (2017)	0.60–0.81	1.56–2.20	5.30–6.93	Cho and Sudduth (2015)
Bulk density	Indirect	0.71–0.83	1.87–2.2	0.12–7.58	Gholizadeh et al. (2014) Viscarra Rossel and Webster (2012)	0.20–0.36	1.12–1.22	0.08–0.11	Cho and Sudduth (2015)
MC	Direct	0.84–0.98	2.36–5.86	0.50–4.88	Chang et al. (2001), Slaughter et al. (2001), Dalal and Henry (1986), Mouazen et al. (2006a,b)	0.68–0.93	2.86–3.98	0.024–1.75	Christy (2008), Hummel et al. (2001), Mouazen et al. (2007), Nawar and Mouazen (2017b), Shibusawa et al. (2001)

[a]Values of R^2, RMSE, and RPD do not just represent the particular studies enlisted in adjacent column, but they are also based on other studies not listed in this table.
[b]RMSE unit is in percentage (%) otherwise specified in the cell.
Avl.P, available phosphorous; *CC*, clay content; *CEC*, cation exchange capacity; *(Exc.) Ca*, (exchangeable) calcium; *Ext.P*, extractable phosphorous; *(In)OC*, (in)organic carbon; *MC*, moisture content; R^2, coefficient of determination; *RMSE*, root mean square of error; *RPD*, residual of predictiom deviation; *TK*, total potassium; *TN*, total nitrogen; *TP*, total phosphorus; *SOM*, soil organic matter.

4.2 Crop sensing

Crop sensing plays a significant role to assess the status of crop health by diagnosing biotic and abiotic stresses (e.g., Katsoulas et al., 2016). Considering crop information individually and/or along with soil quality indicators is suggested to delineate MZ for site-specific applications (Nawar et al., 2017) and yield prediction. In order to measure crop quality indicators (i.e., VI), a wide range of crop sensors has been identified and those could be grouped as proximal and remote crop sensing. This review will discuss RS application for measuring crop quality indicators (e.g., NDVI, biomass and crop density) crucial for SSS and expands the usage of both PS and RS tools for its measurement.

4.2.1 Remote crop sensing

The use of RS in agriculture refers to non-contact measurements of reflected or emitted radiation from agricultural fields. The RS platforms include unmanned aerial vehicle (UAV), airborne (airplanes with onboard pilot) and satellites. Incorporating respective sensors [i.e., Light Detection and Ranging (LiDAR), NIR, red, green, blue (RGB), or multi/hyperspectral camera], RS collect data in the form of images or spectra. It provides specialized capabilities for manipulating, analyzing, and visualizing images. RS has been proven to map the spatial variation in characteristics (Ammad-Udin et al., 2016) with the potential of decreasing considerable amount of labor, cost and time (Manchanda et al., 2002). Among the RS platforms, use of UAV is increasing day by day since it has enormous number of advantages for managing farm resources and exclusively for examining crop growth and biotic and abiotic stresses (Primicerio et al., 2012). Common applications of UAVs are crop sensing for site-specific fertilizer applications and weed control (Candiago et al., 2015; Ehsani et al., 2012; Evaraerts, 2008; Lucieer et al., 2014; Sugiura et al., 2003). The major drawback of copters UAV is that they are slow due to low battery capacity, thus causing shorter flight duration. Scientists are gradually trying to improve the battery technology that powers the copter (multi-propellers) and fixed wing UAVs to increase flight duration (Sankaran et al., 2015). Besides, conventional RS (i.e., satellite) technology has largely been suffering from numerous drawbacks such as prohibited access to free data, high price of images, less frequent and longer revisiting time, poor spatial resolution due to great height (Bansod et al., 2017) and weather conditions like cloud coverage and rainstorm. To overcome problems associated with spatial and temporal resolutions, there are several commercial satellites have been launched in the last two decades, for example, QuickBird (2001), RapidEye (2008), GeoEye (2008) etc., providing finer resolutions (Bansod et al., 2017), but at the cost of higher prices. There should be a recommended trade-off between price and optimum spatial and spectral resolution depending on the management objective, size of the machine used and size of MZ. For example, fine resolution (1–3 m) is required to analyze spatial variation of crop yield and biomass, while relatively coarse resolution (5–10 m) is enough to implement VR fertilization (Mulla, 2013). The 10 m spectral resolution free data offered by Sentinel2 and LandSat8 is potentially sufficient for measuring crop quality indicators. Al-Gaadi et al. (2016) predicted potato yield based on NDVI and SAVI generated by Sentinel2 and LandSat8 images. Model validation revealed that both the Sentinel2 ($R^2 = 0.47$ to 0.65, RMSE = 4.96–8.80 ton) and LandSat8 (R2 = 0.39–0.65, RMSE = 5.25–8.74 ton) showed similar prediction performance. LandSat8 satellite image analysis showed consistent performance over the ground based multispectral imagery (RedLake-MS4100) for developing MZ map of vineyard based on NDVI measurement (Borgogno-Mondino et al., 2018). It can be confirmed that, the free satellite RS is sufficient to measure NDVI with good measurement accuracy, hence, fulfils the requirement for SSS. In order to select proper satellite data, one should be wise enough about the period of sensing and satellite data quality, i.e., radiometric and geometric correction.

4.2.2 Proximal crop sensing

Proximal crop sensing (PCS) is the ground based tools for measuring crop characteristics either with or without direct contact with the crop canopy. The PCS devices can be handheld or machine-mounted type (i.e., tractor, robot, or quadbike). It includes different sensing categories; (i) mechanical, (ii) ultrasonic and (iii) optical techniques. Mechanical (Hammen and Ehlert, 1999) and ultrasonic (Llorens et al., 2011; Shibayama et al., 1985) sensors are mainly used for bulk measurement of canopy volume, biomass density and plant height. Mechanical crop sensor is principally a contact type sensor equipped with a pendulum pushed over the crop. Crop canopy exerts a reaction force against the pendulum that deviates from the original position of pendulum by some extent. This deviation can be related with the crop biomass density (Hammen and Ehlert, 1999). Since this is a contact type sensor, there are possibilities to damage crop by some extend, which is often considered as a major drawback of this technology. Ultrasonic crop sensor is a non-contact sensor, which emits a high frequency sound wave (>100 kHz) to the crop canopy and detect a reflected sound echo. The time difference between sending and detecting the sound echo is linked with the distance between crop and sensors. Several vertically installed sensors measured relative distances, which are used to measure plant height, crop volume and thus linked with crop density (Llorens et al., 2011; Zaman and Salyani, 2004). Optical crop sensors are based on sensing the amount of reflected radiation from crop canopy. Depending on the wavelength and number of wavebands of reflected energy, optical sensors can be classified into different categories (a) RGB, (b) multispectral, (c) hyperspectral, (d) fluorescence, (e) thermal, and (f) laser scanner (LiDAR), as shown in Table 6. Optical sensors can be either active or passive. Passive sensors require an external light/energy source, whereas the active sensors have own energy source of a wide range of light (Birrell et al., 1996; Povh and dos Anjos, 2014). Multispectral and hyperspectral cameras provide spectral and imagery data from few wavebands (5–8) to many wavebands (>100), respectively. Basic differences between hyperspectral and multispectral imaging are in the spectral range, continuity and spectral resolution of bands. Hyperspectral camera can measure crop properties in a finer scale than multispectral camera, although hyperspectral sensors are more expensive (Mulla, 2013). The spectral reflectance characteristics of plant (and their canopies) are determined by the chemical composition and physical properties of the plants and the spectral properties of the energy source (Bauer, 1985; Myneni and Ross, 1991). Plant absorption of light is directly related with plant pigments and water (970, 1450, 1944 nm). The most important absorptions pigments are chlorophyll-a (435, 670–680, 740 nm), chlorophyll-b (480, 650 nm), α-carotenoid (420, 440, 470 nm), β-carotenoid (425, 450, 480 nm), anthocyanin (400–550 nm), lutein (425, 445, 475 nm) and violaxanthin (425, 450, 475 nm) (Bauer, 1985; Myneni and Ross, 1991). As plants leaves contain most of the referred pigments and water, it is obvious to have broader absorption peaks instead of sharp peaks. Most frequent broadband absorption peaks appear in the vis-NIR spectrum at 400–500 nm (blue absorption), 660–680, 740 nm (chlorophyll absorption), 970 and 1450 nm (water absorption) (Myneni and Ross, 1991). In addition to light absorption, reflectance is affected by the plant physical structure and cells structure within the plant leaves (Bauer, 1985; Vogelmann, 1989). However, this physical characteristic is found to be most significant in the NIR spectrum. The reflectance from plant surfaces is due to light scattering from discontinuities in the refractive index in the leaves. The leave cell structure determines the number of air/water/cell-wall interfaces that proportionate the number of scattering

Table 6 Summary of various reflectance crop sensors with key features and their prospective applications and limitations.

Crop sensors	Key features	Prospective applications	Limitations
Red, green and blue (RGB)	Gray scale or color images	Greenness, growth, visible properties, outer defects, texture analysis	Limited spectral bands (visible) and properties
Multispectral/ color infrared camera	Few spectral bands per pixel in visible-infrared zone	Plant nutrient deficiency, water stress, diseases pressure	Limited to few spectral bands (e.g., 3–6 bands)
Hyperspectral camera	Continuous/ discrete spectra per pixel in visible-infrared zone	Plant stress, produce quality, and safety control	Challenging image processing, generally it is expensive sensor
Thermal camera	Temperature per pixel (for sensor with radiometric calibration) related to TIR emissions	Plant responses to water stress, pest and diseases pressure, Stomatal conductance	Ambient conditions affect the measurement performance, sharp temperature deviation is out of sensibility, relatively heavier
Spectrometer	Vis-NIR spectra averaged over a given field-of-view	Crop responses and diagnosing disease, pest infestation and stress	Spectral overlapping possibilities, spectra scattering by background (soil) may affect the sensing data quality
LiDAR sensor	Physical measures resulting from laser (600–1000 nm) flight duration (to and from object)	Estimates plant/tree height and biomass volume	Limited performance when a very small variations in path (flight) length
Fluorescence sensor	Passive sensing-visible and near infrared regions	Photosynthesis, chlorophyll concentrations, water stress	Can be affected by background noise

Adopted from Sankaran, S., Khot, L.R., Espinoza, C.Z., Jarolmasjed, S., Sathuvalli, V.R., Vandemark, G.J., Miklas, P.N., Carter, A.H., Pumphrey, M.O., Knowles, N.R., Pavek, M.J., 2015. Low-altitude, high-resolution aerial imaging systems for row and field crop phenotyping: a review. Eur. J. Agron. 70, 112–123. https://doi.org/10.1016/j.eja.2015.07.004.

points (e.g., cell walls versus intercellular air and heterogeneities within the cell) (Vogelmann, 1989). Different layers of vegetation will enhance the spectral reflectance, effectively increasing the number of refractive index discontinuities (Bauer, 1985).

Among the reflectance based PCSs, CropCircle and GreenSeeker are most common commercially available ones. CropCircle uses reflectance in the green and NIR bands to estimate crop nitrogen (N) deficiencies (Holland et al., 2004). The motivation behind using the green band rather than red reflectance was that as crop LAI increases beyond 2.0, the green NDVI is more sensitive to the changes in chlorophyll concentration and potential crop yield than NDVI (Gitelson et al., 1996; Sripada et al., 2008). This feature of CropCircle sensor can overcome the limitation of using the GreenSeeker sensor at advanced crop growth stages (Mulla, 2013). Therefore, selection a suitable crop sensor should consider the real application conditions and sensing period, which can affect the performance of sensing devices. In this sense, PCS is more flexible to measure crop quality indicators whenever required and suitable for the measurement while RS technology suffers from numerous limitations in this regard.

4.3 Multi-sensor and data fusion

The accuracy of a single sensor is often low because proximal soil sensors response to more than one soil property of interest simultaneously (Adamchuk et al., 2001; Kuang et al., 2012). This shortcoming may be overcome by adopting a relatively new approach designated as multi-sensors and data fusion, aiming at providing complementary, more accurate and robust measurements of different parameters in the agricultural system including soil characteristics (Adamchuk et al., 2004; Al-Asadi and Mouazen, 2014; Castrignanò et al., 2012; Mahmood et al., 2012) and crop properties (Weis et al., 2013). Nawar et al. (2017) reported three key sorts of sensor fusion approaches: (i) proximal-with-proximal sensor fusion, in which just proximal sensors are mutually fused; (ii) remote-with-proximal sensor fusion, in which proximal sensor(s) are fused with remote sensor(s); and (iii) remote-with-remote sensor fusion, whereby only remote sensors are integrated. Multi-sensor data fusion is expected to measure the target quantity with additional accuracy higher than a single measurement technique. The accuracy of measurement is greatly depends on the right choice of the measuring techniques. The selection of a set of sensors to be integrated depends on the objective parameters, practical information, actual application situations and sensor fusibility. Generally, some sensors are moderately easy to blend, for instance EMI and electrical resistivity for soil measurement, others (e.g., vis–NIR, MIR, Gamma & GPR) might need specifically designed software, regular calibration and hybrid data processing and interpretation (Grunwald et al., 2015). Corresponding data can be obtained from laboratory, in situ, on-line measurement, historical record or clouds. Data integration should lead to delineate MZs and generating a recommendation map for the site-specific application of various agricultural inputs.

In order to satisfy the needs for multi-sensor data fusion, scientists proposed several sensor combinations to map soil and crop variations, as shown in Table 7. For example, Wong et al. (2010) and later Castrignanò et al. (2012) proposed combining EMI with gamma ray spectroscopy along with high precision positioning system (RTK-GPS) for successful prediction of plant available soil K and delineating within field homogenous zone. Veum et al. (2017) evaluated the potentiality of fusing vis–NIR spectrometry with a penetrometer (Veris profiler 3000) to estimate cone index (CI) and soil ECa with the aim to assess the soil overall health by scoring the soil biological, chemical and physical proportions. The Soil Management Assessment Framework (SMAF) (Andrews et al., 2004) was established based on the laboratory analysis for BD, MC, texture, total organic carbon (TOC), TN, active C, β-Glucosidase, pH, P_{ext}, K and mineralizable N. The PLSR results indicated that the sensor fusion improved the prediction performance ($R^2=0.78$, RMSE = 7.21%) for the soil health quality quantification in contrast to the measurement ($R^2=0.69$, RMSE = 8.41%) obtained by vis–NIR spectroscopy alone. Most recently, Castrignanò et al. (2018) fused data of EMI and GPR in order to delineate MZs for site-specific fertilizer management and tillage practice. Unexpected but true fact is that, there is no literature reported the multi-sensor data fusion study in relation to the implementation of SSS.

Data fusion between proximal and remote sensing is also an effective approach for measuring soil and crop spatial properties (Blaes et al., 2005; De Benedetto et al., 2013a,b,c; Gao et al., 2017; Grunwald et al., 2015) for site-specific crop management. De Benedetto et al. (2013a,b,c) proposed a fusion approach for satellite remote sensors and proximal soil sensor (i.e., EMI). Particularly, WorldView2 and GeoEye1 were used for the measurement of crop VI, while the EMI sensor was used to measure ECa. Their proposed multi-sensor fusion resulted in an optimum delineation of different MZs. Zhang (2010) discussed the fusion approaches which included very high-resolution data from optical sensors such as panchromatic (PAN),

Table 7 Summary studies of multiple-sensors data fusion in precision agriculture (PA) applications.

Sensors involved in fusion	Type of multiple sensor/data fusion	Objective of fusion techniques	Key findings and discussions	Key reference
EMI, Airborne multispectral scanner	PR-soil and crop sensing	To map soil units as field scale	EM38 data was integrated with LAI, calculated from multispectral airborne remote sensing (Daedalus-ATM). The quality of identified soil individual zone was mostly dominated by AWC and oxygen deficiency during standing water in the field	Sommer et al. (2003)
ER, Gamma	PP-soil sensing	To map ERa, KUTH, MS	Result found higher KUTH for higher clay content; MS was higher and ERa was lower under higher CC	Becegato and Ferreira (2005)
Load cell, vis-NIR, gauge wheel with LVDT	PP-soil sensing	To develop on-line measurement system of soil BD	The soil BD was assessed from draught, cutting depth and MC with $R^2=0.56$. Online measurement of BD was worse for dry areas	Mouazen and Ramon (2006)
EMI, LiDAR	PR-soil sensing	To identify and map key soil indicators and crop yield, thus for delineating MZs	ECa, pH and OC were identified as keys indicators to evaluate field variation and OC was replaced by elevation. The ECa was found positively correlated with CC ($R^2=0.49$) and negatively correlated with sand content ($R^2=-0.49$). Management zones were related to landscape position, and thus soil MC. Crop yield varied over the MZs	Vitharana et al. (2008a,b)

Continued

Table 7 Summary studies of multiple-sensors data fusion in precision agriculture (PA) applications.—cont'd

Sensors involved in fusion	Type of multiple sensor/data fusion	Objective of fusion techniques	Key findings and discussions	Key reference
LandSat7 ETM, ASTER	RR-soil sensing	To measure the soil TP using RS indices and geo-statistics	Log floc TP was best modeled by fusion of Landsat ETM and NDVI effectively with $R^2=0.68$	Rivero et al. (2009)
Vis-NIR, EMI	PP-soil sensing	To measure multiple soil properties	Quality of prediction estimates varied over the sensors used, soil properties, methods of estimation. Among the three study areas, R^2 varied from 0.01 to 0.93. Overall, sensor data fusion produced the best soil property estimations, followed by vis-NIR and EMI sensor alone	Mahmood et al. (2012)
EMI, GPR	PP-soil sensing	To estimate CC	Clay content was estimated with $R^2=0.89$ at 0–20 cm from EMI and GPR data where sensor data fusion through the kriging with external drift (KED) improved the clay content estimations compared to ordinal kriging (OK)	De Benedetto et al. (2012)
2 × EMI, Gamma	PP-soil sensing	To delineate MZ and to estimate and map soil P, avl. K.,OC, pH	Result indicated that K was correlated with Gamma-ray K counts with $R^2=0.41$; Spatial patterns of P, K, OC were positively correlated to each other and negatively correlated with pH. Sensor fusion improved the overall delineation of MZs compared to single a sensor data	Castrignanò et al. (2012)

EMI, 2xGPR	PP-soil sensing	To estimate soil MC	MC at a depth of 0–30 cm was estimated with $R^2=0.60$ from EMI (ECa), GPR and CC. Sensor data fusion through KED improved the MC measurement in comparison to the OK	De Benedetto et al. (2013b)
EMI, GPR, vis-NIR, WorldView2	(PP & PR)-soil and crop sensing	To delineate homogenous MZ	Integrating ECa from EMI with GPR signal allowed to measure soil and subsoil properties simultaneously. Vis-NIR (FieldSpec) and satellite remote sensing (WorldView) integration was used for overlaying crop information (NDVI) with soil properties. ECa and vis-NIR spectra were the most informative properties. GPR should be used in cases where particular spatial structures are expected in the subsoil since data processing for GPR is more complex	De Benedetto et al. (2013c)
EMI, GPR, LiDAR	(PP & PR)-soil sensing	To identify and map the key indicators for delineating MZs. Also, to measure and map wheat yield	Results identified key indicators (ECa, pH and elevation) to map field variation. Fuzzy K-means classification delineated MZs. Crop yield was estimated with R^2 of 0.88 considering full data of ECa and elevation data. ECa alone could predict yield with R^2 of 0.98 using the 10% highest yield data within the range of ECa measurement	Van Meirvenne et al. (2013)

Continued

Table 7 Summary studies of multiple-sensors data fusion in precision agriculture (PA) applications.—cont'd

Sensors involved in fusion	Type of multiple sensor/data fusion	Objective of fusion techniques	Key findings and discussions	Key reference
Single-probe horizontal penetrometer, A dielectric-type soil water content sensor, Gamma-ray sensor (Mole)	PP-soil sensing	To estimate and map multiple soil properties, To map crop yield	BD was estimated with $R^2=0.72$ from MR (mechanical resistance), MC (vol.) and CC, and with $R^2=0.90$ from MR, MC (grav.), CC and OM. Maps of crop yield, MR, MC(vol.), CC and BD showed similarities	Naderi-Boldaji et al. (2013)
EMI, Gamma, Panchromatic aerial imagery, RTK-GPS	(PP & PR)-soil sensing	To measure and map CC	CC was measured with minimum mean absolute error (MAE) of 1.2% from ECa and Gamma-ray, and the addition of aerial photography and topographic variables did not improve these estimations. CC estimations from ECa alone were improved with the addition of gamma-ray or aerial photography. CC estimations from Gamma-ray alone were not much improved by addition of other data. CC estimations from sensor data outperformed OK estimations	Piikki et al. (2013)
EMI, vis-NIR	PP-soil sensing	To delineate MZs and measure crop yield for saline region	Crop yield was measured with $R^2=0.53$ from EC, BD, OC and CC. These soil properties were properly described only by the integration of ECa and bare soil NDVI, thus delineation of MZs required both sensors. Fuzzy c-means clustering algorithm delineated five MZs according to the soil fertility	Scudiero et al. (2013)

CropCircle (ACS-210), vis-NIR	PP- soil and crop sensing	To delineate MZ for VR fertilizer management	MZ delineated using vis-NIR measurands coupled with NDVI from CropCircle outperformed the traditional MZ performance in terms of yield and economic return for oil-seed rape	Halcro et al. (2013)
ER, Hyperspectral satellite imaging	PR-soil sensing	To compare the sensor data fusion techniques for infield estimation of soil properties.	This research reported a joint exploitation of hyperspectral satellite data and geophysical data for estimating soil properties at the field scale. Regression kriging estimated clay, sand and AWC with a sufficient degree of accuracy (RPD > 1.4). PLSR-kriging estimated these variables by using only remote sensing covariates and obtained better results than PLSR in most cases. For other soil variables, the prediction ability was unsatisfactory (RPD < 1.4) due to smaller sample set, and range and weaker correlation with the covariates	Casa et al. (2013)
EMI, Satellite imagery (Worldview2, GeoEye)	PR-soil and crop sensing	To make partition of filed for site-specific irrigation management	Multivariate geo-statistics and a clustering approach were applied to the overall multi-sensor dataset recorded form ECa (EMI) and NDVI (WorldView2 images), whereas the data from GeoEye were clustered to validate the MZ delineation. The approach allowed to integrate different sensors data and to identify three homogenous sub-field areas related to the intrinsic properties of soil and the crop response	De Benedetto et al. (2013a)

Continued

Table 7 Summary studies of multiple-sensors data fusion in precision agriculture (PA) applications.—cont'd

Sensors involved in fusion	Type of multiple sensor/data fusion	Objective of fusion techniques	Key findings and discussions	Key reference
FDR, vis-NIR	PP-soil sensing	To determination MC, BD	MC (vol. and grav.) were measured at $R^2=0.98$ from FDR output voltage and vis-NIR spectra, and then used to measure BD at $R^2=0.81$; This PP sensor data fusion improved the MC and BD estimation	Al-Asadi and Mouazen (2014)
EMI, vis-NIR, load cell, gauge wheel	PP-soil sensing	To delineate MZ for sit-specific irrigation	On-line measurement accuracy for OC and MC were good to excellent where RMSEP 0.06–0.72% and 0.97–2.49% and (RPD) values of 2–2.57 and 1.94–2.1, respectively. For CC and PI, the measurement was of fair to moderate accuracy with RMSEP values of 1.4–3.94% and 2.43–2.77% and RPD values of 1.41–1.77 and 1.25–1.48, respectively. The water holding capacity (WHC) was derived as a function of OC, CC, BD, PI and ECa using the MLR and ANN analyses. The MZs were designated according to the normalized value of WHC. A comparative analysis between WHC and available water content (AWC) reported the similar spatial distribution thus recommended the multi-sensor data fusion to optimize irrigation scheduling	Mouazen et al. (2014)

Vis-NIR, multi-source	Data fusion	To delineate MZ	Based on the vis-NIR spectra, the PLSR model predicted pH, P, MC, K at excellent to moderate accuracy. First regionalized factor produced three MZs of same size. This factor was assumed as synthetic fertility indicator of field since it could reveal 40% of yield-MZs association	Shaddad et al. (2016)
Vis-NIR, Penetrometer (ECa, CI)	PP-soil sensing	To assess the overall soil health based (SMAF)	They calculated the SMAF based on the laboratory data such as BD, MC, texture, TOC, TN, active C, β-Glucosidase, pH, Pext., K and mineralizable N. Sensor fusion could increase the PLSR model' prediction performance ($R^2 = 0.78$, RMSE = 7.21%) of quantifying the soil quality score by reducing 14% the RMSE, whereas, the vis-NIR spectroscopy alone showed lower performance ($R^2 = 0.69$, RMSE = 8.41%)	Veum et al. (2017)

Continued

Table 7 Summary studies of multiple-sensors data fusion in precision agriculture (PA) applications.—cont'd

Sensors involved in fusion	Type of multiple sensor/data fusion	Objective of fusion techniques	Key findings and discussions	Key reference
LandSat, MODIS	RR-crop sensing	To map the progress of crop development	Results showed that the detailed spatial and temporal variability in vegetation can be made by using sensor fusion between the Landsat-MODIS data. The mean difference in NDVI between actual Landsat observations and the fused Landsat-MODIS data is in the range of −0.011 to 0.028 for every year. Results suggested that crop phenology and certain growth stages at field scales (30 m spatial resolution) can be linked and mapped by integrating imagery from multiple remote sensing platforms	Gao et al. (2017)
EMI, GPR	PP-soil sensing	To delineate MZs using geo-statistics	Geo-statistically sensor fusion technique estimated synthetic scale-dependent regionalized factors. Complementary 2D EMI measurement and 3D GPR attenuation effectively delineate MZs for site-specific application	Castrignanò et al. (2018)

ANN, artificial neural network; *ASTER*, advanced space-borne thermal emission and reflection radiometer; *AWC*, available water content/capacity; *BD*, bulk density; *CC*, clay content; *EMI*, electromagnetic induction; *ER*, electrical resistance; *ERa*, apparent electrical resistance; *ETM*, enhanced thematic mapper; *FDR*, frequency domain reflectometer; *GPR*, ground penetrating radar; *KED*, kriging with external drift; *KUTH*, counts for potassium, equivalent uranium and equivalent thorium; *LAI*, leaf area index; *LiDAR*, Light detection and ranging; *LVDT*, linear variable differential transducer; *MAE*, mean absolute error; *MC*, moisture content; *MLR*, Multiple linear regression; *MODIS*, moderate resolution imaging spectroradiometer; *MR*, mechanical resistance; *MS*, Magnetic susceptibility; *MZ*, management zone; *NDVI*, normalized difference vegetation index; *OC*, organic carbon; *OK*, ordinal kriging; *PI*, penetration index; *PLSR*, partial least square regression; *PP*, proximal with proximal; *PR*, proximal with remote; *RMSE(P)*, root mean square error (of prediction); *RPD*, residual prediction deviation; *RR*, remote with remote; *RS*, remote sensing; *SMAF*, soil management assessment framework; *TN*, total nitrogen; *TOC*, total organic carbon; *TP*, total phosphorous; *WHC*, water holding capacity.

multi-spectral, synthetic aperture radar (SAR) and LiDAR. Fusion of RS is used mainly to integrate different resolution sensor data to improve the level of information obtained from these sensors (Grunwald et al., 2015). Over all, this type of sensor combination has been adopted less frequently for soil mapping than proximal-proximal sensor fusion for soil and crop measurement.

Based on the discussion about multi-sensor data fusion, one may expect a better sensor combination including vis-NIR and EMI for better measurement of soil properties, related to SSS applications. With the adoption of proper chemometrics, machine learning, and geo-statistical analysis, the output is expected to be a more accurate MZ delineation. The MZ delineation may further be tuned by coupling crop data including NDVI, crop density and yield with auxiliary data such as terrain characteristics and weather conditions (Halcro et al., 2013). Therefore, future research should focus on which sensing system apart from EMI does perform better when fused with vis-NIR for implementation of SSS.

5. Site-specific recommendation

Defining the desired seeding rate or seed placement depth, for a specific group of affecting parameters, is a key issue for successful implementation of SSS. In this section, a critical review is undertaken on methods adopted for SSS rate and seed placement depth.

5.1 Site-specific seeding rate recommendation

Recommendation for SSS requires detailed information about soil type and fertility, soil and crop microclimatic conditions, crop types and growth, biotic and abiotic crop stresses and topographical information. Different layers of information are then fused by means of relevant geo-statistical tools, modeling and artificial intelligence technologies. In the first step, maps of different layers are developed and visualized. Crop yield relationships with collected multilayer data is then examined, to quantify the yield limiting factors of individual and collective data layers (Whetton et al., 2017a,b). This should be followed by the derivation of MZ maps that mainly reflect the yield potentiality. Based on the analysis of yield potential of each MZ, a decision support scheme for SSS is developed. Finally, a recommendation is generated, which provides guidance to a PA equipment and ensure optimum production inputs for economic and environmental perspectives. There are different methods found in the literature on how the amount of optimum seeding rate have been defined so far, which are discussed in the following subsections.

5.1.1 MZs-specific arbitrary seed rate

After required measurement of all soil and crop quality indicators, MZs need to be delineated based on the within field variability. Once MZs are identified and delineated, one has to assign the most practical seed rate per MZ. For VSR recommendation, an average seed rate or widely pragmatic seeding rate is assigned to the moderately fertile MZ. Higher seeding rates are recommended to the higher fertile zone to produce higher crop yield while low productive zone could deliver better yield at lower seeding rate or plant populations (Hörbe et al., 2013). For the remaining MZs, seed rate recommendations are determined roughly by increasing or decreasing seed rate by given percentage of the average seed rate. For instance, individual farmers would have their own seeding rate respective to the field and the upper, and lower seeding rates would vary by ±30% from the average seeding rate (Smidt et al., 2015). Percentage increase and decrease of seed rate recommendations over the average rate depends on corresponding yield potentiality of MZs (Lovell, 2016). To date all the existing SSS approaches are based on this arbitrary recommendation approach (Table 9), as it is easier and faster to develop, and reliable to the farmers. Arbitrary recommendation also carries higher risk of non-optimal VSR recommendation for most instances across the growing conditions and crops.

5.1.2 MZs-specific optimal seed rate

MZs-specific optimal recommendations has been reported by Kirk (2017), which was designated as "Directed-Rx." Directed-Rx is a system that was developed in an effort to improve arbitrary VSR recommendation. Directed-Rx aimed at the integration of soil properties layers with yield data records to optimize input requirements for a specific zone of a field. This system allows for any spatially observed soil property (MZ proxy) data to be used as a foundational indication of field variation, on which field is divided into different MZ. Strip trial treatments are then allocated to each field study. Generally, one treatment is assigned a seed rate similar to the growers' normal practices, two rates above the normal, and two rates below the normal rate. Georeferenced yield is recorded during harvesting and then a point dataset is created that includes the yield, strip trial seed rate and soil property map. After a proper data pre-treatment, yield data is averaged across each MZ within each strip treatment. As a function of yield, market prices, input rates and input costs, returns above variable input costs (RAVIC) is calculated for each averaged yield. Yield and RAVIC are then regressed as a function of sequentially ranked MZ within each strip treatment. These regression models predict crop yield potential and RAVIC, as a function of MZ proxy for each MZ and each strip treatment (e.g., input rate). From among the strip treatments for each MZ, the treatment producing the maximum yield or RAVIC would be selected as the optimum treatment rate. Afterwards, these optimum rates are assigned to the MZs resulting in the recommendation plan for map-based site-specific application in the subsequent year. Directed-Rx can determine optimum input level for maximizing crop yield for each MZ in the field. Moreover, taking current market prices per unit input, Directed-Rx potentially allows analyzing the economic return on investment over other VR competencies. Kirk (2017) discussed six case studies for site-specific rate recommendations for maize (hybrid: A, B, C and Dual) and soybean seeding, including nitrogen application for cotton production where they considered soil EC as MZ-proxy. Economic benefits of the Directed-Rx are reported for SSS of maize (3–19 $/ac), dual hybrid maize seeding (2–18 $/ac), SSS for soybean (6 $/ac) and VR nitrogen for cotton (11 $/ac).

5.1.3 Model-based optimal seed rate

Model-based optimal VSR recommendations are made according to predefined mathematical formulation of input rate as a function of soil specific quality indicators and/or yield potential. Recommendations are generated in real time by sensing and measuring required soil and crop properties. The hypothesis is that, the real time optimization of input allocation can ensure best utilization of yield potential of a certain field. Several attempts have been reported by many scientists for developing model-based optimal recommendation for site-specific fertilizers application, tillage practices and seeding (Jiang and Thelen, 2004; Licht et al., 2017; Maleki et al., 2007, 2008; Mouazen and Ramon, 2006; Taylor et al., 2000).

Initially, VSR was implemented arbitrarily, ignoring site-specific soil quality or yield potential. Most researches proposed crop yield regression models as a function of plant populations where crop yield was expressed as a nonlinear quadratic function of plant populations (e.g., Assefa et al., 2016; Murányi, 2015; Woli et al., 2014). Vories et al. (2015) investigated the relationship between maize plant populations and yield, reporting a stronger relationship between the final stalk counts and yield than the relationship between target seeding rate and stalk counts. Scientists have been trying to incorporate more soil parameters into the yield models beside plant populations (Jiang and Thelen, 2004; Licht, 2015a,b; Licht et al., 2017; Taylor et al., 2000), with a view to build more universal models for prescribing seeding rate. Several researchers have developed index-models for determining the optimum seeding rates of maize based on the soil quality status (Table 8). Taylor et al. (2000) reported a seeding rate model based on soil EC only, which showed inconsistent estimation of seeding rate across the sites and years. The EC showed variable (positive and negative) correlation with crop yield and seeding rate for different site years. Based on one site-year interaction, the optimum predicted seeding rate for maize was approximately 28,000 seeds/ac, which was slightly higher than (26,000 seeds/ac) proposed by other researcher (Staggenborg et al., 1999). Research conducted by Licht et al. (2017) for optimizing seeding rate of maize in Iowa State University considered average measured soil physical and chemical properties (P, K_{exh}, pH, SOM, CEC and Texture) and topographical features (e.g., elevation, aspect, slope and curvature). Only three among nine site-years could reflect the acceptable optimization of seeding rate ($R^2 \geq 0.50$). Both Licht (2015a,b) and Taylor et al. (2000) reported closely likewise maize yield model as a function of seed rate along with other soil properties.

5.2 Site-specific sowing depth recommendation

Placing seeds should be where the soil offers the optimum nutrients, water, aeration, and microclimate conditions during both germination and post-germination periods. Surface compaction (e.g., crust) could reduce or in extreme cases prevent seed germination (Masaka and Khumbula, 2007). Therefore, seeds should not be placed too deep to prevent germination or two shallow that gives problems associated with roots anchoring (Rosolem et al., 2002), hence, may considerably affect crop yield (Abu-Hamdeh, 2003). Optimal seeding depth enhances highest germination, emergence and growth rate and thus maximum yield by ensuring proper soil moisture, oxygen availability, temperature and soil-seed contact. Recommendation of optimal seeding depth could essentially be made based on inherent within-field soil variabilities with a view to ensure uniform seed emergence and growth. Reports indicated that soil moisture (Weatherly and Bowers, 1997), temperature (Håkansson et al., 2002) and texture (Lukas et al., 2009; Fulton et al., 2015) are the most influencing parameters on recommendations

Table 8 Potential seed-rate-index models for optimal recommendation development.

Maize yield models as the functions as follows	R^2	Site	Year	References
$-0.42\ VFSD - 2.1\ CL$	0.67	Field-1	1996	Jiang and Thelen (2004)
$23.8\ pH + 2.0\ VFSD + 52.2\ K$	0.85		1998	
$-6.7\ TB$	0.28		2000	
$-9.9\ SL$	0.37	Field-2	1997	
$-11.1\ SL - 6.0\ VFSD$	0.62		1999	
$-4.2\ E - 11.4\ SL + 29.6\ EC$	0.73		2001	
$135.76 + 1.35e^{-5}\ SR - 8.6e^{-10}\ SR^2 + 0.05\ K + 0.1\ pH - 0.02\ SOM - 0.14\ CEC - 6.0e^{-3}\ SD - 0.02\ CL - 0.07\ SL - 0.37\ E$	0.65	Ames	2012	Licht et al. (2017)
$19.76 + 0.01\ K - 0.35\ pH - 0.17\ CEC - 0.01\ SD - 0.01\ CL - 0.05\ SL - 0.25\ C$	0.2		2013	
$17.54 - 3.90e^{-5}\ SR - 4.02e^{-10}\ SR^2 - 0.01\ P + 0.01\ K - 0.77\ pH + 0.01\ SOM - 0.07\ CEC - 9.54e^{-4}\ SD - 0.02\ SL$	0.77		2014	
$93.73 - 2.93e^{-5}\ SR - 0.03\ P + 0.01\ K - 0.68\ pH + 0.16\ CEC - 8.86e^{-3}\ CL + 0.05\ SL - 0.34\ C + 0.49\ A - 0.27\ E$	0.50	Kelley	2012	
$85.04 - 1.37e^{-5}\ SR - 2.37e^{-10}\ SR^2 - 0.01\ P + 2.34e^{-3}\ K - 0.24\ pH + 0.03\ CEC - 2.54e^{-3}\ CL + 0.04\ SL - 0.23\ E$	0.16		2013	
$-193.34 - 2.07e^{-5}\ SR - 0.01\ K - 0.90\ pH + 0.06\ CEC - 0.01\ SD - 0.01\ CL + 1.60\ C - 0.28\ A + 0.68\ E$	0.41		2014	
$186.85 - 8.87e^{-6}\ SR - 7.95e^{-10}\ SR^2 + 0.03\ P + 7.76e^{-3}\ K + 5.66e^{-6}\ SD - 0.06\ SL - 0.33\ C - 0.26\ A - 0.51\ E$	0.19	Ogden	2012	
$-333.64 - 4.32e^{-10}\ SR^2 + 0.01\ P - 4.91e^{-3}\ K + 1.56e^{-3}\ SD + 4.64e^{-3}\ CL + 0.06\ SL - 0.19\ C + 1.03\ E$	0.32		2013	
$69.85 - 6.21e^{-6}\ SR - 6.23e^{-10}\ SR^2 + 0.02\ P - 0.30\ pH + 0.01\ CEC - 0.02\ SL + 0.07\ C - 0.08\ A - 0.17\ E$	0.39		2014	
$10.36\ SR - 0.186\ SR^2 + 0.007\ SR * EC$	0.79	OC	1998	Taylor et al. (2000)
$15.83\ SR - 0.242\ SR^2 - 0.141\ SR * EC$	0.89	DC	1996	
$11.83\ SR - 0.162\ SR^2 - 0.136\ SR * EC$	0.88	DC	1997	

A, aspects; *BS*, base saturation; *C*, curvatures; *CEC*, cation exchange capacity; *CL*, clay; *E*, elevation; *EC*, electrical conductivity; *K*, potassium; *P*, phosphorus; *SD*, sand; *SL*, slope; *SOM*, soil organic matter; *SR*, seeding rate; *TB*, total bases; *VFSD*, very fine sand.

Table 9 Summary of management zones (MZ) proxies and their measuring technique, MZ delineation approaches and recommendation methods for map-based site-specific seeding (SSS) implementation.

Country	Year	Crop	Key MZ proxy property	Property measuring technique	MZ delineation approach	No. of class	Seed rate range	Recommendation method	Key reference
Kansas, USA	1996, 1997	Maize	Historical yield, ECa	EMI sensing (Veris 3100)	Proximal sensing, Yield map	4	22,000–34,000, (seeds/ac)	Arbitrary	Taylor et al. (2000)
Germany	2003	Wheat (Winter)	Yield potential, soil quality: 1(worst) to 100 (best)	Undefined (as it used historical data)	Yield map	3	136–163 (site1), 116–150 (site2), (kg/ha)	Arbitrary	Reining et al. (2003)
Ohio, USA	2002, 2003	Maize (hybrid)	ECa	EMI sensing (veris 3100)	Proximal soil sensing	4	64,925–85,750, (seeds/ha)	Arbitrary	Ehsani et al. (2005)
NSW, Australia	2002, 2003, 2005	Canola, Wheat	Yield data, ECa Elevation	EMI sensing (EM38, 31, Veris3100), RTK-GPS, Yield monitor (CaseIH AFS)	Data fusion	3	50–125 (kg/ha)	Arbitrary	Taylor et al. (2006)
Albama, USA	2006, 2007, 2008	Maize, Cotton	Terrain attributes, ECa	NA	Proximal and remote soil sensing	NA	18,000–30,000 (dryland maize), 22,000–34,000 (irrigated maize), 35,000–80,000 (cotton), (seeds/ha)	Arbitrary	Fulton et al. (2010)
USA	2013	NA	Yield history, ECa, Elevation and slope,	EMI sensing (Veris) RTK-GPS	Proximal soil sensing	NA	Expert consultations	Arbitrary	Dwight et al. (2013)
New Zealand	2015, 2016	Maize	Historical yield record	NA	Yield map	3	75,000–120,000 (seeds/ha)	Arbitrary	Holmes (2017)
Netherlands	2015	Potato	Soil map	VerisMSP3 EM38	Proximal sensing	NA	NA	Arbitrary	Kempenaar et al. (2017)

for sowing depth. Depending on the soil environment, recommended maize seeding depth could vary from 3.75 to 5.0 cm (Elmore et al., 2014) and potato planting depth from 5.0 to 20.0 cm (Chang et al., 2016). However, farmers always prefer to sow at a shallower depth because they believe that the tiny seed may not emerge if they are placed too deep (Forcella et al., 2000; Gazanchian et al., 2006).

5.2.1 Soil texture specific sowing depth

Soil texture class varies by the percentage sand, silt, clay that drives some textural characteristics like temperature, water-holding capacity, field capacity and soil water potential. Clay soils naturally have higher water potential and water holding capacity due its inherent pore size distribution followed by loamy and sandy soils (Li et al., 2014a,b). Consequently, optimal seeding depth decreases with the increase in clay content or alternatively increases with the increase of percentage sand content. For instance, maize seed should be planted as deep as 7.5–8.75 cm in clay soils, 10–11.25 cm in silt soils, and 12.5–15 cm in sandy soils (Elmore et al., 2014). Soil texture is traditionally determined by laboratory standard methods, which are slow, expensive and provide limited information about the within field variability. Both EMI and vis-NIR (discussed above) are among the best candidates to map within field variability in soil texture (Tümsavaş et al., 2019). Lukas et al. (2009) reported that soil ECa was correlated with sand ($R^2 = 0.548$) and clay ($R^2 = 0.406$) content. However, among the all PSS technologies mentioned above, only ECa was used for practicing SSS so far. Fulton et al. (2015) found that by the use of ECa, seeding depth of maize was highly variable between different zones with different textures, and that the shallowest optimum depth was reported for the heavier textured soil.

5.2.2 Soil moisture specific sowing depth

Adjusting seeding depth based on soil moisture availability can significantly improve seed germination and emergence. Adequate moisture for proper germination can be ensured by increasing seeding depth but challenges in the increased soil mechanical impedance with planting depth are to be expected (Adamchuk et al., 2001). Therefore, optimum seeding depth should be selected as to be deep enough to assure required moisture, while not far from the soil surface so that the magnitude of impedance is low and the stored seed nutrients are sufficient for the seedlings (Weatherly and Bowers, 1997). During early stages of seed germination, a rapid rise in seed respiration requires sufficient quantity of oxygen for proper germination

(Vidaver and Lue-Kim, 1967). The poor germination observed in soils at or near saturation has been attributed to reduced oxygen diffusion as a result of thick water films around the seed (Grable and Siemer, 1968). Therefore, germination and emergence increase with the increased soil MC (Lindstrom et al., 1976) up to field capacity. Further rise in soil MC up to saturation level generally results in a delay in germination and increase in emergence time (Dasberg and Mendel, 1971) due to limited respiration of germinating seeds. However, once the soil MC is adequate at a specific soil depth, there is no reason to differ planting depth shallower or deeper. Elmore et al. (2014) suggested placing maize seeds at an adequate depth where MC is at the field capacity, since crop seeds are expected to absorb water of about 30% of their weight to begin germination.

5.2.3 Soil temperature specific sowing depth

Like soil texture and MC, soil temperature also affects the seeding depth and the optimal soil temperature depends on soil type, MC, soil color, plant residue, mulching, and direction of slope. Researchers reported that the influence of soil temperature dominated the maize emergence time over the influence of soil MC (Larson and Hanway, 1977), when soil MC is near the field capacity. Both germination and emergence increased with soil temperature (Lindstrom et al., 1976), which was found to vary with changes in soil depth (Cui et al., 2011; Florides and Kalogirou, 2005). Additionally, maize could not germinate when the temperature was lower than a specific minimum temperature, i.e., 10 °C (Blacklow, 1973). Maize (radicle and shoot) growth and development showed a linear but positive relationship with rising temperature from 10 to 30 °C and the growth reached a peak at 30 °C (Blacklow, 1973). Beauchamp and Lathwell (1967) reported that the time needed for emergence for maize seeds planted at a 5.0 cm depth increased from 3 to 4 days at 25 °C to 16 days at 12.5 °C. Within a range, soil temperature can accelerate or decelerate the germination and emergence rate without affecting too much the final plant counts (Evert et al., 2009). In order to ensure uniform emergence, seeding depth recommendation could be developed based on the concept of constant cumulative degree-days or thermal time (called heat unit) (Alessi and Power, 1971; Baskin and Baskin, 1998; Håkansson et al., 2002) required to seed germination. The idea is that, one can ensure a specific emergence time for entire field while soil temperature variation could be adjusted by variable seeding depth according to the heat unit.

6. Implementation of map-based site-specific seeding

The implementation of the map-based SSS necessitates a well-defined MZ map, by which the field is divided into different zones having different yield potential or soil fertility levels. The MZ concept is being widely used in various map-based PA applications including SSS. Very few studies have been conducted on SSS than other site-specific applications such as fertilizer and pesticide applications (Esau et al., 2014a; Maleki et al., 2008). Table 9 shows a summary of available studies of map-based SSS including respective MZ proxies and their measuring techniques. Reining et al. (2003) evaluated a GIS-based software module for calculating winter wheat seed rates depending on the corresponding yield potential of specific zones of a field, which was derived from the historical yield records over several years. The software module calculated the seed rate for different yield potential zones and transformed seed rate directly to an application map. It was flexible to adjust the yield potentiality according to algorithms developed in advance [e.g., such as the one developed by Roth et al. (2001)] for seed rate calculation respective to the expected yield margin. Ehsani et al. (2005) reported a 2-year field experiment to investigate the potential application of soil EC for SSS. They mapped soil EC using a commercially available sensor to measure electrical resistivity (Veris-3100, USA). Based on EC map, the research team implemented variable seeding within an experimental set up, where treatments were arranged in strips. The study quantified a clear relationship among soil EC, seed rate and yield data and it recommended EC as a reference property for SSS implementation. Jeschke et al. (2012) used some or all of the following reference data to delineate MZs for SSS: yield history, field productivity, dryness and wetness of the field, soil EC and color, remote sensing images for crop, soil and crop VI, environmental response index, soil type and topography. Heege (2013a,b) reported SSS to be affected by several parameters ranging from crop type and species, planting time, soil water availability and soil texture. Among all the discussed properties, authors indicated that soil texture is a relatively static property over the years and other properties do vary within a year and during a cropping season. They discovered some seed rate converting factors for wheat, by which respective seed rate could be adjusted based on soil texture and annual precipitations. In addition, the influence of soil texture on the seed density was more distinct in contrast to the influence of annual precipitations. As an effective alternative to the soil texture, research suggested EC, which is more flexible for sensing, mapping, and maps are relatively stable, hence, could be utilized for several decades to come for SSS (Heege, 2013a,b). Fulton et al. (2010) conducted a case study in Tennessee valley, Albama for map-based SSS of maize with four seeding rates and four replications during 3 years. Maize seeding rates included 18,000, 22,000, 26,000, and 30,000 seeds/ha for dryland trials and 22,000, 26,000, 30,000 and 34,000 seeds/ha for an irrigated field setup. MZ was delineated using various terrain attributes, soil EC and soil survey data. The spatial analysis revealed that the terrain and soil type influenced the maize yield with varying seeding rate both for the dry and irrigated fields. Dwight et al. (2013) on behalf of CropQuest, a leading crop consulting commercial service provider in USA, proposed the yield map as a potential basis of VSR. However, considering the yield map for 1 year only was not enough to define MZs for map-based SSS. Consequently, they emphasized on the need for generating MZs based on yield maps of several years along with soil EC, topography and crop (hybrids) characteristics, such as fixed ear, canopy architecture and stalk quality. Recently, Holmes (2017) considered 6 years long historical yield records for analyzing the spatial and temporal variabilities for SSS based-on MZs approach. The normalized yield data created three separate MZs with respect to a certain threshold of coefficient of variances (CV). Having a CV value <30% over the project years associated with highly stable yield, CV value close to 30% referred to low stability and CV value higher than 30% indicated unstable MZs.

It can be noticed (Table 9), that the map-based seeding approach was more practiced in the United States than in any other country worldwide. Maize was the most adopted crop for SSS compared to other crops (e.g., wheat, potato, canola), which might be attributed to economic reasons. Most of the studies agreed that MZ proxies were very limited to ECa and yield data. The majority of studies adopted Veris 3100 for measuring soil EC while some reports were found on the use of EM38. This section realizes that selecting a single or multiple soil, crop, weather and topographic characteristics is crucial for delineating MZ as representative of yield potential.

7. Economics of site-specific seeding

Economic analytics can play a great role in convincing farmers and policy makers to adopt and invest in site-specific applications, respectively. Cost-benefit analyses should prove the economic feasibility, e.g., the return of investment of a technology in concern. In this regard, several researchers have analyzed the economics of SSS, taking into account the economic plant population, degree of in field variability, cost effectiveness of VR technologies, seed costs and yield. Bullock et al. (1999) reported that the optimum maize seed density for SSS varied from 44,000 to 104,000 seeds/ha with yield variability ranged within 5.1–18.3 Mg/ha. Positive Pearson correlation was recorded between site-specific field quality and optimal seeding rate, and simulation revealed that farmers could increase revenue up to $12/ha by practicing VSR in comparison with USR. In addition, their research suggested in-depth analyses of both the soil quality and seeding density to present clear economic benefits of SSS to the farmers. Robert et al. (1999) documented the economic implications of site-specific planting of maize using maize-yield response curve developed by Pioneer hybrid scientists. The study established several combinations of various yield potentials (low, medium, high) and included costs of seed and VR technologies used in the cost-benefit analysis. Two separate strategies were used for making SSS recommendations, namely, agronomic and economic seeding rate recommendations according to the yield potential of each MZ. Seeding rates were 44,460, 69,160, 74,100 seeds/ha based on the agronomic recommendation and 49,400, 64,220, 74,100 seeds/ha based on the economic recommendation to the low, medium and high yield potential MZ, respectively. Results revealed that SSS had profit potential for fields, which have parts of low yield potential (<100 bu./a). For fields with 10% of the area is of low yield potential SSS has resulted in economic benefits, while fields with medium and/or high yield potential responded better to the USR scenario. Results were particularly insensitive to the cost of seed or investments in VR technologies.

In course of time, technological advancement has made concurrent site-specific applications profitable compared to the earlier single site-specific application. Most probably, this is happened due to the price drop and availability of VR technologies. Dillon (2013) found concurrent site-specific applications as economically viable over the USR applications, whereas SSS is reported to be less economically viable. It was anticipated that the additional cost for VR technologies outweigh the agronomic benefits of SSS alone, although SSS coupled with site-specific fertilization (N) showed greater economic potential.

Some studies concluded that USR is a better economical choice than SSS in terms of net return due to the costs of soil sensing, data collection as well as VR technologies, which could overshadow the increased maize yield from SSS.

Taylor et al. (2000) evaluated the potential of SSS in eastern Kansas, United States for 3 years. The study considered soil ECa as the soil quality indicator. Economic analysis revealed the SSS is not profitable under the growing conditions studied. They also suggested to search for a less expensive method to make SSS economically feasible. Elmore and Abendroth (2008) critically reviewed several researches, concluding that the SSS is an uneconomic technology. Although high plant population's density can lead to increase yield, one should be aware of whether the yield benefit of planting higher seed rate be economically viable or not. Economic viability should acknowledge the cost of investment and associated yield increment. Reports identified a general maize seeding rate of 86,450 seeds/ha as a good rate for field experiment, but not necessarily true from economic point of view. It was also pointed out that the optimum maize plant density can vary from 12,350 to 29,640 plants/ha in a given year depending on the purpose of the crop (i.e., grain, silage) and growing conditions. Considering more fields and by inclusion of environmental information in the analysis, seeding rate could be further fine-tuned, whereas economically optimum seeding rate may vary frequently within field but probably it is difficult to determine exactly for point to point. Jeschke et al. (2012) reported that DuPoint Pioneer, a worldwide leading developer and supplier of genotypes/varieties to farmers, has implemented SSS of maize hybrids. The DuPoint Pioneer suggested the economic optimum seeding rates after considering the overall return and additional seed costs, while seed rate response to productivity function was calculated according to Woli et al. (2014). One should not expect more savings from seed costs, instead higher yield may result from optimal redistribution of total seeds according to the land site specific yield potentiality (Dwight et al., 2013; Lovell, 2016).

8. Integration, research gaps and future prospects

This section will discuss research gaps, technological requirement and prospects of site-specific seeding.

8.1 Research and technology gaps

Refereeing to previous studies discussed throughout the current review, it is worth to identify key research gaps and technological impairments, necessary for future technological development for optimizing and maximizing the benefits of SSS. The following research gaps were identified:

(a) No data available in the literature to clearly identify key quality indicators and indexes affecting seed rate and seed depth. In this regard, it is essential to define the most affecting indicators, which should be followed by establishing new quality indexes that account for the most affecting indicators on optimal seed rate and depth.

(b) Limited research have been reported on soil and crop sensing, including multi-sensor and data fusion for SSS. This includes: (i) improper selection of sensing techniques for measuring key soil and crop quality indicators, and (ii) no study has reported the optimal combination (fusion of data) of proximal and/or remote sensing for quantifying key indicators related to SSS, and

(c) Despite the existing decision support tools discussed above using EC and manual soil sampling, no decision support algorithms are available to determine the optimal seed rate and seeding depth using data derived from vis-NIR sensing, or combination of vis-NIR, EC and/or crop data. This is true for both the map-based and sensor-based applications.

(d) The literature does not report any successful implementation of sensor-based SSS.

(e) The literature lack of data on the socio-economic and environmental benefits of SSS.

8.2 Discussions and future prospects

The current world status of PA technologies is highly rich and facilitate all sort of site-specific applications, whereas particularly SSS is lagging far behind in technology development and adoption (Daberkow and McBride, 2000). It is worth to note that all the available technologies are map-based SSS where MZs are defined in advance on the basis of key affecting parameters (e.g., soil types, EC, field topography and historical yield are the most accounted for among others) on emergence, crop growth and yield. Map-based SSS has an important advantage since it allows for sufficient time for recommendation development between sensing and VR application. Synchronization of the position between the measured field data with the application map is mandatory to ensure the right application rate is placed at right position. Seeds may also be placed at different locations than the prescribed points on application map due to the inaccuracy of positioning system and/or longer than anticipated response time of the machine actuation. As this system is more time consuming for data processing, it may limit its suitability due to unexpected weather conditions.

The above mentioned disadvantageous of the map-based system can be partially overcome by adopting the sensor-based approach, which does not need to follow georeferenced application map. Sensor-based SSS is much faster, as it does not require to generate an application map in advance by analyzing of extensive data (Grisso et al., 2011). In order to implement this SSS, an on-line sensor to measure key soil properties affecting the seed germination and plant establishment is essential. To our best knowledge, no on-line soil sensor-based SSS is reported in literature. Therefore, this review points out two key future prospects of SSS technology development. First, there is a need for designing and development of an approach and technology for sensor-based SSS. Second, this review introduces a new approach designated as map-sensor-based SSS. This proposed new seeding approach relay on adjusting the seed density according to the predefined field fertility map, allowing to account for all affecting parameters in the agriculture system (e.g., static soil properties, crop growth, yield data, topography and micro-weather conditions). The application rate is then decided in real time, by integrating the information obtained in real time using an on-line soil sensor (e.g., Mouazen, 2006) on key soil properties with the fertility map developed in advance. In addition, it will be also possible to adjust the sowing depth during on-line operation corresponding to dynamic soil properties, like soil MC.

In early stages of implementing SSS, scientists suggested applications based on the input data of soil texture. Later and with the introduction of EMI sensor, soil ECa measurement was recommended instead of soil texture because of the good correlation between ECa and soil texture. Since ECa gives information on several soil properties (Ehsani et al., 2005), today all available SSS are based on soil ECa and/or yield map. An important question is whether or not ECa quantifies the key soil fertility parameters in sufficient accuracy for decision making on SSS. Accurate assessment of field quality should consider soil and crop quality indicators in the form of quality indexes. Soil quality indicators include physical (texture, EC, MC, BD) and chemical indicators (pH, $P_{(avl.)}$, $K_{(avl.)}$, TN, OC, CEC, SOM, Mg, Ca) responsible for field variability in yield. Besides, spectral vegetation indexes (i.e., NDVI) indicate crop quality as a measure of overall crop growth and yield. It has a great scope to identify key soil and crop quality indicators and integrate these indicators to define an integrated field quality index including soil and crop information in order to delineate MZs for SSS.

If soil ECa was the best option for MZ delineation for SSS, then the current review suggests to take into account the field elevation instead of or together with soil ECa for SSS recommendation since elevation and ECa are strongly correlated to each other (Vitharana et al., 2008a,b). In the former case, the cost of generating topography map by a GIS software package is cheaper, compared to the case of soil sensing by EMI sensor. To be confirmed, a further study is needed to compare between the two scenarios not only from economic but environmental point of view, as well.

This review has shown the potential of proximal soil and crop sensing techniques for SSS. Besides, satellite RS is also documented to provide relevant information about key crop characteristics and soil information of the top layer with appreciable spatial and temporal resolution for site-specific applications. Despite having large flexibility of UAV borne RS, this technology also conveys several complexities that include flight planning, need for expert pilot, legal permission, shorter flight duration and lower pay load capacity, which collectively diminish the farmer's interest to adopt such a technology. Consequently, a reliable sensing solution using either proximal (EMI and/or vis-NIR spectroscopy) or satellite RS or both for SSS application is recommended. However, it should be noted that the main shortcomings associated with satellite RS are the cloud cover and high-resolution satellite images are expensive unless offered by the free of charge alternatives like Sentinel2. Similarly, there is cost associated with the implementation of proximal sensors, either if they are purchased or rented from PA service providers (e.g., paying per ha fee), something to keep in mind while evaluating the economic benefits of SSS. Above all, it is about the need rather than the cost, or the balance between both that should be taken into account while making a decision on the best sensing scenario. Therefore, there is research need on the best sensor technology that should be used to optimize the output of SSS. The choice of the best sensor technology is not easy to achieve and requires further study to evaluate agronomic and socio-economic benefits of different scenarios for different crops, soil types and climate conditions.

It is suggested to consider a combination of sensing technologies to achieve the final requirements for SSS. For example, vis-NIR spectroscopy has been proven to provide quantitative information on key soil quality indicators. The information is provided with high-resolution sampling when on-line sensor are used. Multi-sensor data fusion approach is a promising and relatively new technology. Several combinations can be considered, but this should be decided after a long-term study comparing different options. For example, fusion between vis-NIR spectroscopy and satellite RS (i.e., Sentinel-2), vis-NIR spectroscopy with other PSS techniques (e.g., EMI) should be tested for optimal combination of and creation of a multi-soil sensor platform. This multi-sensor platform provides input soil data necessary for SSS in one run. Once it is established, the output data from the soil platform can be combined with satellite images to acquire information on crop characteristics. As an alternative of satellite RS based crop NDVI layer, it is also worth to incorporate NDVI calculated from proximal crop sensor like CropCircle, and/or GreenSeeker. Selection of crop sensing device depends on cost, accuracy and suitability of sensing. Soil quality indicators and crop properties (e.g., NDVI, yield) data can then be fused with topographical attributes and weather data to enable mapping of soil fertility, or yield potentiality, which is the main step toward successful implementation of SSS.

The most positive aspect of Directed-Rx driven VSR recommendation is that it allows the use of "on spot" data to prescribe variable rate inputs for map-based application. It allows implementing variable rate with strip rate treatments on the same fertility spot and finding the best rate for a specific fertility level. Moreover, it can be used to develop recommendation for on-line application, since it contains sufficient data about soil and crop variabilities and yields from previous (strip treatments) experiments. However, Directed-Rx is a time consuming technique, as it takes a full growing season for developing a recommendation. A primary season is needed for experimental field treatments and collecting data for recommendation development. In the second year and once algorithms are established for SSS recommendation, the Directed-Rx could be adopted for prescribing variable rate inputs. On the other hand, MZs based prescribing method considers a wide range of soil properties, crop growth indices and historical yield data that are collected for several years. It takes into account the soil topographical attributes and regional weather conditions (Fraisse et al., 2001). In this way historical records, practitioners and expert opinions can also be accounted for in developing map-based SSS recommendation. Recommendation based on historical yield might be faster, since it does not need a full year of experiment separately for recommendation generation. However, in the case of arbitrary recommendations, if MZs have not been assigned the optimum input rates, these MZs would not produce maximum yield thus losing profit of site-specific applications (Koch et al., 2004). Like Directed-Rx method, MZ-based SSS also requires reference soil and crop data for many years. During the time of data processing and recommendation developing, some changes might occur in soil properties, e.g., MC, changes that should be accounted for when a recommendation for SSS is made. This is not possible, for a dynamic soil property like MC, which necessitates on-line measurement of MC, particularly for seed depth control.

A unique feature of model-based site-specific recommendations is that it can be implemented for on-line SSS in contrast to the other methods of recommendation discussed above (e.g., the MZ and Directed-Rx methods). Once, a model is calibrated and satisfactorily validated, it can be used for a longer term in future, assuming that the relationships between seed rate and affecting parameters are relatively stable. However, it should be noted that models relating crop yield and plant density are based on year-site-specific climatic conditions, indicating that these yield models are local and has no universal utility, as they are dependent of the external parameters of local weather conditions. Comparatively, more robust models were developed by inclusion of numerous soil and crop features. However, they were developed based on average values of field attributes instead of site-specific infield quality indicators. That is why, this review suggests a future study to develop models that account for within field variability for SSS optimization per specific MZs. Comparing among the existing MZ [namely, Directed-Rx and model-based (average field data-based)] methods for deriving SSS recommendation, we believe the Directed-Rx is the most suitable and efficient method. Directed-Rx overcomes the limitations of other methods by accounting for 'on spot' information where to apply the variable rates. In addition, findings from Directed-Rx with strip treatments could be applicable to derive an optimal model that may well be applicable for on-line SSS.

The optimal model for seed rate prediction could be termed as seed-rate-index-model, which seems most effective or implementing the sensor-based SSS. Only few studies considered several soil physical and chemical properties to calculate optimal SSS. By examining these models, it would be worth to make two important notes. First, all models incorporate only soil information, ignoring information on crop growth and development like NDVI and LAI. Second, models showed inconsistent performances although more layers of soil information were accounted for, which was expected to increase the accuracy of predicting the seed rate, due to the increase of number of predictors. Inconsistence model performance might be due to the inappropriate identification of key soil fertility indicators and ignorance of crop information in the recommendation models. Therefore, optimum seed rate models can be established by including multiple soil properties and crop information along with identifying and quantifying the most significant causal properties like topography and weather conditions (Whetton et al., 2017a) for better model selection and performance.

Optimum seeding depth varies with the soil microclimate conditions, namely, soil temperature and moisture content. Seeds should be placed at a suitable depth where soil can offer optimum physical and chemical environment for higher seed germination and emergence rate. This is essential, as one of the major causes of reducing crop yield is the poor crop establishment, attributed to the poor seedbed preparation (Børresen and Njøs, 1994). Therefore, soil information particularly MC and temperature is essential for SSS depth recommendation that should be optimized toward maximum seed germination potential and later for optimal crop growth and development, and finally maximum yield. Unfortunately, this review could not find any research, which takes into account the soil microclimate conditions to optimize the seeding depth. Therefore, a seeding depth model that takes into account the joint influence of soil temperature and MC is needed. A decision support tool is also essentially needed for determining optimal seeding rate and sowing depth by using data derived from vis-NIR sensing, or combination of vis-NIR, EC and/or crop data.

Literary data on economic analysis of SSS are very ambiguous to draw clear conclusions whether it is economically viable or not. Some studies reported SSS as an uneconomic approach, while others found it as an economic practice. This contradictory information may originate from the improper economic analysis and biased representations of actual economics behind SSS. Most often researches considered only increasing gross production without calculating net profit by including all the input and output costs. This one sided goal of increasing the gross margin may not always offer higher economic return rather than raising the investment costs. It is about to confirm that SSS may produce higher yield rather than saving in seed costs. Of course, insight economic analysis of all the costs regarding the required sensing, modeling, and control technologies along with production costs and market price of output yield is essential before making conclusions on economic benefits. Along with economic return, SSS when correctly adopted may support environmental sustainability (i.e., reducing soil erosion, water and air pollution) by optimizing plant populations and thus optimizing agrochemical applications. Unfortunately, there is no literature that has extensively analyzed the economics of SSS for concurrent practice with agro-chemical applications auditing both the economic returns and environmental benefits.

9. Conclusions

This review has reported the principles and technologies available for implementing site-specific seeding (SSS) with a view to explore the future research thrust by analyzing present researches and technology gaps. It attempted to identify the key reference soil and crop quality indicators, to discuss the sensing and modeling technologies to measure soil and crop quality indicators, to study site-specific recommendation generation methods for variable rate seeding and sowing depth site-specifically, and to examine finally economic and environmental potential expected from adopting SSS.

Between the two principles, still now only map-based SSS application is being practiced at a minimal scale compared to other site-specific applications. Most of SSS systems are available at research level although some commercial systems are also available, and these relay on the measurement of soil electrical conductivity (EC) and/or yield map to define management zone (MZ). Considering a single soil or crop property is not the right decision since it cannot be presentative of soil fertility and yield potentiality of a MZ. Therefore, multiple soil and crop properties like pH, P, K, total nitrogen (TN), texture, organic carbon (OC), ECa, cation exchange capacity (CEC), moisture content (MC), bulk density (BD), Mg, Ca, normalized difference vegetation index (NDVI), and yield should be collectively accounted for better simulation of the yield potentiality to delineate MZ maps. Certainly, map-based application has some advantages and disadvantages, which could be overcome by sensor-based application. Although sensor-based SSS is potentially applicable, this was more commonly implemented for fertilizer and pesticide applications. There is no report available on sensor-based SSS application. Moreover, integration between map- and sensor-based applications so-called 'map-sensor-based SSS' is introduced in this report for the first time as the next generation technology synthesis for SSS application.

In order to measure several soil and crop properties, a single sensor is not the right choice for securing acceptable measurement and mapping accuracy. Therefore, it is essential to adopt a multi-sensor approach even for measurement of one soil property (e.g., soil bulk density). Despite the extensive use of electromagnetic induction (EMI) to map soil physical properties for SSS, the visible and near infrared (vis-NIR) spectroscopy provides extra data on soil fertility and nutrients. In addition, when vis-NIR is combined with EMI data it is potentially possible to optimize SSS toward maximizing seed germination, crop establishment, crop development and yield. Satellite image or proximal crop data for the estimation of crop growth and yield potential can be integrated with soil data collected with proximal soil sensors (PSSs) by means of advanced data fusion and clustering techniques to derive MZ for SSS. The choice for the best combination of proximal-proximal sensors and proximal-remote sensing will necessitate further studies, which should be carried out for different crops and crop varieties, environmental conditions and soil types.

Appropriate and science-based development of recommendations is crucial for allocating the right amount of seeds in the right depth and density within a specific MZ with a certain yield potentiality. Available map-based seeding applications are based on arbitrary recommendations, which have major limitations. Therefore, an alternative approach to develop recommendations for SSS is a perquisite that is to adopt a modeling approach to derive a seeding rate index per MZ. In order to develop a seed rate index, Directed-Rx is the most suitable candidate. The Directed-Rx approach may result in an optimal recommendation for SSS rate, since it takes into account 'on spot' measured soil and crop properties. An optimal depth for seed placement was found essential as to maximize seed germination and crop establishment. It was recommended to consider both the soil MC and temperature in the recommendation development for optimal seed depth.

Information available in literature are insufficient to conclude whether SSS is economically viable or not. Most of the literatures emphasized different aspects of economic analysis rather than full spectrum analytics covering the socio-economic and environmental benefits. To some extent, it could be concluded that SSS can potentially increase yield, whereas it is limited to save seed costs. Increasing yield may or may not overcome the input cost of implementing SSS. It will definitely increase the gross investment together with the other variable VR technologies implemented on the farm. Therefore, in depth economic analysis can only reveal the actual scenario and allow drawing a clear conclusion about profitability of SSS.

It can be concluded that SSS is a promising PA practice to manage within field soil variability. At present, a wide range of sensing (i.e., proximal and remote) and modeling technologies are being used for mapping soil and crop variabilities. Although previous VR technologies were limited to expand the implementation of SSS largely, present technological advancements suggests a second wave of SSS implementation is possible. SSS is still lagging behind in comparison to the other site-specific applications. Particularly, there is no optimum seeding rate index model, which can prescribe the optimal seeding rate per specific yield potential zones in the field either for map-based or sensor-based applications. In addition, technological integration has not been well studied specially for multi-sensor data fusion approach. Selectivity of sensing technology can affect the overall outcome delivered from SSS. For instance, utilizing multi-sensor data fusion approach is worth to consider in a future research for better technology synthesis, although profitability analyses would be essential to enhance adoption by farmers.

Acknowledgment

Authors acknowledge the financial support received from the Flemish Scientific Research (FWO) for Odysseus I SiTeMan Project (Nr. G0F9216N).

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