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REVIEW ARTICLE

Remote sensing of soil properties in precision agriculture: A review

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Abstract The success of precision agriculture (PA) depends strongly upon an efficient and accurate method for in-field soil property determination. This information is critical for farmers to calculate the proper amount of inputs for best crop performance and least environmental effect. Grid sampling, as a traditional way to explore in-field soil variation, is no longer considered appropriate since it is labor intensive, time consuming and lacks spatial exhaustiveness. Remote sensing (RS) provides a new tool for PA information gathering and has advantages of low cost, rapidity, and relatively high spatial resolution. Great progress has been made in utilizing RS for in-field soil property determination. In this article, recent publications on the subject of RS of soil properties in PA are reviewed. It was found that a large array of agriculturally-important soil properties (including textures, organic and inorganic carbon content, macro- and micro-nutrients, moisture content, cation exchange capacity, electrical conductivity, pH, and iron) were quantified with RS successfully to the various extents. The applications varied from laboratory-analysis of soil samples with a bench-top spectrometer to field-scale soil mapping with satellite hyper-spectral imagery. The visible and near-infrared regions are most commonly used to infer soil properties, with the ultraviolet, mid-infrared, and thermal-infrared regions have been used occasionally. In terms of data analysis, MLR, PCR, and PLSR are three techniques most widely used. Limitations and possibilities of using RS for agricultural soil property characterization were also identified in this article.

Keywords soil, soil property, precision agriculture (PA), remote sensing (RS), near-infrared reflectance spectroscopy, sensor

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1 Introduction

Over the past few decades agricultural production has progressed from the machinery age to the information age and has seen growing use of the term, precision agriculture (PA), which implies small-scale information-based optimization of inputs for overall gains in profitability and environmental stewardship. Geo-spatial technologies including geographic information systems (GIS), the global positioning system (GPS), and remote sensing (RS) are extensively utilized in PA. Presently, PA has been deployed in almost all aspects of agriculture production. As an information- and computation-intensive technology, the success of PA depends strongly upon highly efficient and reliable methods for site-specific field information gathering and processing.

RS involves using electromagnetic energy to determine properties of targeted objects from a distance and has the advantages of extensiveness, non-invasiveness, timeliness, and flexibility. It has already been widely applied to many environment-related disciplines including ecology, oceanography, climatology, geology, and agriculture.

Soil is one of the most important components of agricultural production and can have a dominant effect on crop yields and quality. In-field soil information has been used for centuries by farmers to make decisions concerning crop management practices. Traditionally, soil property information gathering is done by grid sampling. USDA's Natural Resource Conservation Service (NRCS) implements a nation-wide soil survey (USDA, 1993), which is conducted with grid sampling and regarded as a useful source of soil information at regional and local scales. While grid sampling is common, it has disadvantages. First, the cost associated with it increases exponentially as the spacing of grids decreases. According to Samuelson et al. (2002), a soil map at a scale of 1∶31680 (a map unit size of 4.0 ha, or 10 ac) has an average cost of 4.2 USD/ha (1.7 USD/ac). In comparison, the average cost for a map at a scale of 1:3000 could be 47 USD/ha (19 USD/ac), a price farmers would not pay. Second, observations at sampling points are sparse with respect to all possible locations throughout a field. Extrapolation of soil properties from a limited number of locations where they are known to a much greater number of locations where they are not known introduces error. With the development of PA, which can demand high spatial resolution of in-field soil properties, the disadvantages of grid sampling become more pronounced, and agricultural scientists and engineers have looked to RS for in-field soil property characterization.

Many studies in soil science have used both RS bare-soil images and spectroscopic reflectance of soil samples for soil survey, mapping, and quantitative soil-property characterization (Dalal and Henry, 1986; Agbu et al., 1990; Ben-Dor and Banin, 1994; Ben-Dor and Banin, 1995). Compared to conventional methods (e.g., the pipette method for soil textures and the dry combustion method for soil organic carbon concentration), RS has proven to be cheaper, faster, and fairly accurate for certain applications.

It should be pointed out that RS, as discussed in this article, includes both remote (e.g., satellite and aerial imagery) and proximal (e.g., spectroscopic reflectance) techniques, because both are made at a distance from the target object. The term "remote" herein reflects more the non-contact nature of the measurement than the degree of distance. However, it should also be noted that remote and proximal techniques are quite different in terms of sensing platform, data structure, data analysis technique, and research objectives. Generally speaking, satellite and aerial bare-soil images obtain a large coverage and a simultaneous view of study areas with reasonably detailed spatial information but a low degree of spectral information. Spatial extensiveness allows researchers to interpret soil properties at field and potentially regional scales. However, the lack of spectral information tends to limit interpretation to qualitative determinations. On the other hand, spectroscopic reflectance measurement of soil samples obtains detailed spectral information, allowing quantitative analysis of soil properties. Soil samples for spectroscopic analysis are usually collected from grid-sampling and thus provide poor spatial resolution.

In recent years, PA has experienced rapid growth in the use of RS for in-field soil-property characterization. RS images and spectroscopy are in the process of becoming established methods for soil property determination in PA.

2 Brief history of remote sensing of soil properties

Nearly 80 years ago when optical and radiometric instruments were in limited use, colors were the most obvious and useful attributes to document differences among soils (Rice et al., 1941; Munsell Color, 1975). Although great progress was made in standardizing methods to measure and designate soil color since the concept was first introduced, measurement of soil color remained subjective and in many cases non-repeatable (Baumgardner et al., 1986). Soil scientists anticipated new devices and methods for measuring soil spectra and relating them to soil properties more accurately and objectively, and they turned to RS.

Evidently the earliest attempt to use RS for soil studies occurred in the 1930s when black-and-white aerial photographs were prepared as the base maps for soil surveys in the US (Baumgardner et al., 1986). In the late 1960s and early 1970s, soil scientists began to investigate using multispectral-sensor (MSS) data to delineate differences in surface soils (Kristof, 1971). Soon thereafter Kristof and Zachary (1974) reported partial success in delineating soil series in an Alfisol-Mollisol region through digital analysis of aerial MSS data. Development was slow because RS images were not readily obtainable. However, the first satellite to provide publicly available RS data in the US, LANDSAT-1, was launched in 1972. After that, several imaging satellites were placed in orbit and images have become more and more available to researchers.

An early attempt to quantify soil reflectance and define differences between soil reflectance spectra by means of proximal sensing was conducted by Condit (1970, 1972). He collected 160 soil samples from 36 states in the US and classified soil spectral curves into three general types based on near-infrared reflectance spectroscopy (NIRS). However, no attempt was made to quantitatively relate these spectral properties to physical and chemical properties of the soils. Stoner et al. (1980) collected duplicate soil samples representing more than 240 soil series from 17 different temperature-moisture regimes and measured visible and infrared reflectance (0.52–2.36 μm). They categorized the spectral curves into five basic forms and related them to five soil types (organic dominated, minerally altered, iron affected, organic affected, and iron dominated).

Baumgardner et al. (1986) reviewed reflectance properties of soil in 1985 and confined their discussion to soil colors, principles and limitations of RS, and effects of soil constituents on soil reflectance. Moran et al. (1997) included several sections on RS of soil properties in their overall discussion of image-based RS in PA. Pierce and Nowak (1999) briefly discussed RS of soils as one of many aspects of PA. These two reviews summarized studies conducted over 15 years ago and highlighted early application of RS to PA, but later developments need to be reviewed as well. Ben-Dor (2002) and Ben-Dor et al. (2003) reviewed quantitative RS of soil properties with hyperspectral sensors. They included almost all important issues regarding RS of soil properties and provided detailed information on the state of the art at the time. Nevertheless, PA practitioners may not derive great benefit from these reviews because they were written more from an RS perspective than an agriculture perspective.

RS has witnessed concurrent advancement of sensing technology and data analysis techniques in recent years. As RS soil spectra data are recorded in hundreds or even thousands of contiguous narrow bands that contain detailed information on soils, sophisticated data analysis techniques have been designed to extract useful soil property information from these extremely large data sets. Recent literature has included how these techniques have been deployed for soil property determination in PA.

Despite rapid development, RS of soil properties in PA is far from mature due to the complex natures of RS, agricultural production, and soils. Different researchers aim at different soil properties and encounter different environmental conditions in their fields. They also use different sensing platforms, sensor types, and data analysis techniques. The procedures for selecting appropriate devices and techniques are more art than science. No single sensor type or data analysis method has yet been reported as ideal for a particular soil property.

2.1 Objectives

The objectives of this review are to:

- Compile recent literature on RS of soil properties in the context of PA and suggest what is the state of the art on this subject;
- Identify current technological limitations and future trends of RS of soil properties in PA.

2.2 Categorization of past research

The literature has been categorized according to various types of information. The first category includes years, authors, and soil properties under investigation (Table 1), the second category involves sensing techniques (Table 2), and the third involves data analysis techniques (Table 3). Future researchers should benefit from having a resource that enables them to engage the literature in this way.

As can be seen in Table 1, soil properties frequently investigated by different researchers include texture (clay, silt, and sand percentages), organic matter (OM), nitrogen, pH, nutrients (phosphorous, P; potassium, K; calcium, Ca; magnesium, Mg; zinc, Zn; and sodium, Na), and hydrologic properties (electrical conductivity, EC; moisture content, MC; and cation exchange capacity, CEC). These properties are known to have significant effects on crop growth and environment, but those using RS for soil characterization have typically been more interested in primary minerals and clay minerals, which are closely related to soil genesis and soil formation processes.

It is clear that the soil properties studied by different authors varied greatly, and the variation is influenced by the geographic region where a study was conducted. This is to be expected since soil properties with dominant effects on crop yields and environmental impacts can differ from region to region. For example, agricultural P is a known water pollutant in Florida, USA, so P concentrations in Florida soils were intensively studied by researchers in Florida (Lee et al., 2003; Bogrekci and Lee, 2005a; b). Furthermore, Illinois agricultural soils tend to have high OM, a major yield determiner for Illinois crops, so OM was intensively studied by researchers there (Sudduth and Hummel, 1991; Sudduth and Hummel, 1993a; b; Sudduth and Hummel, 1996).

With respect to sensing techniques, some early studies used multispectral satellite images for soil surveys and soil mapping. However, these endeavors were deemed inappropriate for PA since the images were generally unable to provide quantitative information concerning specific soil properties. A recent trend is to use laboratory spectrometers for hyperspectral soil data acquisition. Due to the highly detailed spectral information, it is anticipated that soil properties can be quantitatively determined through proper data manipulation. Almost all of the studies reported involved wavelengths in the visible (VIS) and near-infrared (NIR) regions of the electromagnetic spectrum. Most fundamental spectral signatures of soil components occur in the mid-infrared (MIR) and thermal-infrared regions. However, combinations of fundamental features have overtones that can cause spectral signatures in the VIS and NIR regions, making the VIS and NIR regions potentially useful in determining many soil components.

Data analysis techniques are dependent on the dimensionality (i.e., number of spectral variables) of the soil spectral data. Qualitative data analysis (including band ratios, discriminant analysis, and classification) is suitable for bare-soil images captured by satellites and aerial platforms. Hyperspectral soil data captured by spectrometers are often noisy and difficult to evaluate, even in well-controlled laboratory conditions. For this reason, data-preprocessing procedures are used to “clean” them. Smoothing (including running-average, Savitzky-Golay smoothing, mean and median filtering) is the most widely applied method for noise suppression. Derivative analysis is frequently used to minimize other extraneous factors that can affect hyperspectral soil data. For example, the first derivative is good at accounting for solar angles and viewing geometry. As can be seen in Table 3, regression analysis, including multiple regression analysis (MLR), principal component regression (PCR), and partial least squares (PLS) regression, is the most popular data analysis technique to relate soil properties to reflectance. Actually, PCR and PLS can be understood as special cases of MLR in that they include pre-processing procedures (matrix transformation for independent and response variables) to reduce the dimensionality of the hyperspectral data. Although regression analysis is empirical and has many

Table 1 Summary of information reported for remote sensing of soil properties in precision agriculture on soil chemical, physical, and other properties

Year	Author	Soil properties §															
		P	K	Ca	Mg	Zn	Na	N	pH	OM	EC	CEC	Clay	Silt	Sand	MC	Others
1986	Dalal and Henry							×								×	Organic C
1991	Coleman et al.									×			×	×	×		
	Morra et al.							×									Total C
1993	Abdel-Hamid									×		×	×		×		$CaCO_3$, Fe, salt
	Coleman et al.									×			×	×	×		Iron oxide
	Sudduth and Hummel									×		×				×	
1995	Ben-Dor and Banin									×		×	×				$CaCO_3$
	Coleman and Tadesse									×			×	×	×		
1996	Hummel et al.											×				×	
1998	Palicios-Orueta et al.									×			×	×	×		Iron content
1999	Ehsani et al.							×									
	GopalaPillai and Tian																Soil type
	Malley et al.	×	×	×	×		×		×		×						S, Mn, Fe
	Varvel et al.	×								×							
2000	Barnes and Baker												×	×	×		
2001	Chang et al.	×	×	×	×	×	×	×	×			×	×	×	×	×	
	Ehsani et al.							×									
	Hummel et al.									×						×	
	Merry and Janik							×	×		×	×	×	×	×		
	Thomasson et al.	×	×	×	×	×	×		×				×	×			
	Slaughter et al.															×	
2002	Kaleita and Tian									×						×	
	Lobell and Asner															×	
2003	Cozzolino and Moron		×	×	×								×	×	×		Mn, Fe
	Hutchinson															×	
	Kaleita et al.															×	
	Lee et al.	×	×	×	×				×	×							
	Leon et al.	×	×	×	×				×				×	×	×		
	Stangeland et al.	×	×	×	×	×			×								Buffer pH
2004	Bogrekci et al.	×															
2005	Bogrekci and Lee (a)	×															
	Bogrekci and Lee (b)	×											×	×	×		
	Bajwa and Tian	×	×	×	×				×	×	×						
	Stamatiadis et al.	×	×	×	×	×		×	×		×					×	
2006	Ge and Thomasson	×	×	×	×	×	×						×	×			
2007	Waiser et al.												×				

Note: § Soil property code definitions: P = phosphorous, K = potassium, Ca = calcium, Mg = magnesium, Zn = zinc, Na = sodium, N = nitrogen, OM = organic matter, EC = electrical conductivity, CEC = cation exchange capacity, MC = moisture content, C = carbon, S = sulfur, Mn = manganese, Fe = iron

Table 2 Summary of information reported for remote sensing of soil properties in precision agriculture on sensing platforms, sensor types, and wavebands

Author & Year	Sensing technique											
	Sensing platform ¶				Sensor type §		Waveband ‡					
	Satellite	Aerial	Laboratory	Field	Multi	Hyper	UV	VIS	NIR	MIR	TH	MW
Dalal and Henry, 1986			×		×				×			
Agbu et al., 1990	×				×			×	×			
Coleman et al., 1991				×	×			×	×	×	×	
Morra et al., 1991			×			×			×			
Coleman et al., 1993	×				×			×	×	×	×	
Sudduth and Hummel, 1993a			×			×			×			
Ben-Dor and Banin, 1994			×			×		×	×			
Ben-Dor and Banin, 1995			×			×			×			
Coleman and Tadesse, 1995		×			×			×				
Hummel et al., 1996				×	×			×	×			
Galvdo et al., 1997			×			×	×	×	×			
Palacios-Orueta and Ustin, 1998			×			×	×	×	×			
Ehsani et al., 1999			×			×			×			
GopalaPillai and Tian, 1999		×			×			×	×			
Malley et al., 1999			×			×		×	×			
Varvel et al., 1999		×			×			×	×			
Barnes and Baker, 2000	×	×			×			×	×		×	
Chang et al., 2001			×			×			×			
Ehsani et al., 2001			×			×				×		
Hummel et al., 2001			×			×			×			
Slaughter et al., 2001			×			×		×	×			
Thomasson et al., 2001a			×			×		×	×			
Thomasson et al., 2001b	×		×		×	×		×	×			
Cozzolino and Moron, 2003			×			×		×	×			
Hutchinson 2003	×											×
Lee et al., 2003			×			×		×	×			
Leon et al., 2003		×			×			×	×			
Odhiambo et al., 2003	×											×
Stangeland et al., 2003			×			×		×	×			
Bajwa and Tian, 2005		×				×		×	×			
Bogrekci and Lee, 2005a			×			×	×	×	×			
Bogrekci and Lee, 2005b			×			×	×	×	×			
Stamatiadis et al., 2005				×	×			×	×			
Kaleita et al., 2005				×		×		×	×			
Sullivan et al., 2005	×				×			×				
Ge and Thomasson, 2006			×			×		×	×			
Waiser et al., 2007			×			×		×	×			

Note: ¶ Sensing platform code definition: Satellite = satellite imagery, Aerial = aerial imagery, Laboratory = laboratory spectrometer, Field = field spectrophotometer; § Sensor type code definition: Multi = multispectral sensor, Hyper = hyperspectral sensor; ‡ Waveband code definition: UV = ultraviolet, VIS = visible, NIR = near infrared, MIR = mid infrared, TH = thermal infrared, MW = microwave

Table 3 Summary of information reported for remote sensing of soil properties in precision agriculture on data analysis techniques.

Author & Year	Data analysis technique		
	Preprocessing ‡	Qualitative ¶	Quantitative §
Dalal and Henry, 1986			MLR
Frazier and Cheng, 1989		BR	
Agbu et al., 1990		BR	MLR
Coleman et al., 1991		DISC	MLR
Morra et al., 1991	Derivative		MLR
Coleman et al., 1993		DISC	MLR
Sudduth and Hummel, 1993a	Averaging		MLR, PCR, PLS
Ben-Dor and Banin, 1994	Averaging, derivative		MLR
Ben-Dor and Banin, 1995	Averaging, derivative		MLR
Coleman and Tadesse, 1995		DISC	MLR
Hummel et al., 1996			MLR, PLS
Galvdo, et al., 1997		BR	PCA, MLR
Palacios-Orueta and Ustin, 1998	Averaging	CDA	BD, PCA
Ehsani et al. 1999			PCR, PLS
GopalaPillai and Tian, 1999		UnCls	
Malley et al., 1999	Averaging, derivative		MLR
Varvel et al., 1999			CORR
Barnes and Baker, 2000		UnCls, SuCls	
Chang et al., 2001	Averaging, derivative		PCR
Ehsani et al., 2001	SG, FFT, wavelet	BR	CORR
Hummel et al., 2001			MLR
Slaughter et al., 2001			PLS
Thomasson et al., 2001a	Averaging		MLR
Cozzolino and Moron, 2003	Averaging, derivative		PLS
Lee et al., 2003			PLS
Leon et al., 2003		BR	PCA, MLR
Odhiambo et al., 2003		F-NN	
Stangeland et al., 2003	Averaging, derivative		PLS
Bajwa and Tian, 2005	Derivative		PLS
Bogrekci and Lee, 2005a	SG, derivative	BR, DISC	MLR, PLS
Bogrekci and Lee, 2005b	SG, derivative	DISC	PCA, MLR, PLS
Stamatiadis et al., 2005		BR	MLR
Kaleita et al., 2005	K-mean smoothing		PLS
Ge and Thomasson, 2006	Wavelet		MLR
Waiser et al., 2007	Averaging, derivative		PLS

Note: ‡ Preprocessing code definition: SG = Savitzky-Golay smoothing, FFT = fast Fourier transform; ¶ Qualitative data analysis code definition: BR = band ratio, CDA = canonical discriminant analysis, DISC = discriminant analysis, UnCls = unsupervised classification, SuCls = supervised classification, F-NN = fuzzy neutral network; § Quantitative data analysis code definition: MLR = multiple linear regression, PCA = principal component analysis, PCR = principal component regression, PLS = partial least squares regression, BD = band depth, CORR = simple correlation limitations, numerous researchers have reported good results with regression analysis for soil property characterization.

2.3 Evaluation of past research

2.3.1 Complexity of soil components and soil spectra

A principal difficulty with using RS for soil property characterization is the complexity of soil components and soil spectra. Ben-Dor (2002) stated that soil contains many chemical components including clay minerals, carbonates, OM, water in different states (hygroscopic water, hydration water, and free pore water), salts, etc. Some of these components have strong and distinct spectral signatures (e.g., the clay mineral montmorillonite), and some exhibit weak to non-existent signatures (e.g., quartz and feldspar). Moreover, many of these spectral signatures overlap one another. For example, absorptions at 1.4 and 1.9 μm are common in soil spectra and can be caused by many soil chemical components. Additionally, absorption overlapping may not be a linearly additive process. Finally, agriculture soils are frequently subject to management practices like vehicle traffic that leads to compaction, tillage, and irrigation; each of these affects soil moisture content and aggregate soil particles size, which can have great influence on soil spectra. For these reasons, agricultural soils can exhibit very complex spectra, and characterization of soil properties is difficult.

2.3.2 Data-analysis and sensing techniques

The spectral resolution of the sensor heavily influences the information content in the soil spectra. The higher the spectral resolution, the more information that can potentially be extracted for soil property determination. Bare-soil imagery sensed remotely from space platforms tends toward lower spectral resolution (multispectral or panchromatic) and is usually suited to information extraction for qualitative determinations. Although precise information concerning soil properties is not obtained with qualitative methods (color composites, band ratios, discriminant analysis, etc.), they are effective at discriminating and mapping soil surface units. Using RS images of bare soil as baseline maps for soil survey and classification has been an established method since RS images became commercially available. However, as Moran et al. (1997) summarized, when satellite-sensor capability was still multispectral rather than hyperspectral, RS was not being employed for characterizing soil properties regularly because soil reflectance properties were often confounded with variations in soil moisture and surface roughness, etc.

A recent trend in RS of soil properties is toward using hyperspectral data and more sophisticated quantitative methods for data analysis. Mustard and Sunshine (2003) summarized commonly used quantitative data analysis methods for RS data including principal component analysis, minimum noise fraction (MNF), absorption feature mapping, band modeling, spectral detection, and spectral unmixing. However none of these methods has been applied for hyperspectral soil data collected in PA. A possible reason for this is that most of these quantitative data analyses were developed with some level of mathematical and statistical rigor, and majorly for mineral identification. Compared to mineral spectra, soil spectra are much more complicated because of the complex physical, chemical, and biologic components that soils commonly include. Thus, relating soil spectra to specific properties through theoretically derived models is not practical; thousands of factors (including soil properties under investigation) can influence soil spectra. As Ben-Dor (2002) summarized, “soil and soil spectra are rather complex phenomena and this prevents a straight-forward prediction of reflectance properties by physical theories or models.” As can be seen in Table 3, regression analysis (MLR, PCR, PLS) is the most frequently used quantitative method for hyperspectral soil reflectance data. An advantage of this empirical method is that rigorous physical and mathematical reasoning considering the interactions between incident energy and soil surfaces and constituents can be ignored.

Ge and Thomasson (2006) and Ge et al. (2007) put forward a new method to incorporate wavelet analysis into regression analysis for soil property determination. They found that wavelet decomposition is an excellent technique for hyperspectral data smoothing. The resultant wavelet regression models for soil properties had similar prediction capabilities as those developed with conventional methods, but wavelet models include fewer regressors and the possibility of physical interpretation of wavelet models because variation in bandwidth is considered.

Brown et al. (2005) used the so-called boosted regression trees (BRT) method on soil reflectance spectra of samples collected from around the world. They found that BRT outperformed PLS in estimating clay, soil organic carbon, inorganic carbon, Fe, and CEC. They attributed BRT’s superior predictive power to its ability to account for multiple, high-level interactions as well as linear and nonlinear correlations. PLS regression can be used primarily to model linear correlations but has no ability to account for interactions or to fit nonlinear relationships.

2.3.3 Global characterization and soil-property sensors

Multiple articles (e.g., Christy et al., 2003; Lee et al., 2003) have mentioned that quantitative analysis of RS soil spectra for soil property determination is a preliminary step toward proximal soil property sensors that could measure soil properties real-time in situ. However, even the latest research achievements cannot provide the basis for a practical soil-property sensor for the following reasons:

- A one-in-all sensor that can measure all soil physical and chemical properties is probably not possible;
- Most of the research studies were conducted in well-controlled laboratory conditions, and the results cannot be extended to real-world situations;
- Soil property models having good prediction capability and developed with hyperspectral soil data were complex, sometimes containing hundreds of narrow bands. This fact makes a simple and light soil property sensor impractical;
- Even for a specific soil property (e.g., clay content), models developed at different geographical regions are quite different from each other. Thus, a soil property sensor based upon the model developed from one region may not be able to measure the same soil property in another region. This fact makes a commercial soil sensor, which is supposed to be universally applicable, not practical;

Apparently the biggest obstacle for commercial soil sensor development is inconsistency of models obtained from different studies at different locations. This problem is not unexpected, since large variations exist among soil spectra due to soil genesis, soil forming, and limitations of RS which were discussed in Ben-Dor (2002). One possible solution to this problem is to collect an exhaustive number of soil samples from around the world, develop a universal model, and base the soil property sensor on this model. Brown et al. (2005) showed that even with some simplifying assumptions, 5.2×10^9 carefully selected calibration samples would be required to span the global soil compositional size. Considering the time and the cost needed to collect and analyze pedons, this is almost an impossible mission.

An alternative method for global soil characterization is to establish a global soil spectral library (Shepherd and Walsh, 2002). The library would be used to predict soil properties for new samples that have been screened for spectral similarity. Spectrally dissimilar soil samples would be submitted to the laboratory for characterization with subsequent inclusion in an expanded spectral library.

Adamchuk et al. (2004) reviewed the current state of the art in on-the-go soil sensors for PA and found that optical and radiometric sensors are in the stages of theoretical study, prototyping, and laboratory testing. Such sensors have been able to measure soil physical and chemical properties including soil moisture content, OM, CEC, EC, pH, etc. with promising results. Issues still remain for real-time in situ soil property sensors in terms of accuracy and robustness.

3 Conclusions

In this article, recent publications on the subject of RS of soil properties in PA were reviewed. Information regarding the soil properties under investigation, sensing techniques, and data analysis techniques were collected to establish the current state of the art and predict future trends on this subject. A large array of agriculturally-important soil properties (including textures, organic and inorganic carbon content, macro- and micro-nutrients, moisture content, cation exchange capacity, electrical conductivity, pH, and iron) were quantified with RS successfully to the various extents. Applications varied from laboratory-analysis of soil samples with a bench-top spectrometer to field-scale soil mapping with satellite hyperspectral imagery. The visible and near-infrared regions are most commonly used to infer soil properties, with the ultraviolet, mid-infrared, and thermal-infrared regions being used occasionally. In terms of data analysis, MLR, PCR, and PLSR are three techniques most widely used. Limitations and possibilities using RS for agricultural soil property characterization were also identified. These included the development of optical soil sensors for real-time in situ analysis of soil properties and establishment of large soil spectral libraries to facilitate laboratory and in situ soil analysis. The authors expect that future researchers would benefit from information presented in this article by choosing appropriate sensing techniques and data analysis methods for their specific research purposes.

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