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Remote Sensing of Soil and Water Quality in Agroecosystems

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Abstract Mismanagement of soil and water resources may not only contribute to an escalation of global poverty but also jeopardize ecosystem services, with significant costs to the environment. Although not concentrated within one geographic location (3,500 million hectares), an equivalent of approximately 24 % of the earth's land surface is degraded land, and about 2 billion people (one third of the global population) lack access to safe and affordable water for domestic purposes. It is therefore critical to develop strategies targeted at the root causes of these problems. However, to do so would require a rapid and reliable information system that has been elusive because of the complexity of the environment and the limitations of the existing tools. The increased availability and development of remote sensing and geographic data analysis tools have opened up new possibilities for exploring and monitoring environmental variables influencing key land use and soil management options. Here, we explore the major concepts, describe the constraints, and the future potential of remote sensing for mapping and providing near real-time information on soil and water quality in the context of major land use practices employed at the global scale.

Keywords Mapping · Remote sensing · Soil quality · Sustainable resource management · Water quality

Acronyms and Abbreviations

ASTER	Advanced space borne thermal emission and reflection radiometer
ASD	Analytical spectral device
AVIRIS	Airborne visible/infrared imaging spectrometer
SPOT	Satellites pour l'observation de la terre or earth-observing satellites
SWIR	Short-wave infrared sensor
WHO	World health organization

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1 Introduction

The principal global issues in the twenty-first century include rapid population increases, food insecurity, water scarcity, and accelerated greenhouse gas (GHG) emissions (Bouma and McBratney 2013; Lal 2004b; Maeder et al. 2002; Rijsberman 2006; Stockmann et al. 2013; WHO 2013). With the global population projected to increase to 9.4 billion by 2050, and to 10.1 billion by 2100 (http://esa.un.org/wpp/Analytical-Figures/htm/fig_1.htm; Lal 2001), food and water insecurity problems might escalate especially with the adoption of nonsustainable solutions such as land conversion and indiscriminate agricultural intensification. Although promising in terms of improved yields, the dangers of indiscriminate agricultural intensification which relies on excessive fertilizer usage, pesticides, animal waste; include degradation of land and water resources, and increase the likelihood of adverse weather conditions (Laurent and Ruelland 2011; Mueller-Warrant et al. 2012). Land degradation is the long-term decline in ecosystem functions and productivity caused by disturbances whereby the land cannot recover unaided (Bai et al. 2008). Increasing solute (e.g., nitrogen and phosphorus concentration) transported from agricultural runoff to waterways following indiscriminate agricultural intensification pollutes water resources (Arnold et al. 2012; Mattikalli and Richards 1996). Reports estimate that 2 billion people lack access to safe and affordable water (WHO 2013). While more research is required to minimize the repercussions of indiscriminate agricultural intensification, we also need rapid, reliable techniques that can be used to assess changes in soil and water quality within agro ecosystems.

Soil quality is defined as "the capacity of a soil to sustain biological productivity, maintain environmental quality, and support human habitation" (Doran and Zeiss 2000; NRCS 2012). Soil organic carbon (SOC) is one of the key soil properties that influences plant growth, water holding capacity, soil structure, soil fertility, and therefore is a proxy for soil quality (Bartholomeus et al. 2011; Bouma and McBratney 2013). The possibility to improve the soil quality, food and water security, ecosystem services and sequester atmospheric CO_2 simultaneously just by increasing SOC stocks (Bouma and McBratney 2013; Lal 2004a, 2004c) has stimulated research on the estimation of C fluxes between soil and the atmosphere (Parton et al. 1987; Ryan and Law 2005; Sa and Lal 2009). However, despite the research progress, teething problems include: (a) lack or absence of adequate baseline and validation datasets, (b) abstraction resulting to loss of critical information, and (c) lack of precision equipment (Bouma and McBratney 2013; de Paul Obade and Lal 2013; van der Meer et al. 2012).

The physical, chemical, and biologic characteristics of water can be used to define its quality (http://ga.water.usgs.gov/edu/waterquality.html). However, defining a single water quality to satisfy all uses and user needs is difficult, because the parameters used to categorize water as suitable for human consumption may be different from those qualifying water as suitable for industry or agricultural fields. Thus, terminologies to describe water quality are fragmented into: (a) green water, which is the precipitation water that infiltrates into the soil, becomes soil moisture and evapotranspires without entering rivers or groundwater and may be useful in agriculture; (b) blue water, which includes the runoff into streams and rivers plus the recharge to aquifers; (c) grey, or recyclable water from domestic activities; and (d) black or nonrecyclable waste water that is contaminated by human or industrial waste (OECD 2012). Most of water directly used by humans for domestic purposes can be recycled, whereas only 40 to 90 % water used in agricultural production is consumed (i.e., evapotranspired) and therefore not reusable (Rijsberman 2006). About 2.5 % or 35.2×10^6 km^3 out of a total of 1.4 billion km^3 of Earth's water is fresh water (Oki and Kanae 2006). Here, quality water refers to water that is fit for direct human consumption, based on the international standards established by the World Health Organization (WHO) (http://www.who.int/water_sanitation_health/dwq/en/).

The choice of land use or management will affect the biogeochemical cycles, the availability of soil nutrients, as well as the quality of water in ecosystems (Bouma and McBratney 2013; Power 2010). Ecosystem perturbations and land management are intertwined, for example, irrigation with poor drainage increases salinity of agricultural lands, whereas tillage type and residue management influence the amount of surface runoff, soil erosion and sediment transport (He et al. 1993; Laurent and Ruelland 2011). Minimizing the risk or abatement of extreme weather related events (e.g., drought, floods, and epidemics) demands quick information on the spatial extent of the vulnerable areas, so as to decide on the: (a) type of socioeconomic safety nets required and (b) recovery and restoration of the environment to original pre-catastrophe status. However, despite the increased knowledge on the consequences of nonsustainable agricultural practices, the overall impacts to ecosystems are not yet fully understood, largely because of the inconsistencies and lack of standard tools for quantifying the different environmental drivers especially over large spatial extents. Thus, the critical question is how to continuously generate precise information on the soil and water quality processes and changes over complex landscapes?

The determination of the spatial extent of soil and water resources is not a difficult task at a specific site. The problem is monitoring the soil and water quality. Existing alternatives, such as remote sensing-based systems which observe surface features across a wider spectral wavelength range than the unaided human eye, and provide inexpensive repetitive spatial continuous data, even across administrative boundaries, may provide the answer. Despite a range of advanced approaches for acquiring information from remotely sensed data, the objective of this article is neither to advocate abandonment of field-based methods which remain crucial, nor to discuss in detail the remote sensing-based systems, approaches and accuracy assessment, which have already been extensively reviewed (Ben-Dor et al. 2009; Chatterjee et al. 2009; Coppin et al. 2004; Croft et al. 2012; Foody 2002; Lu et al. 2004; Metternicht 1999; Metternicht 1998; Sahin et al. 2005; Singh 1989; Smits et al. 1999; van der Meer et al. 2012). Rather, this paper reviews some of the key concerns in the use of remote sensing data as information source for assessing the impacts of different agricultural land use, and management practices on soil and water quality. Thus, this paper demonstrates with a case study some challenges in the current remote sensing of soil and water quality, reviews some of the recent advances, and outlines future research priorities.

1.1 Synergy Between Soil and Water Quality

Land management choices may drastically alter ecosystem process through emitting significant quantities of GHGs thereby affecting weather patterns, or polluting natural resources (Volante et al. 2012). Land conversion (e.g., from forest to agriculture) has been associated with biodiversity reduction, agrochemical contamination, aggravated sedimentation of waterways, and soil quality reduction (Power 2010). Water quality is affected by materials transported to a water body through point source (PS), nonpoint source (NPS), or both (Fig. 1). PS pollution is the discharge of effluents through a confined or discrete conveyance (e.g., pipe); whereas NPS pollution occurs through diffuse sources (e.g., from surface runoff, snowmelt, or precipitation). Pollution is enhanced in environments prone to: (a) water or wind erosion, (b) salinization, (c) compaction, (d) reduction in soil organic matter, and (e) landslides (Bouma and McBratney 2013). The severity of PS and NPS pollution is controlled by the soil type, crop sequences, topography, and climate (Laurent and Ruelland 2011). The major factors affecting water quality include: (a) excess fertilizers, herbicides, and insecticides from agricultural lands and residential areas; (b) oil, grease, toxic gases, and chemicals from industries, urban runoff, and energy production; (c) suspended sediments (e.g., chlorophylls and carotenoids); (d) salt from irrigation practices and acid drainage from abandoned mines; (e) bacteria and nutrients from livestock, pet wastes, and faulty septic systems; and (f) thermal releases (e.g., from industrial discharge). These pollutants are a danger not only to crops but also to the food chain and to human health. In the USA, PS pollution is regulated through laws and relevant governmental agencies (e.g., the Clean Water Act in the USA; 33 U.S.C. Chapter 26).

Pollution can be reduced by: (a) an efficient use of all farm inputs; (b) reduced leakage or losses through leaching, volatilization, and erosion; and (c) maintenance or enhancement of soil quality through adopting recommended management practices (RMPs; Lal 2004b; Ritchie et al. 2003). The properties of soil and water vary across horizontal space, with time and depth, making it difficult to precisely determine the quality status of each of these resources. Other than real-time information, the pollution control is a complex undertaking because of the inter-related nature of the causes of pollution; therefore, remedial strategies should involve *trans* and *interdisciplinary* teams of scientist and other concerned parties (Bouma and McBratney 2013).

1.2 Risks and Potential Impacts of Inaction

Although directly affecting the livelihoods of over 1.5 billion people, the spatial extent of degraded agricultural land caused by unsustainable management practices remains highly uncertain (Bai et al. 2008); for example, from a total of 13.3×10^9 ha global land area (i.e., land and excluding inland water bodies), approximately 3.5×10^9 ha or 26 % of total land is considered degraded land (Bai et al. 2008; Lal 2001, 2009). The estimated global economic cost of soil erosion is US $ 400 billion/year, with the USA accounting for over 10 % of this estimate (Pimentel et al. 1995). The environmental cost resulting from unsustainable agricultural production in the US is between US $ 5.6 to 17 billion, with US $ 3.8 billion allocated for restorative measures (Tegtmeier and Duffy 2005) (Table 1).

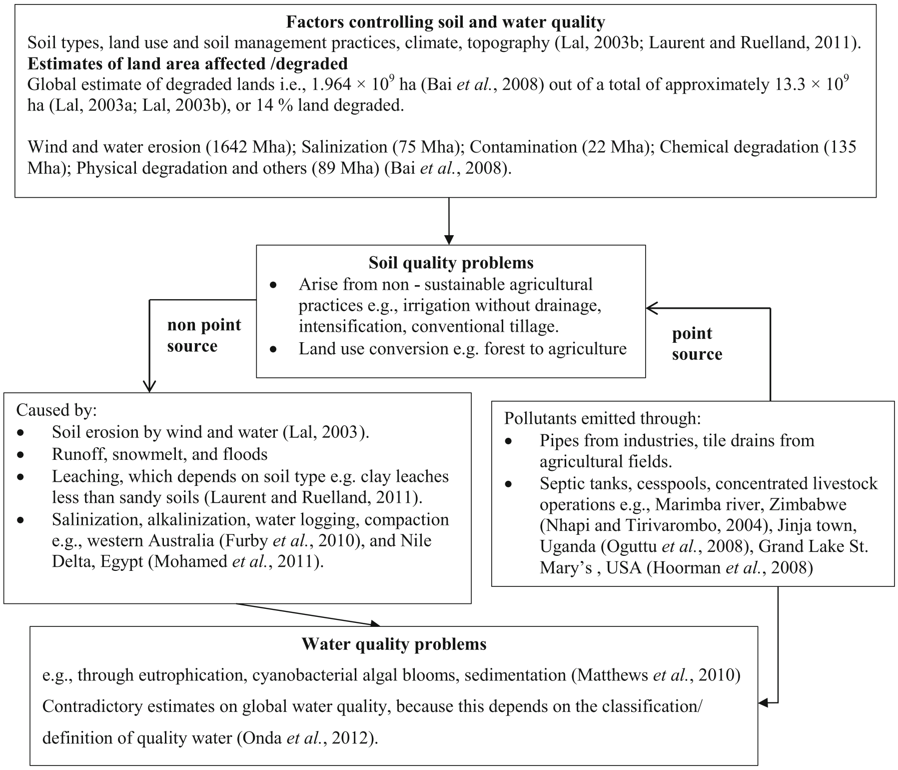

Fig. 1 Link between soil and water quality (*Mha* million hectares)

Agricultural waste contributes a substantial proportion of NPS pollutants in the USA. The damage to soil and air were in excess of US $ 2.7 billion (i.e., 30 to 50 % of the total costs), although the funds allocated to ameliorate impacts to the soil and air resources are unknown. The major contaminants from agricultural runoff include phosphates, nitrates, sulfates, and heavy metals, such as arsenic (As), cadmium, lead, zinc (Zn), and mercury (Anderson and Basta 2009; Beak et al. 2007; Dayton et al. 2003; Minca and Basta 2013; Schroder et al. 2003).

Rehabilitating degraded lands, although possible through adoption of RMPs, may be a costly undertaking

Table 1 Annual cost (in US dollars) estimates of resource damage by US agricultural production and budgetary allocation to minimize the pollution (Tegtmeier and Duffy 2005)

Damage to	Costs[a] (million $)	Budgetary allocation[a] (million $)	Deficit or surplus (i.e., cost allocation; %)
Water resources	432	158	−63
Soil resources	2,310–13,797	–	–
Air resources	464	–	–
Wildlife and ecosystem biodiversity	1,179–1,209	3,347	>180
Human health-disease by pathogens	429–455	207	−19 to 21
Human health-poisoning from pesticides	1,039	133	−87
Total:	5,853–17,396	3,845	

The computation assumes that the US agricultural cropland area remained the same (i.e., 184.1 million hectares) as reported by Tegtmeier and Duffy (2005)

[a] Estimates revised based on average inflation rate of 3 % from the years 2004 to 2012 http://www.usinflationcalculator.com/inflation/current-inflation-rates/

depending on the level of severity (Lal 2004b). Principal RMPs include afforestation or reforestation, intercropping, appropriate crop rotations, no till (NT), and crop residue retention, cover crops, and controlled farm inputs through integrated nutrient management, and integrated pest management (Laurent and Ruelland 2011). However, a land management practice suitable for one site might not be equally sustainable at another. Therefore, techniques which provide timely feedback on the success of a land management practices need to be explored.

1.3 Role of Agricultural Intensification and the Promise of Precision Farming

Precision agriculture, or site-specific crop and soil management rely on integrated information sources from Global Positioning Systems (GPS), Geographic Information Systems (GIS), and remote sensing, communication networks to maximize agronomic production (Basso 2003; Blackmer and White 1998; Doraiswamy et al. 2003). Although the economic benefits of precision farming are known (Basso et al. 2011; Bryan et al. 2011; Maine et al. 2010; McConnell and Burger 2011), information on the magnitude and impact from this farming system to environmental health are not conclusively verified (Lu et al. 1997). This is partly attributed to the inconsistent information on the degree of pollution and the limitations of available technologies with regard to: (a) scale, (b) calibration issues (e.g., for remotely sensed data), and (c) variability in data collection techniques (Pinter et al. 2003). Real-time spatial information on soil properties, soil nutrients, and yield are critical for sustainable cropping systems. Currently, this information may be acquired through GPS enabled yield monitors, although such tools may not be accessible to all farmers (Doraiswamy et al. 2003). Some information on soil and water properties for different locations is available online, although with conflicting accuracy, and may not be up to date.

2 Technical Approach and Methodology

In situ soil quality assessments are conducted through laboratory-based analyses (Cohen et al. 2007; Minasny and Hartemink 2011), or visual examination of soil color using the Munsell soil color chart (Gobin et al. 2000; Staff 1951), whereby darker soils indicate higher soil organic matter and therefore good quality soil (McBratney et al. 2002; Shepherd and Walsh 2002). However, in situ approaches of assessing soil quality may be prohibitively expensive over large areas. Table 2 provides an outline of the approaches for assessing land management impact on natural resources, beginning with expert judgment which may be highly subjective.

Pedo-transfer functions (PTFs) which are regression equations derived by comparing easily measurable soil properties with difficult-to-measure soil properties for interpolation or prediction purposes have been proposed as a rapid assessment for computing missing soil properties (Cohen et al. 2007; Minasny and Hartemink 2011). PTFs have been used to compute missing model inputs (e.g., soil bulk density, SOC, and soil moisture) used for digitally mapping natural resource threats (McBratney et al. 2002; Minasny and Hartemink 2011). However, PTFs may not be accurate beyond the range of initial data used to construct the PTF (Bouma and McBratney 2013; Kwon and Hudson 2010; Wan et al. 2011).

SOC concentration (a proxy of soil quality) can be determined either directly or indirectly. Direct methods include: (a) the Walkley-Black method (Walkley and Black 1934), (b) dry combustion (Nelson and Sommers 1996), (c) inelastic neutron scattering, and (d) the portable laser-induced breakdown spectroscopy (Chatterjee et al. 2009; Wielopolski et al. 2011). SOC is indirectly determined through PTFs or by remote sensing (Brown et al. 2006; Hartemink 2008; Minasny and Hartemink 2011).

Although in situ measurements are accurate for point measurements, they do not give the spatial or temporal view needed for comprehensive evaluation of land management choices on natural resources (Cohen et al. 2007; Cohen et al. 2005). Furthermore, ground inventory not only fail in inaccessible locations (e.g., wetlands), but are time consuming over large areas (Ritchie et al. 2003). The integration of different data sets (e.g., field and remote sensing data) has been suggested as a feasible technique to produce continuous data especially for monitoring purposes (Ben-Dor et al. 2009; Bowden 1976; Chander et al. 2009; Chatterjee et al. 2009; Coppin et al. 2004; Croft et al. 2012; Kester et al. 1996; Mulder et al. 2011; Singh 1989). To do so requires a GIS which is a tool used to input, store, manage, and analyze large volume data that may include field and remotely sensed data (Mattikalli and Richards 1996). Thus, to get acceptable

Table 2 Methods for assessing agricultural impact on soil and water quality

Method	Requirements and comments	References
Expert judgment	Subjective, particularly in the definition of quality and degradation classes: not degraded; slight, moderate, severe, and very severe Hardly reproducible Relatively low cost	Furby et al. (2010)
In situ		
Field surveys	Costly, depending on the spatial extent, data requirements, because measure points samples, e.g., secchi disk INS for SOC determination and Wireless lysimeters Requires sampling strategy	Chatterjee et al. (2009), Kim et al. (2011), and Lobell (2010)
Ex situ		
Laboratory	Determination of chemical, physical, and biologic properties Expensive depending on the number of test	Chatterjee et al. (2009) and Wielopolski et al. (2011)
Remote sensing	Repetitive acquisition enables monitoring Cost depends on platform and sensor used Modeling performed based on relations between spectral reflectance of feature of interest and surrogate variables	Croft et al. (2012)
GIS modeling	Based on established models, e.g., SWAT Data integration possible, e.g., direct field measurements, remote sensing, and socioeconomic Future prediction possible Can be subjective, especially with over reliance on secondary data	He et al. (1993)

INS inelastic neutron scattering, *SWAT* soil and water assessment tool

accuracies with these tools, it is critical to understand the data, data requirements, processing steps, error sources, and auxiliary tools. Among the critical questions asked towards this end are:

(a) What is the appropriate field sampling strategy?,
(b) Are spectral characteristics for studying soil and water quality consistent under different management scenarios?,
(c) How to handle scale related issues?,
(d) What are the sources of error?,
(e) What is the effect of vegetation on the remote sensing of soil or water?, and
(f) How to validate the remote sensing derived soil and water quality products?

One way of gathering information on water quality is through quantifying the clarity using the secchi disc method (Heiskary et al. 1994; Heiskary and Wilson 2008). This secchi disk method is described briefly in the next section. The paper then focuses on the potential and challenges of remote sensing and GIS techniques in soil and water quality assessment.

2.1 Secchi Disk Method

The secchi disk is a circular disk that costs about US $ 25 and is used to measure water transparency in rivers, lakes, and oceans. The depth at which the pattern on the disk is no longer visible is taken as a measure of the clarity or quality of the water. This measure is referred to as the secchi depth, and is related to water turbidity. Secchi disk readings do not provide an exact measure of transparency, as there can be errors due to the Sun's glare on the water, or have variation in clarity depth between practitioners. Furthermore, secchi disk method is a tedious undertaking that is not only time consuming and expensive but would require a large workforce or volunteers. The secchi disk method has been used to monitor the eutrophication level at the Minnesota lakes (Heiskary et al. 1994; Heiskary 1989).

2.2 Remote Sensing Systems

The spectral reflectance of soil and water varies depending on the environmental conditions at the time, the scale, and the land use and management. Remote sensing may capture these variations, because it exploits the distinctive nature of energy reflected from materials, from which empirical or analytical models are constructed. However, the optimal wavelength for measuring water quality is difficult to establish because this will vary depending on the concentration of wanted and unwanted materials/chemicals in water, and the sensor capabilities to distinguish them (Ritchie et al. 2003).

Studies demonstrate that the near-infrared (NIR) and mid-infrared wavelength bands may be used to detect variability in natural resources (Bricklemyer and Brown 2010; Croft et al. 2012; Griffith 2002; McCarty et al. 2002; Stevens et al. 2008), although with caution because individual bands are not only highly correlated but may significantly change with bidirectional reflectance properties of the targets, solar illumination angles, sensor viewing direction, or even plant row orientation and spacing (Holben and Justice 1981; Huete 1987; Huete and Tucker 1991). Spectral indices derived by combining individual spectral bands, minimize topographic and bidirectional effects to produce unitless spectral information representing surface sensed, and are less dependent on the illumination differences within the day (Haboudane et al. 2004; Huete et al. 1994; Lilburne and North 2010). However, unlike the Enhanced Vegetation Index which remains sensitive to biomass variations, the Normalized Difference Vegetation Index (NDVI) may saturate asymptotically at high biomass (Bolton and Friedl 2013; Huete et al. 2002).

The platform and resolution of remote sensing sensors control the products accuracy. Compared with ground-based sensors, air or spaceborne sensors have a low signal-to-noise ratio (SNR) attributed to the larger atmospheric path length, decreased spatial resolution, geometric distortions, and spectral ambiguity caused by recording multiple signals from adjacent features. Furthermore, differences between sensors in available wavelength bands and in the mechanics of imaging influence the accuracy (Kasischke et al. 1997). In the shorter wavelengths (e.g., the visible part of the electromagnetic spectrum), features can be observed by virtue of reflected solar energy, but in the longer wavelengths (e.g., microwave, thermal, etc.), sensing of emitted energy predominates.

Depending on the source of energy utilized in the data acquisition, remote sensing imaging instruments may be classified as active or passive. Active sensors produce their own energy to sense objects, whereas the passive satellite sensors depend on external energy sources (e.g., sun or earth). Table 3 provides an overview of the remote sensing sensors. The following section elaborates further on passive, active sensing, and GIS-based models.

2.2.1 Passive Sensors

Information on the effectiveness of land management choices can be gleaned from data observed at different spatial scales using passive optical and thermal sensors on boats, ground, air, or space. The thermal bands may be useful for mapping of thermal pollution (i.e., changing temperature) in water bodies caused to anthropogenic activity (e.g., electric power plants). Water bodies also may experience seasonal temperature changes. Passive sensors detect natural radiation that is emitted or reflected by the object or surrounding areas. Passive remote sensors include the eye, normal film photography, optical aerial and satellite photographies, charge-coupled devices, and radiometers. The aerial photography allows normal color observation and has been used to detect the spread of aquatic weeds or in mapping in land cover and use (Ritchie et al. 2003).

In comparison to ground-based sensors, air- and space-based sensors have larger ground coverage (de Paul Obade and Lal 2013). Data from some satellites (e.g., Landsat, advanced spaceborne thermal emission and reflection radiometer (ASTER), and moderate resolution imaging spectroradiometer (MODIS) may be freely downloaded, whereas others are commercial (e.g., Systeme Probatoire de l'Observation de la Terre (SPOT), high-resolution satellite operated by GeoEye, and Quickbird). The MODIS instrument has low spatial resolution but high temporal (i.e., daily acquisition) resolution and is hyperspectral. The ASTER and Landsat-enhanced thematic mapper plus (ETM+) have similar features.

Landsat 7 ETM+ has six multispectral bands and a thermal band that acquires data over an area of 185×170 km, with a 14.5-day revisit capability (Williams et al. 2006). Other than the scan line corrector failure in Landsat 7 ETM+ which creates data gaps, clouds, and shadows in the Landsat satellite imagery also reduce mapping capabilities (Hansen et al. 2011; Roy et al. 2010). ASTER however, has three bands in the very NIR spectral range, six bands in the short-wave infrared (SWIR) region with a 30-m spatial resolution, and five bands in the thermal infrared with a 90-m

Table 3 General characteristics of some space, air, and ground-based remote sensors

Sensor	Spatial resolution (nadir, m)	Spectral range (μm, unless otherwise stated)	No. of bands	Temporal resolution (revisit frequency)
Space-borne sensors				
ASTER	15, 30, and 90	0.52–11.65	15	16 days
AVHRR	1,100	0.58–12.4	4 and 5	Daily
Hyperion	30	0.40–2.50	196	16 days
IKONOS	1–4	0.45–0.83	4	3–5 days
IRS-AWiFS	56	0.52–1.7 (multispectral)	4	5 days
Landsat MSS (1–3), TM (4 and 5), and ETM+(7)	MSS, 80 m TM and ETM+, 30 (multispectral)	MSS, 0.5–1.1. ETM+, 0.52–0.90 (pan)	4, 7, and 8	Landsat 1–3, 18 days
Landsat 8[e], Launched 11th February 2013	TM, 120 (thermal) ETM+, 60 (thermal) ETM+, 15 (panchromatic)	TM/ETM+, 0.45–2.35 (multispectral) 10.40–12.50 (thermal)		Landsat 4–7, 16 days Landsat 8, 16 days
ENVISAT MERIS	300	0.39–0.90	15	3 days
MODIS	250, 500, and 1,000	0.40–14.40	36	Daily
Quickbird	0.6–2.4	0.45–0.89	4	1–3.5 days
RapidEye A and E	6.5	0.44–0.89	5	1–2 days
SPOT 1–4	20 (multispectral) 10 (panchromatic)	0.50–1.75 (multispectral) 0.51–0.73 (panchromatic)	4 and 5	3–5 days
RaDAR				
ERS 1 and 2	26 m (across track) and 6 to 30 m (along track)	C	1	3–168 days
SRTM	100≤250 m	C[a] and X[d]–band		1 month
RADARSAT 1 and 2	3–100	C	1	4–6 days
SMOS	35 km	L[b]–band		3 days
GeoSAR	~32 m (along track)	X and P[c]–band		6–24 h
LiDAR				
Leica Geosystem's ALS40 (EarthData Technologies)	>1, 5 to 25 m	1.06		
Airborne optical sensors				
Aerial photographs	Variable depends on flight height	Variable depending on spectral range of sensor		
AVIRIS	4–20	0.38–2.50	224	
Hymap	2–10	0.45–2.48	128	
Ground-based sensors				
ASD Fieldspec	Variable	0.35–2.50	Hyperspectral	
Cropscan 16 MSR	Variable	0.35–1.75	Maximum 16 (variable)	
Electromagnetic Induction Sensors, e.g., EM38-MK2 (Geonics Limited, Mississauga, Canada)	Variable	Visible/NIR~(0.7–4[a])		

Modified from (Bruno et al. 2006; Chatterjee et al. 2009; Croft et al. 2012; del Valle et al. 2010; Melesse et al. 2007; Metternicht and Zinck 2003)

Landsat 1–3 MSS multi-spectral scanner, *Landsat 4 and 5 TM* thematic mapper, *Landsat 7 ETM+* enhanced thematic mapper plus, *SRTM* shuttle RaDAR topography mission, *SMOS* soil moisture and ocean salinity, *SPOT* satellites pour l'observation de la terre or earth-observing satellites, *RapidEye A and E* satellite constellation from Rapideye, a private German company, *IRS-AWiFS* Indian remote sensing satellite-advanced wide field sensor, *IKONOS* high-resolution satellite operated by GeoEye, *Hyperion* hyper-spectral sensor onboard earth observing-1 (EO-1), *GeoSAR* geographic synthetic aperture RaDAR, *ERS* European remote sensing, *ENVISAT* environmental satellite, *AVIRIS* airborne visible/infrared imaging spectrometer

[a] C band, 4–8 cm

[b] L band, 15–30 cm

[c] P band, 30–85 cm

[d] X band, 2.5–4 cm

[e] http://www.nasa.gov/home/hqnews/2013/may/HQ_13-160_Landsat_8_Begins.html (online: 26th June, 2013)

spatial resolution. ASTER has a swath width of 60 km and a temporal resolution of less than 16 days. ASTER cannot produce natural color composite imagery, because unlike Landsat ETM+, ASTER does not have a blue band. Furthermore, ASTER can be affected by the "crosstalk" instrument problem, which occurs when light is reflected from the optical components of band 4 to the other SWIR band detectors (van der Meer et al. 2012). Other than Landsat with high spatial but low spectral resolution, MODIS, with low spatial resolution (i.e., 250 to 1,000 m) but high spectral resolution, high spatial resolution hyperspectral sensors such as the NASA Hyperion Earth Observing (EO)-1 with 220 spectral bands and 30 m spatial resolution may be useful for mapping soil and water quality. The European Mapping and Analysis Program are planning to launch a new hyper spectral sensor in April 2015 with a spatial resolution of 30 m and a 4-day revisit (van der Meer et al. 2012). However, it is difficult to assess the vertical (i.e., depth) variability of soil or water quality with only passive sensors, because these sensors have a low energy/signal strength to penetrate the surface of materials.

2.2.2 Active Sensors

Active sensors provide their own energy source which can penetrate the ground, and are useful for measuring surface features in three dimensions. Active sensors are less affected by atmospheric effects, in comparison to passive systems (Hyde et al. 2006; Hyde et al. 2007). Active sensors measure the radiation that is reflected or backscattered from the target, and the time delay between emission and return of signal, processed to determine the height of an object. Radio detection and ranging (RaDAR), and light detection and ranging (LiDAR) are examples of active remote sensors. Active sensors were originally designed to measure canopy heights, and topography. Active sensors have also been used to map urban features (Metternicht and Zinck 1998, 2003); to model seasonal flooding in the Congo River basin (Rosenqvist and Birkett 2002), and to map waterlogged and salt affected areas (Zhu et al. 2012).

Active sensors have very low swath width and may therefore be costly for mapping over large spatial extents. Moreover, the high cost of flight time, the need to limit scanning to near nadir in order to prevent ranging errors, and the presence of coverage gaps due to aircraft pitch and roll, limit their effectiveness (Hyde et al. 2006). Given the side-looking illumination geometry, sensor images from RaDAR and LiDAR are slightly distorted. RaDAR waves are sensitive to surface roughness and depend on the target's dielectric constant that measures how well electromagnetic waves couple with a given type of material (e.g., rock and regolith) (Kasischke et al. 1997). Therefore, the geometric and electromagnetic interactions of RaDAR waves with natural surfaces must be factored in, for accurate interpretation of Synthetic Aperture RaDAR images (Greeley et al. 1997).

A returned active sensor signal (e.g., from RaDAR) varies considerably in response to differences in terrain morphology, topography, and surface cover (Ridley et al. 1996). To explain these variations, it is necessary to study the trends between the sensed signals and the specific characteristics or composition of the materials being scanned and to determine which of these properties may serve as indicators of these variations. As backscatter depends on the geometric and electric properties of a given terrain, it is critical for extracting structural information about the terrain (Dobson et al. 1995a; Dobson et al. 1995b).

Few studies have used active sensor data to assess spatial variation in soil quality (Chaturvedi et al. 1983; Metternicht 1998; Schmullius et al. 1997). Environmental satellite ASAR data have been used to monitor soil moisture in the upper soil profile at high spatial resolution for the Okavango delta and to predict areas with drought and flood risks (Milzow et al. 2009).

2.2.3 GIS-Based Models

Integrating field and remotely sensed data through GIS technology opens up infinite possibilities for manipulating geospatial information. Among the input components in GIS models for soil and water quality assessment are: soil types, depth and temperature, precipitation, potential evapotranspiration, erosion and sedimentation rates, plant types, land management practices, infiltration, and surface runoff. Although not an exhaustive list, some GIS-based models used for providing information critical for assessing the spatial variability in soil quality (i.e., SOC) include: General Ensemble biogeochemical Modeling System, CENTURY, Daily Century model, Rothamsted Carbon Model, and the Erosion Depositional Carbon Model (Bannari et al. 2006; Batjes 2008; Dieye et al. 2012; Gomez et al. 2008; Grunwald 2009; Ladoni et al. 2010; Lillesand et al. 1983; Liu et al. 2011; Lobell 2010; McCarty et al. 2002; Mulder et al. 2011; Parton et al. 2004; Parton et al. 1987; Tan et al. 2009; Wielopolski et al. 2011).

Sediment deposition and pollution within watersheds have been monitored using GIS-based hydrologic models. Hydrologic models are classified based on their design and functionality, into: (a) manual or statistical based, which are simple, rely on in situ data, and therefore may not be valid beyond the range of data collected, and (b) automated or numerical, which are process based and use mathematical and empirical relationships to model complex physical and dynamical processes within earth systems (Arnold et al. 2012; Boyle et al. 2000; Meng et al. 2010). Statistical-based methods analyze in situ data in the laboratory. Although these measurements may be accurate, they do not give the spatial and temporal view needed for comprehensive assessment and management (Ritchie et al. 2003).

Numerical models may be further subdivided into: (a) lumped models, which require substantial calibration data, and vary with scale, or (b) physically based distributed parameter models, which simulate physical processes across time and space. Physical models estimate the yields of sediment, soil nutrients from agricultural runoff. However, physical models are data intensive, and require computer software knowledge and coding skills. Examples of numerical models are the Agricultural NonPoint Source Pollution Model, the Dynamic Watershed Simulation Model, and the European Hydrological System model or MIKE SHE, Precipitation-Runoff Modeling System (Borah and Bera 2003; Young et al. 1989), Annualized Agricultural Nonpoint Source (Hua et al. 2012; Pease et al. 2010; Wang and Lin 2011a; Wang and Lin 2011b), Areal Nonpoint Source Watershed Environment Response Simulation 2000 (Migliaccio and Srivastava 2007), Hydrological Simulation Program-FORTRAN (Diaz-Ramirez et al. 2011), Watershed Assessment Model (Bottcher et al. 1998; Migliaccio and Srivastava 2007), the CLimate, Organisms, Relief, Parent material, Time model (Arrouays et al. 1998), and Water Erosion Prediction Project (WEPP) (Defersha et al. 2012; Hubbart et al. 2011; McClellan et al. 2012; Singh et al. 2011, 2012; Wade et al. 2012).

Hybrid hydrologic models combine the characteristics inherent in lumped and physically based models. The Soil and Water Assessment Tool (SWAT) is a hybrid model that operates with continuous daily time step data and was developed by the US Department of Agriculture Agricultural Research Service to study the impact of agricultural land management on water resources at different spatial scales (Arnold et al. 2012; Arnold et al. 1998; Lee et al. 2011). The accuracy in SWAT depends on the calibration parameters, which should be within the realistic uncertainty range verified through actual knowledge of the watershed (Arnold et al. 2012). SWAT has been used in catchments worldwide to monitor sediment flows, deposition, and nutrient balances within the watershed (Betrie et al. 2011a, b; Santhi et al. 2001; Srinivasan et al. 1998).

3 Case Studies

Attempts to monitor and develop early warning systems for monitoring natural resources is ongoing research albeit the piecemeal, and often problem-driven assemblage of tools and resources to improve flexibility in assessment at different spatial extents (Atkinson 2013; Migliaccio and Srivastava 2007). Considering the limited sample sizes and the need for real time synoptic coverage at flexible spatial and temporal scale, monitoring natural resources is currently feasible through integration of multiple data sources. Within the Great Miami River in Ohio, researchers reported that an agglomeration of data from field and sensor measurements using a Secchi disk, hyperspectral data from a hand-held and laboratory spectroradiometer, and Airborne Spectrographic Imager sensor could accurately assess the spatial and temporal variability of chlorophyll *a*, turbidity and total suspended solids (Senay et al. 2002).

Behera and Panda (2006) used a SWAT model to simulate daily runoff, sediment yield, nutrient concentration in the runoff, so as to assess the water quality over a 973-ha agricultural watershed located in the Midnapore district of West Bengal state in eastern India. The model inputs included micro-meteorological data, topographical map, a soil map, land resources data, and satellite imagery. The critical sub-watersheds under the risk of pollution were identified by the model. In a separate study conducted within the republic of Korea, SWAT was able to show that the modeled simulated runoff and water quality values were highly correlated with the observed field data (Soltanpour and Delgado 2002).

The efficacy of an export coefficient GIS model to estimate nitrogen (N) losses from land to inland water bodies was tested in South Lincolnshire, Eastern England, based on the premise that the solute concentrations in waterways exceeded that of the WHO directives on drinking water quality (Mattikalli and Richards 1996). The model inputs were measured point effluents, N fertilizer application rates, and current and historical land use statistics from remotely sensed data. The model accuracy was verified through comparing the estimated and actual nitrogen losses. N in waterways was found to have increased between the years 1931 and 1984 but remained steady thereafter. These findings were attributed to increases in fertilizer usage and land conversion. Phosphorous losses were not studied because of absence of data.

In the Jezre'el Valley, northern Israel, an experiment was conducted to study the effects of low quality saline irrigation water, on soil structure, and infiltration rate. A validation was conducted on the salinity map produced, and found to have a “good fit” with the laboratory salinity measurements, demonstrating the accuracy of remote sensing in salinity measurements (Goldshleger et al. 2012). In another study, Kim et al. (2011) monitored drainage water flux in agricultural fields, using the passive capillary wick-type lysimeters, which are wireless lysimeters developed for Web-based real-time online monitoring of drainage water. The study found a high correlation between estimated and actual drainage.

Dall'Olmo et al. (2005) assessed the suitability of alternative spectral wave bands for quantifying chlorophyll *a* concentration (Chl) in productive turbid waters. Previously, algorithms for remote estimation of Chl in waters were based on the blue and green spectral regions. However, high atmospheric scattering in the blue wavelength range of the electromagnetic spectrum severely degrades the remote sensing signal in the blue band (Jiang et al. 2008; Miura et al. 2000; Pahlevan et al. 2012). Using 251 water samples from different lakes and rivers, reflectance spectra were measured in situ across a broader wavelength range with a hyperspectral sensor, and correlated with the Chl and water constituents (e.g., dissolved organic matter that do not co-vary with Chl). The models were upscaled using the NIR and red bands of SeaWiFS and MODIS sensor. This study concluded that as long as an atmospheric correction scheme for the red NIR spectral region was available, SeaWiFS and MODIS imagery could quantitatively monitor Chl in turbid productive waters. Studies conducted at other sites by other workers corroborate these findings (El-Alem et al. 2012; Furby et al. 2010; Moses et al. 2009).

A review of soil degradation in Latin America by Metternicht et al. (2010) identifies Landsat as the widely used remote sensing data source in studies conducted in Latin America. Information on the impact of agricultural practices on soil and water quality within the African continent is scattered and scarce. Table 4 provides a summary of research conducted in Africa from ten countries out of a total of 57 countries that applied remote sensing data to assess the impact of agricultural practices on the natural resources.

4 Limitations of Remote Sensing in Assessing Soil and Water Quality

The limitations in the application of remote sensing in soil and water quality assessment arise from: (a) spectral confusions (i.e., impure pixels) from simultaneous detection of reflectance signals at the sensors, (b) difficulty in distinguishing plant species, (c) scaling issues, (d) low accuracy due to soil and water heterogeneity (e.g., spectral complexities of incomplete plant cover), and (e) absence of long-term satellite data (e.g., Landsat satellite data were available from only 1972 and MODIS from 2000).

Models may be too simplistic or incomplete (e.g., omit soil depth variability or assume one type of soil everywhere), because the model design and functionality depend on the professional background of the model developer (Bouma and McBratney 2013). The misuse of PTFs in deriving soil physicochemical properties (e.g., bulk density, texture, soil moisture content, available water capacity, SOC, etc.) may generate erroneous results. Soil characteristics (e.g., bulk density and texture) which are crucial for assessing soil quality are difficult to assess using only remote sensing data (Dematte et al. 2010; Jana and Mohanty 2011).

Some workers report a high correlation between SOC concentration and spectral reflectance under controlled laboratory conditions (Bartholomeus et al. 2008; Stevens et al. 2008), however, from aerial- or space-based platforms the lower SNR attributed to atmospheric scattering, bi-directional reflectance, adjacency effects, topographic variation, and geometric and radiometric errors may lower this accuracy. Furthermore, the

Table 4 Some notable studies on the application of remotely sensed data to assess the impact of agricultural management on soil and water quality in Africa

Country	Technique	Key finding and limitations	References
Burkina Faso	SAR	Improve prediction of flood and drought events. New calibration approach proposed	Ciervo et al. (2011)
Egypt	Landsat TM, secchi disk, water samples, and total biomass of aquatic plants	Water quality parameters, K^+ and Na^+; total phosphorus, total nitrogen, dissolved oxygen, pH, salinity, secchi disk depth. Pioneer application of Landsat data in extrapolating water quality parameters	Dewidar and Khedr (2001)
Egypt	Electrical conductivity, pH, temperature, water level tested on 47 groundwater samples. Landsat TM/ETM+ satellite data and GIS used for mapping and change detection	Salinization is major threat to groundwater aquifer and agricultural production. Topographic depression found to have induced flow pattern, leaching, and degree of salinization in Lakes. Excessive pumping of aquifer and land management affected the quality of ground water. Regions that had low water levels had high salinity and alkalinity	Masoud and Atwia (2011)
Ethiopia	Multiple data sources, i.e., Landsat, field observation, and topographic maps	Lake Basaka expanded by (45.8 km^2) over the past 50 years. Potential risks include saltwater intrusion which might affect irrigated agriculture	Dinka (2012)
Kenya, Uganda, and Tanzania	MODIS and NOAA satellite data. Time series of NDVI	El Nino events linked to water hyacinth blooms (Study site: Winam Gulf of Lake Victoria). Difficult to assess exactly the source of agricultural nonpoint pollution causing the eutrophication	Kiage and Obuoyo (2011)
Senegal	NOAA AVHRR data. MIKE SHE hydrological model. Spatial data on topography, soil types, vegetation characteristics, and precipitation data	Calibrated with 11 years data in 9 stations. Spatial resolution of input data found insufficient for calibration and validation. Spatial resolution of precipitation as input significantly influenced model performance. Dryness index from NOAA AVHRR data does not improve calibration or validation of MIKE SHE model. Time series analyses with Meteosat to be done in future	Andersen et al. (2002)
South Africa	MERIS and Secchi Disk	The MERIS network algorithms had poor correlation with in situ measurements of water concentration constituents, i.e., concentration of cynobacterial blooms and sediments. Atmospheric correction applied on MERIS imagery did not significantly improve the model accuracy	Matthews et al. (2010)
South Africa	Landsat TM/ETM+ and NDVI	Correlated water quality with the proportion of land under vegetation in semi arid areas. Bare land areal extent used as criteria to rate the water quality. The rivers passing through the degraded areas had darker colors and were turbid	Munyati and Ratshibvumo (2011)
Tanzania	Landsat ETM+, SRTM (DEM). Data integration with a decision tree	Regional scale assessment of erosion risks. High erosion risk areas identified. Model can be extrapolated to other parts of East Africa subject to data availability	Vrieling et al. (2006)

MODIS moderate resolution imaging spectroradiometer, *SAR* Synthetic Aperture RaDAR, *NDVI* Normalized Difference Vegetation Index, *NOAA AVHRR* National Oceanic and Atmospheric Administration Advanced Very High Resolution Radiometer, *MERIS* Medium Resolution Imaging Spectrometer, *SRTM* (*DEM*) Shuttle RaDAR Topographic Mission (Digital Elevation Model)

variability in composition or concentration of heterogeneous mixtures of soil or water (i.e., SOC, Fe_2O_3, soil moisture, mineralogy, and chlorophyll) may significantly influence the characteristics of the reflectance signal detected by the sensor (Bartholomeus et al. 2011; Bartholomeus et al. 2008). Deciphering information from remote sensors is difficult within heterogeneous landscapes (Bai et al. 2008; Lobell et al. 2007).

The spectral bands on some passive optical satellites (e.g., Landsat and SPOT) cannot discriminate chlorophyll from water with high sediments, even in the red-edge region because of the spectral confusion from the differential reflectance arising from the variability in concentration of the suspended sediments (Ritchie et al. 2003). Furthermore, separating different species or groups of algae or phytoplankton with only the passive sensors is difficult (Ritchie et al. 2003). Developing stress detection algorithms that can accurately identify the unique spectral signatures for specific vegetation stresses over different background landscapes or locations, time or climate is another hassle (Senay et al. 2002).

Insufficient data for validating historical data, and the scaling incompatibility between remote sensing, and actual field measured data constitutes another challenge. To monitor impacts of agronomic practices on water quality, information from historic imagery should be analyzed together with current data. However, data acquired at different times, may have incompatible formats. Other drawbacks include the uncertainty in the cost of new technology/sensors, and training required.

Spectral mixture analyses (SMA) technique may reduce spectral ambiguity in satellite data that occur due to mixed reflectance signals from heterogeneous surfaces (Metternicht and Fermont 1998). The SMA distils information from all available spectral reflectance bands into fraction images, using the pure spectral signature representing each of components within the pixel (i.e., endmembers) (Dennison and Roberts 2003; Garcia-Haro et al. 1999). Bartholomeus et al. (2011) argued that spectral unmixing can be improved with the development of sensors with better SNR.

Although GIS-based models play a critical role in soil and water quality assessment, the major limitations that compromise accuracy are: (a) lack of up-to-date inputs (e.g., soil information), (b) generalization (e.g., soil types assumed to be same or "standard soil" everywhere), (c) variability of soil with depth and time (Bouma and McBratney 2013), and (d) limited data and proper definition of the problem (Rijsberman 2006). The debatable definition of the problem of water scarcity (e.g., is it a "demand or supply problem?") have slowed down the advancement and adoption of complex indicators. Furthermore, easy to use models for assessing water scarcity (e.g., Falkenmark) provide limited information with questionable accuracy. Land management choices not only affect water quality and availability (Rijsberman 2006) but may also alter the soil micro-climate and moisture which may trigger soil biologic activity thereby impacting on soil (e.g., C sequestration), and water processes (Arnold et al. 1998; Maeder et al. 2002).

5 Answering the Key Questions

This section discusses the approaches for tackling the limitations discussed previously, so as to obtain reliable results in the soil and water quality assessments using remote sensing. Although an attempt is made to address each questions individually, remote sensing techniques generate similar issues with regard to methodology and error sources, therefore in practical situations these concerns are intertwined.

5.1 The Promise of Statistical Sampling

Efficient and accurate determination of soil and water quality can be done cost effectively through developing statistical approaches that utilize the least number of field measurements. Selecting a sound sampling scheme enhances the efficiency, cost effectiveness, and reliability of the measurement parameters (Stehman et al. 2005). Examples of field sampling strategy to be selected during the planning phase are the random, grid, and stratified. Stratified sampling is preferable to random in situations where accessibility to sampling locations is difficult especially in highly heterogeneous fields. Stratification groups land management units with similar characteristics. Other criteria such as ecological variables may be incorporated in stratified sampling for defining non-overlapping units, e.g., through utilizing the interrelationship between physical (e.g., geology) and climatic factors, e.g., rain, temperature, etc. (Eva and Lambin 1998). The advantages of stratification are that: (a) separate estimates of means and variances can be computed for each land cover class and (b) stratification yields more precise estimates than simple random sampling of the same size (Stehman et al. 2005). Regression techniques may evaluate the degree of fit between modeled and observed values, for accuracy assessments and prediction. However, inconsistent results may occur with limited sample size and/or high variability of the phenomenon being investigated (Gallego 2004; Stehman et al. 2005).

5.2 Are the Soil and Water Quality Spectral Patterns Consistent Under Different Management Practices?

5.2.1 Study Site and Methods

A field investigation was performed in May and July, 2012 to determine the soil and water quality using spectral reflectance. Soils were sampled from the following field sites: Miami (40°10′12″ N, 84°07′41.7″ W), Seneca site 1 (41°00′25″ N, 83°16′21″ W), Seneca site 2 (41°12′43″ N, 82°54′39″ W), Preble (39°46′09″N, 84°36′52″ W), and Auglaize (40°27′34.5″ N, 84°26′14.8″ W) within the state of Ohio, USA. A total of 80 core and bulk soil were sampled at a depth of 0 to 10 cm at similar landscape position (i.e., summit) but different land management practices. The soils sampled were the crosby silt loam (taxonomic class: fine, mixed, active, and mesic Aeric Epiaqualfs), kibbie fine sandy loam (taxonomic class: fine-loamy, mixed, active, and mesic Aquollic Hapludalfs), Glynwood silt loam (taxonomic class: fine, illitic, and mesic Aquic Hapludalfs), Crosby Celina loams (taxonomic class; fine, mixed, active, and mesic Aquic Hapludalfs), and Pewamo silty clay loam (taxonomic class: fine, mixed, active, and mesic Typic Argiaquolls). The agricultural management practices in the field were NT with and without cover crops or manure, natural vegetation (NV; i.e., forest), and conventional tillage (CT). The soils were analyzed for SOC and nitrogen (N) concentration, pH, electrical conductivity (EC), and soil moisture content (Table 5).

Soil moisture content was determined gravimetrically by oven drying a fraction of the soil at 105 °C (Topp and Ferre 2002). Soil pH and EC were measured with 20 mL of liquid with a 1:1 soil/water suspension using a hand-held portable probe (Lal 1996; Peech 1965). Soil pH and EC are critical parameters for soil quality assessment because in concert they can influence soil reaction, salinity, and nutrient availability (Arnold et al. 2005; Bastida et al. 2008). Anion analysis (i.e., chlorides and sulphates) were determined with the ion chromatograph (LaCroix et al. 1970). Total organic carbon (TOC) was determined in 40 mL vials by combustion (Nelson and Sommers 1982, 1996). The soil pH was less than 7.6, suggesting insignificant or absence of inorganic carbonates in the soil (Brown et al. 2006; De Vos et al. 2005).

The carbon/nitrogen (C/N) analysis were done with the bulk disturbed soil samples, which were air dried, gently ground, and passed through a 2-mm sieve. The C/N ratio was determined by the dry combustion method at 900 °C with a Vario Max C/N analyzer (Nelson and Sommers 1996). Prior to spectral measurement, the soil samples (i.e., those that were air dried and sieved at <2 mm) were placed in labeled plastic cups (i.e., 10 cm diameter and 5 cm height) and screeded (at 3 cm depth of soil in cup) so that the entire surface of the soil sample was level, thus guaranteeing a uniform soil sample depth of approximately 3 cm, and ensuring that reflectance measurements recorded the soil surface, and not the sample background. Each sampled soil was scanned five times (i.e., by pointing analytical spectral devices (ASD) optics at nadir to the center of plastic cup, approximately 2 cm above soil) outdoors under clear sky visibility using a [1]FieldSpec Pro spectrometer ASD (wavelength range of 350 to 2,500 nm) and following the established scanning protocols. Except for the tap water samples where the spectral reflectance was measured with FieldSpec ASD water but in plastic basin (i.e., dimension of 30 cm diameter and 10 cm height) under natural sunlight, the reflectance of the water from Grand Lake St. Mary (40°32′ 37.5″ N, 84°30′29.3″ W), and Aurora Pond (41°19′ 52.5″ N, 81°23′24.4″ W) were measured on site. In both cases, the median ASD spectra data were selected for analyses, and reflectance from atmospheric water vapor manually removed from data. Soil moisture effects on reflectance were assumed negligible because of low variation (i.e., <15 %).

5.2.2 Results and Discussion

From Fig. 2a, the tap water had the highest spectral reflectance between the wavelengths of 350 to 1,700 nm (nm), although that from Grand Lake St. Mary was higher between 1,700 and 2,100 nm. Reflectance of water bodies is influenced by absorbance and scattering cross-sections of water, plant pigments, dissolved organic carbon (DOC), and suspended inorganic matter (Vertucci and Likens 1989). The reflectance of the water from Aurora Pond was higher than that of the water from Grand Lake St. Mary between 350 and 750 nm, but the reverse trends were observed at the longer wavelengths (i.e., 1,700 to 2,100 nm). Vertucci and Likens (1989) reported similar findings within the 400 to 600 nm where plant pigments, DOC, and suspended

[1] http://www.asdi.com/products/fieldspec-spectroradiometers/fieldspec-4-hi-res

Table 5 Sampling locations and averaged soil carbon (C)/nitrogen (N) ratio's for surface soil (0–10 cm) under different management practices within the state of Ohio, USA

Field site	Coordinates	Soil type	C/N ratio				
			CT	NV	NT	NT cc	NT ccm
Miami	40°10′12″ N, 84°07′41.7″ W	CrA	10.37	11.87	10.03	10.41	–
Seneca (1)	41°00′25″ N, 83°16′21″ W	kbA	10.11	11.38	–	10.15	10.30
Seneca (2)	41°12′43″ N, 82°54′39″ W	GWA	9.93	10.71	–	10.07	–
Preble	39°46′09″ N, 84°36′52″ W	CtA	10.13	9.89	–	–	9.29
Auglaize	40°27′34.5″ N, 84°26′14.8″ W	Pw	9.11	11.21	9.55	–	–

Soil type description follows the US Department of Agriculture soil classification system

CT conventional tillage, *NV* natural vegetation, *NT* no till, *NT cc* no till with cover crops, *NT ccm* no till with cover crops and manure, *CrA* Crosby silt loam, *kbA* Kibbie fine sandy loam, *GWA* Glynwood silt loam, *CtA* Crosby celina silt loams, *Pw* Pewamo silty clay loam

material were negatively correlated with reflectance but positively correlated from 600 to 750 nm; parameters associated with lake acidification, pH, alkalinity, and aluminum concentrations are poorly correlated with reflectance. The relatively higher reflectance pattern observed for tap water may be attributed to: (a) absorption of radiation by the sediments in the lake water, and (b) directional reflectance from the non-Lambertian (i.e., rough) lake surface from the signal scattering, thus fewer signals received at the remote sensor (Peltoniemi et al. 2009). An important observation is the variability in water reflectance with wavelength; especially within the 350 to 1,000 nm wavelength which would therefore be critical for distinguishing between tap (i.e., purified) and lake water (i.e., unpurified).

Generally, the C/N ratio was high under NV management, except at Preble site where C/N was high under CT (Table 5). NTccm managed soil had lower C/N than the CT soil at Preble site. This is strange because soil under CT is more aerated because of the tillage which triggers the soil biologic activity with resultant consumption or decomposition of organic matter (Dungait et al. 2012; Tuomisto et al. 2012). Alternatively, the soil under CT management at Preble site had substantial and regular addition of residue.

The soil under CT management at Auglaize had the highest spectral reflectance, whereas the soil at Miami site had the least (Fig. 2b). This appears defendable based on the C/N ratio, under the assumption that high C/N (e.g., at Miami) would imply darker soil and thus relatively higher absorbtion of solar radiation but less reflected to the sensor. The lab determined C/N (i.e., 9.1) for the soil at Auglaize site was the lower than soil at Miami site (i.e., 10.4), under CT. Similarly, the soil at Preble site had the highest reflectance under NV management with a low C/N (9.2), with the least reflectance observed with soil from Miami site, with C/N (11.9) (Fig. 2c). Although the C/N were similar for both soil types, the soil under NT management at Miami site had the highest reflectance, and Seneca (site 2) the least (Fig. 2d). The reflectance for soil under NTccm at Preble site was less than 0.10.

The water had relatively higher pH than the soil; although the soil was more salty based on the relatively higher electrical conductivity (Table 6). Interestingly, the pH for tap water was similar to that of water from Aurora pond, both of which had a higher pH than water from Grand Lake St. Mary. Aurora pond was more salty having an EC that was 44 % higher than the EC of water from Grand Lake St. Mary, and almost double the EC of tap water. Aurora pond had double the chloride concentration compared with tap water, and almost five times that of water from the Grand Lake St. Mary. However, sulfates were three times less in Aurora pond compared with the tap or water from the Grand Lake St. Mary. The TOC for tap water was double that of water from Grand Lake St. Mary, and 40 % higher than the water from Aurora pond. Other than the pH, the solutes (e.g., chlorides and sulfates), or TOC might have caused the difference in reflectance patterns between the tap water and lake water, but it is difficult to pin-point or select the main factor. Alternately, the pH of soil at Seneca site (1) was the highest, and preble site, the least. Miami had the highest EC, and Seneca site (2) the least.

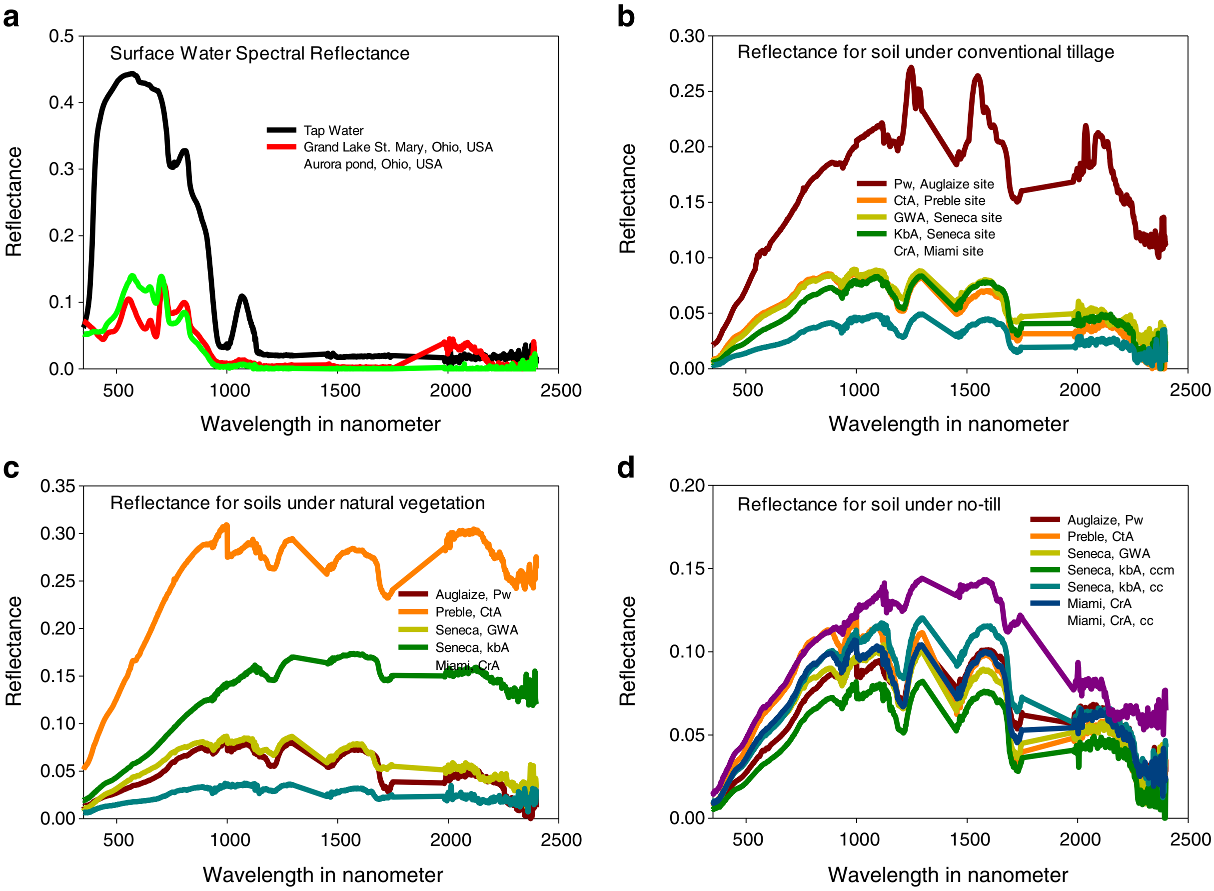

Fig. 2 Surface spectral reflectance from Grand Lake St. Mary, Aurora pond, tap water (**a**); and of different soil under 3 different land management practices (**b**, **c**, and **d**), for the different field sampling sites within the state of Ohio, USA. *CrA* is crosby silt loam, *kbA* is kibbie fine sandy loam, *GWA* is glynwood silt loam, *CtA* is crosby celina silt loams, *Pw* is pewamo silty clay loam; whereas *cc* represents cover crop, and *m* represents manure. The spectral reflectance was acquired using a FieldSpec 3 Spectroradiometer

Figure 2a–d shows fluctuating results on reflectance from the different soils and water; for example, the graphs of soil reflectance under different management showed similar trends across wavelengths for soil under CT and

Table 6 Mean pH, electrical conductivity (EC), chlorides (Cl^-), sulfur from sulfates (SO_4–S), and total organic carbon (TOC) for Grand Lake St Mary, Aurora pond, and soils sampled within sites in Ohio, USA

	Water			Field sites (soil sampled)				
	Tap water	Grand Lake St. Mary[a]	Aurora pond[b]	Seneca (1)	Seneca (2)	Miami	Preble	Auglaize
pH	8	7.6	7.9	6.9	6.5	6.8	6.3	6.7
EC (μS cm^{-1})	342	455	657	535	290	619	345	539
Cl^- (μg mL^{-1})	72.7	39.3	150.7					
SO_4–S (μg mL^{-1})	20.3	21.6	6.2					
TOC (mg L^{-1})	5.3	2.0	3.8					

[a] Grand Lake St. Mary, 40°32′37.5″ N, 84°30′29.3″ W

[b] Aurora pond, 41°19′52.5″ N, 81°23′24.4″ W

NV, but were slightly different for NT, demonstrating why it can be difficult to develop a general or universal soil quality model based only on spectral reflectance information. Furthermore, the reflectance in each of the land management practices varied depending on the specific spectral window (i.e., 350 to 2,500 nm) of observation. This could suggests significant scattering of the spectra by the different materials in the soil matrix. Soils contain water, air, and solid, with the solid composed of different mineralogy; therefore the reflectance of soil will be highly variable depending on the proportionality and interaction effects of each of the soil components or elements. However, there was no way no estimate the level of uncertainty from noise (e.g., atmospheric scattering) because the soil reflectance had low sensitivity (i.e., <0.4 in magnitude). The spatial heterogeity and complexity of soil materials may explain the sporadic pattern in reflectance signal from the different soil types (Mattikalli and Richards 1996; Stockmann et al. 2013). Although difficult to pin point exactly whether it is the sediments, chlorophyll concentration, or solute concentration influencing the reflectance difference between tap (i.e., purified) and lake water (unpurified), the relative homogeneity of surface water in comparison to soil may have made the purified and unpurified water spectral characteristics more visually apparent.

5.3 Scale Issues

Scale may be defined as: (a) the spatial-temporal variability of a phenomena or (b) the fraction of the earth's surface on a piece of paper, represented as the ratio between the distance on a map and the equivalent distance on the ground (Goodchild 2011). Scale is a major factor influencing the level of detail in the final map product because scale may determine the spatial extent of coverage or spatial resolution, and the time frame or temporal dimensions. Scale in digital data may be manually defined or vary naturally depending on the data acquisition platform. Because an optimal resolution in raster data depends on the feature to be studied and therefore does not exist, different data sources may be combined through models and upscaled or downscaled depending on the intended application (e.g., development of regional scale climate circulation models, hydrology, ecology, or population mapping). Upscaling is the transformation of data to a coarse spatial resolution, whereas downscaling refers to a decrease in the pixel size (i.e., achieved through increasing the spatial resolution) with a goal of increasing the information content within the pixel (Atkinson 2013). Downscaling entails the prediction of continuous or discontinuous variables at finer spatial resolution than the input, a challenging feat of interpolation from area to point, the reverse of kriging (Goovaerts 2010; Kyriakidis 2004; Kyriakidis and Yoo 2005).

Synchronizing data from different sensors or platforms is a challenging undertaking (Atkinson 2013; Dungait et al. 2012; Goodchild 2011; Smith 2004), because of spatial-temporal variability of earth objects, which are difficult to precisely map using remote sensing (Angers and Eriksen-Hamel 2008; Stockmann et al. 2013). Monitoring soil quality using maps derived from different dates would not only require maps developed at different time which may be incompatible, but also precisely characterizing the soil property variability with depth, which is an almost impossible feat, given the heterogeneity within the transition zones in the soil profile. However, comparing maps derived with sensors having different spatial resolution is doable using regression (e.g., artificial neural network and boosted regression trees) (Atkinson 2013; Tatem et al. 2011) or Mapcurves which does not require rigorous georeferencing. Mapcurves are "polygon" rather than "cell" based, therefore useful for quantitative evaluation of fit between maps generated from sensors with different spatial resolution (Hargrove et al. 2006).

5.4 Effects of Vegetation in Remote Sensing-Based Soil and Water Quality Assessment

Determining the soil quality in highly vegetated fields is difficult because of obstruction of the soil by vegetation (Foody 2000; Stockmann et al. 2013). A "quick fix" would be to mask out vegetation, so as to remain with only bare soil (Wester et al. 1990). However, this would create data gaps as the soil information in the masked out vegetated areas will be missing. In heterogeneous landscapes multiple reflectance are captured and merged by the sensor creating a blur object having more than one class within the pixel size, referred to as the mixed pixel problem. Subpixel mapping approaches have been applied to minimize the mixed pixels problem (Roberts et al. 1998; Roberts et al. 1993). Adjacency effects may also occur in pixels arising from reflectance of neighboring surfaces. The combination of several different spectral indices has been used to reduce the vegetation influence on soil properties depiction using remote sensing (Bartholomeus et al. 2007).

Models have been developed that relate vegetation types to SOC. Asner et al. (2003) related SOC and N field observations to fractional cover data for photosynthetic and non-photosynthetic vegetation and observed trends in these specific soil properties at an ecosystem level. Kooistra et al. (2003) used vegetation phenology as a proxy to estimate SOC and Zn concentrations in flood plains. Separating species of plants or even crop types using remote sensing alone is difficult because of similarity in spectral signatures. Efforts have been made to separate the two most common notorious aquatic weeds (i.e., water hyacinth and hydrilla) that invade and clog waterways using remote sensing (Ritchie et al. 2003).

5.5 Effects of Snow in Remote Sensing-Based Soil and Water Quality Assessment

Snowmelt may contribute to agricultural NPS pollution through leaching, or transporting animal wastes, sludge's, and other industrial wastes to streams and rivers (Bradford et al. 2010; Walker et al. 2006; Zege et al. 2011). Studies show that global warming has melted snow in the Arctic and Antarctic, with anticipated feedback effects that may control weather patterns, ocean current circulation and global sea rise (Achberger et al. 2012). However, because of the vastness and hostile conditions, it is difficult to make in-situ measurements within this polar region (Achberger et al. 2012). Remote sensors on board ships have been used to map the thickness and distribution of sea ice (Worby et al. 2008), radio-echo sounding used to investigate the subsurface properties of the polar ice sheets and ice caps (Bingham and Siegert 2007), the albedo of sea ice shown to be increasing based on measurements from microwave sensor and imager (Lubin et al. 2003), and the spatial extent of snow cover mapped from air or satellite platforms (Frei et al. 2012; Rittger et al. 2013), but because of technical and logistical constraints, detailing the pollution hotspots may still be difficult (Heygster et al. 2012; Sun et al. 2010). It is difficult to quantify snow pollution because of the disagreement in accuracy of assessment methods and the difficulty in modeling the complex multi-angle polarized snow reflectance (Frei et al. 2012; Peltoniemi et al. 2009).

5.6 Calibration and Validation

Calibration is the alternate to validation, except that calibration is normally undertaken on the equipment by the manufacturers, or before actual field measurements or modeling is conducted, whereas validation is an accuracy assessment performed through comparing measured data with data predicted by the remote sensor or model (Chander et al. 2009; Furby et al. 2010; Robinson and Metternicht 2006). Calibration is critical in remote sensing, because the sensor reflectance is not equal to the reflectance emitted or reflected from the earth's surface because of interference from atmospheric gasses on the signals and distortions arising from the imperfections in sensor equipment. Other than the distortions due to sensor imperfection; age, and surface, heterogeneity may create errors in the products.

Aerial or satellite remote sensors are calibrated using selected homogeneous targets such as clouds, deserts, or oceans (Chander et al. 2009). Clouds are identified in satellite imagery by: (a) contrast test which is based on the fact that clouds are colder and brighter, (b) spectral test which relies on radiative transfer to identify spectral band behavior that can uniquely identify a pixel that is cloudy, and (c) spatial test which is based on the premise that clouds are texturally different than a clear sky. In calibration, a portion of the dataset is set aside for computing predicted values, and the remainder to check the accuracy of the fitted model (Davis 1987).

Accuracy in remote sensing may be determined through the error matrix (Congalton et al. 1983; Foody 2002). Accuracy assessment can also be undertaken through a higher step validation procedure, namely cross validation. Cross validation is performed through the removal of one observation from the dataset, estimation of the value of the variable removed based on the model and remaining observations, computing the error, and repeating this process for each of the remaining observations (Davis 1987; Robinson and Metternicht 2006).

5.7 Data Fusion

Remotely sensed data are currently available in large volumes, at low cost from different sources and with different data specifics. However, the trade-off between the spatial, spectral and temporal resolution creates a limitation on what is achievable during analyses or modeling which generally require standardized data bases, or matchable maps. It is common knowledge that the more the details in a map and the finer the resolution; the less will be the spatial extent, and the sensor will have a lower revisit frequency; for example, identification of earth surface features will be relatively clearer on imagery acquired with the thematic mapper sensors onboard Landsat satellites which provide 30-m spatial resolution data after every 16 days cover a land mass of 185 by 170 km, compared with those from the MODIS onboard the Terra and Aqua satellites which provide on daily basis, over a larger swath width of 2,330 km, but lower spatial resolutions of 250 m, 500 m, and 1 km. Therefore, sensor coverage over large spatial extents, generally translates to less detailed information of the real world.

In situations with heterogeneous landscapes, missing or limited data, data fusion, which combines data from different sources (i.e., field, air, and space) acquired at the same time (i.e., anniversary date) may suffice (Bowden 1976). Roy et al. (2008) demonstrated a data fusion approach for filling data gaps after cloud removal from satellite imagery. Stevens et al. (2008) compared the performance of three different instrumental settings (i.e., laboratory, field, and airborne spectroscopy) for quantifying SOC and found similar results between the ground-based spectrometers and the laboratory Walkley–Black method (± 1 g kg^{-1}). As anticipated, the airborne spectrometer had a lower SNR and therefore less accurate than field measurements. The overall accuracy depended on soil type. Hansen et al. (2009) investigated a hybrid soil mapping approach that combined expert knowledge, and decision trees with multispectral and topographic remote sensing data within an area of 2,214 km^2, in central Uganda. SPOT 4 satellite data was merged with topographic inputs from a Shuttle RaDAR Topography Mission digital elevation model. The metrics for the decision tree were the: spectral reflectance data, NDVI, the Normalized Difference Infrared Index, the shortwave infrared reflectance, GPS locations, and slope. The overall classification accuracy of 75.5 % and Kappa coefficient of 0.67 was within acceptable limits (Foody 2002). The spatial variability in soil texture, color, SOC, base saturation, pH, effective cation exchange capacity, and clay mineralogy were defined.

6 Future Perspectives

The causes, extent, and degree of natural resource degradation in one area may differ from that in another, depending on the land management practices or climate. An ideal sensor should provide data in real time information for modeling and assessing directional change (Stockmann et al. 2013). However, complexity and heterogeneity of the natural environment is a major hassle when gathering this information. A case in point is the dynamic soil processes occurring because of the biologic activity of soil organisms in search of food thereby continuously transforming the soil environment by redistributing soil nutrients (Dungait et al. 2012; Maeder et al. 2002; Tuomisto et al. 2012).

Clear water may have a high degree of pollutants (e.g., highly acidic or alkaline) invisible to the human eye (Tong and Chen 2002; Tuomisto et al. 2012). The identification of optimum spectral ranges for identifying water pollutants (i.e., chemicals, chlorophyll, and sediments) is an ongoing research (Arnold et al. 2012; Mattikalli and Richards 1996; Ritchie et al. 2003). Although laboratory methods exists for detecting chemical constituents in water (e.g., chlorides detected by using colorimetric methods, ion selective electrodes, or by ion chromatograph), these approaches are still rudimentary (Kurita et al. 2005; Zhang et al. 2013).

Innovative approaches for enhancing mapping accuracy need to be embraced. For example, the principle of "the whole to part" used by geodetic surveyors (Bannister et al. 1998), whereby the critical parameters serve as a baseline, and are measured with high accuracy, so that other measurements fall within the accuracy limits. The classification of remotely sensed data requires selection of good training data for plausible accuracies (Foody 2002). A major problem with classified satellite data are the loss of information/details during the processing stages (e.g., atmospheric correction/cloud removal) (Proud et al. 2010; Roy et al. 2008). The European Space Agency plan to launch by 2013 five new satellites called Sentinels that have both RaDAR and LiDAR technologies, and multi-spectral imaging instruments capable of not only generating accurate, timely, and easily accessible data to correct for atmospheric effects, but also for monitoring land, ocean, thereby providing current information for enhancing environmental awareness (http://www.esa.int/Our_Activities/Observing_the_Earth/GMES/Overview4).

The long-term practicality and accuracy of existing algorithms and remote sensors for monitoring soil and water quality is uncertain, because of changes in the characteristics of surface features (i.e., mineralogy, color, and temperature), technological advancements, and seasonality of watersheds. Furthermore, the definitions of phenomena may vary depending on the level of generalization or the capability of the tools to distinguish the phenomenon of interest. It is important to remember that the existing algorithms have been developed with reference to readily available data, and user needs, therefore strategies for ensuring consistency for future comparability purposes need to be continuously explored.

7 Conclusions

This review evaluated the potential strengths and limitations of remote sensing as a nondestructive and rapid assessment tool for detecting, mapping, and monitoring the impacts of agriculture on soil and water quality and shed new insights on the data processing options available for increasing the reliability of the information. In this review, the spectral reflectance of tap water (i.e., purified) is found to be remarkably different from that of lake water (i.e., unpurified) between the 350 and 2,500 wavelength ranges. However, although some trends were observed in reflectance for the specific soils under specific land management, these findings need verification. This is because the soil reflectance patterns change sporadically with wavelength compared with water, probably because of the heterogeneity and complexity of the soil materials. Ground data selected from rigorous and appropriate sampling design, is a prerequisite for calibration and validation. For heterogeneous landscapes, subpixel mapping techniques may reduce spectral ambiguities in the imagery.

A major issue in remote sensing-based applications is the gap between understanding the complexities in the environment, and advising designers of sensors the critical modifications needed. Further research is needed on identifying wavelengths within the electromagnetic spectrum that may detect variability in soil and water quality with depth from the surface. This would be useful for building future sensors, because active sensors such as LiDAR and RaDAR have specific wavebands which were designed for other resource mapping initiatives. Data fusion or integration of field and sensor data may provide missing data that may improve the outcome of monitoring. In the future, the combination of passive and active sensors may be useful for filling data gaps, and assessing soil and water quality at variable spatial and temporal scales.

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