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Review on soil sensing technologies: devices, statistical models, and future perspective

Eleonora Iaccheri,[1,2] Luigi Ragni,[1,2] Annachiara Berardinelli[3,4]

[1]Department of Agricultural and Food Sciences, University of Bologna, Cesena; [2]Inter-Departmental Centre of Agri Food Research, Cesena; [3]Centre Agriculture Food Environment, University of Trento, S. Michele all'Adige; [4]Department of Industrial Engineering, University of Trento, Povo, Italy

Abstract

Soil sensors play a crucial role in agriculture and environmental monitoring, especially in the context of sustainability and related social benefits. Traditional soil analysis methods are typically costly, time-consuming, and rely on physical sampling and laboratory testing, which limits their ability to provide spatially continuous, field-scale information. In contrast, precision agriculture requires affordable, fast, and reliable sensing techniques that can deliver actionable insights at scale. Emerging indirect sensing technologies -based on electromagnetic, radioactive, and optical principles- are increasingly used for measuring individual parameters or estimating multiple soil attributes through sensor fusion. To enhance measurement accuracy, considerable efforts have been devoted to the development of statistical and machine learning models that account for interactions among soil properties and utilize multivariate data. The growing availability of computational resources has further emphasized the value of integrating large volumes of data from sensors, computer vision, and hyperspectral imaging into decision support systems for agricultural and environmental applications. This review summarizes the main technologies and statistical approaches for soil quality assessment, highlighting current capabilities, limitations, and future directions.

Key words: soil sensors; multivariate data analysis; soil moisture; electromagnetic sensor; low-cost sensors.

Correspondence: Annachiara Berardinelli, Department of Industrial Engineering, University of Trento, via Sommarive 9, 38123 Povo, Italy.
E-mail: annachiara.berardinelli@unitn.it

Graphical Abstract.

Introduction

Electromagnetic soil sensors investigate the interaction between the material and the electromagnetic field producing a response as a function of the different chemical and physical properties. Soil electromagnetic properties change as a function of the physical structure, in terms of solid, liquid, and gaseous components. The varying proportions of these constituents cause electromagnetic wave mismatches that can be leveraged to infer material properties. This principle is at the core of sensing applications, with frequency and temperature being two of the main influencing factors.

One of the most investigated and reviewed parameters influencing electromagnetic field mismatch is the soil volumetric water content. The great importance of water in soil management is testified by the huge number of soil moisture sensing techniques developed to estimate the water content indirectly instead of using the time-consuming and standard thermo-gravimetric method performed in a laboratory environment (ASTM International, 2008). The indirect correlation of the broadband electromagnetic wave response and the soil physical variable of interest allow the low-cost and rapid assessment that is useful for sensor technologies development.

Sensors can be categorized, according to the mobility concerns, into three types, such as stationary sensors, installed permanently or for a long period, on the go sensors, installed on a moveable system collecting data in movement continuously and stop-and-go sensors that are on a moveable system but need a pause to acquire data (Bah and Balasundram, 2012). Today and increasingly in the future, optimizing farming management, spatial and temporal variability, and accurate soil ground information are parameters that sensors should detect to create digital soil mapping and continuous measurements. Airborne and spaceborne remote sensing and on-the-go applications are then requested. The on-the-go sensors are ground-based and bring direct soil contact or a proximal measurement that allows soil properties investigations in depth, as a function of the principle of detection of the sensors applied (Boiarskii *et al*., 2024). On-the-go applications are suited for soil nutrient monitoring across the spatial variability of soil (Bah and Balasundram, 2012).

The technology that facilitates the non-destructive assessment of soil nutrients in an efficient time concern sensor already developed, and mostly presented in this review, such as radiofrequency and microwave sensors, optical and radiometric spectroscopy, and radioactive techniques and X-ray fluorescence spectrometry.

Another important aspect of dealing with sensor development regards the huge quantity of data management belonging to these techniques. New advanced statistical tools able to develop robust calibration models for the prediction of soil parameters, and multiparameter assessment open the possibility of improving data accuracy and availability, promoting agricultural field advancement.

The present review will introduce the state-of-the-art and future perspectives concerning soil quality assessment in the agricultural and environmental fields. Point-scale and remote sensing will be described, and the main advantages of these indirect techniques concerning time-consuming conventional tools and methods of soil surveys will be evidenced. The recent combination with powerful statistical tools will also be outlined, in addition to the possibility of a fusion of different kinds of sensors for multiple-purpose assessments. Future directions for monitoring and managing soil sensors and multivariate data analysis will be provided in addition to a comparative analysis among sensors.

Radiofrequency and microwave sensors

The response of a material to an electromagnetic field can be described by the dielectric permittivity,

$$\epsilon_r{}^* = \varepsilon'_r - j\left(\varepsilon''_r + \frac{\sigma_{dc}}{2\pi f \varepsilon_0}\right)\ with\ \varepsilon_0 = 8.854\ \times 10 - 12\, f,$$ which

depends on the material properties ($s_{dc,}$ electrical conductivity), the frequency of the oscillating field (*f*) and the temperature. Simplifying for linear, isotropic materials in the frequency domain, it is commonly characterized by a real (ε'_r) and an imaginary part (ε''_r) and, expressed as a complex scalar. The real part characterizes how much energy is stored in a material, while the imaginary part represents how dissipative or lossy a material is. Soil is a porous material composed of a solid, a liquid, and a gaseous phase. In the case of such complex media (non-linear, anisotropic, non-homogeneous, non-instantaneous responding, and frequency dependent), permittivity can be described as a complex tensor. Water molecules exhibit a relative (compared with the vacuum) dielectric permittivity of about 80 at 20°C (at frequency up to 3 GHz). This value is higher than that of the air (1.00059 at 101325 Pa) and of the other soil constituents, ranging from 4.5 to 10 (Nelson, 2010).

The dielectric permittivity of water in soils is related to the degree of bonding of water molecules around soil particles, as their dipolar movement may be restricted. Consequently, low dielectric permittivity values characterize tightly bound water molecules near the mineral particle's surface. The polarization phenomenon can be observed when the electromagnetic wave interacts with a dielectric material. It consists of a deformation and orientation of the molecules in the direction of the external electromagnetic field due to the necessity of minimizing the electrical potential. Water in soil can be estimated using the water's high dielectric permittivity value by stimulating molecules spread in the soil through an electromagnetic wave in the MHz and GHz frequency range (Szypłowska *et al*., 2021). For over forty years, the dielectric behavior has been investigated across a wide frequency range from kHz to 10 MHz (Knoll, 1996) and from hundreds of MHz to GHz (Heimovaara *et al*., 1996). The assessment of its permittivity was used to estimate soil moisture content (Topp *et al*., 1980; Noborio, 2001), porosity (Sen *et al*., 1981), soil density (Feng *et al*., 1999), and specific surface area (Or and Wraith, 1999). Notably, the water content estimation through permittivity measurements regards several sensing techniques from remote to proximal measurements.

Several commercial sensors are available mainly based on time domain reflectometry (TDR, Spectrum Technologies, Inc., Aurora, IL, USA; TDR 100), frequency domain reflectometry (FDR, ECH2O EC-5, METER Group, Inc., Pullman, WA, USA), capacitance (10 HS, METER Group, Inc.; S616 and CS625, Campbell Scientific, Inc., Logan, UT, USA), and radiofrequency detectors (Hydra Probe, Stevens Water Monitoring Systems, Inc., Portland, OR, USA). Recent developments, continue to propose new prototypes aimed at reducing cost while maintaining accuracy (Berardinelli *et al*., 2018; Iaccheri *et al*., 2024).

Calibration is a fundamental step affecting measurement accuracy and helping compensate measurement differences due to several factors, such as soil properties and environmental conditions. Commercial instruments generally provide different calibration models as a function of soil composition and temperature. New prototypes also include several parameters and adjustments to the calibration models developed. Nevertheless, the dependence of the method's reliability on calibration models remains a key challenge for advancing smart agriculture (Mane *et al*., 2024).

Among the most established and widely studied techniques are TDR, FDR, and microwave sensors. Their main characteristics are summarized in Table 1.

Time domain reflectometry

TDR is a widely known technique, commercially available, useful for soil attribute assessments, and helpful to develop sensors and to study hydrologic processes (Jones *et al*., 2020).

The generation of a fast rise time step at different frequency ranges (20 kHz-1.5 GHz) and the analysis in the time domain of the reflected signal characterize devices based on the TDR technique. A reflection appears because the impedance of the material under test represents a discontinuity in the transmission line. The assessment of the time dependence of the voltage reflection coefficient (ratio of the reflected wave to the incident one) for permittivity measurements was suggested by Fellner-Feldegg in 1969. According to this pioneering study, conducted by using step pulses from 1 MHz to 5 GHz in a cylindrical waveguide and on solutions characterized by different alkyl alcohols, the voltage reflection coefficient was related to the permittivity in the time domain by a simple function. These assumptions were further elaborated in soil science by Hoekstra and Delaney (1974) and successively by Topp *et al*. (1980).

A TDR measurement system is characterized by a transmission line (usually coaxial cable) that carries the step pulse to the probe (parallel metal rods) inserted in the soil. Examples of successful applications of the TDR technique are represented by numerous devices, stainless steel brass rod-shaped probes, set up as prototypes, and then developed and commercialized in the soil science panorama. Literature on this topic is extensive and is full of theoretical studies on design (probe length, space between probe rods, and rod diameter), construction and calibration of two-rod and three-rod TDR probes, the most common solutions used for in-field assessments (Dalton *et al.,* 1984).

According to the TDR theory, the relative dielectric constant of the medium is calculated by extrapolating from the reflection signal the wave travel time through a probe inserted into the sample under test. The wave travel time $t = \frac{2l\sqrt{\varepsilon_r}}{c}$ is represented by the time (s) required for the signal to travel back and forth through the probe and c is the velocity of light (≈ 3 ´ 10^8 m s^{-1}) (Robinson *et al*., 2003).

As evident, to calculate the permittivity, it is necessary to measure the travel time from the TDR waveform. The waveform analysis represents a crucial step in the two-stage procedure. The assessment of the travel time is traditionally based on identifying the intersection point between a tangent line on the descending limb of the first peak and a horizontal line across the top of the first peak. An example of the method traditionally used to identify the travel time is shown in Figure 1.

This step can drastically affect the goodness of dielectric parameter calculation, and according to Robinson *et al*. (2003), the relaxation phenomenon can "round" the waveform.

More recently, to overcome the problem related to the intersection point accuracy, research has proposed a different approach based on a one-step procedure and the analysis of the entire reflection waveform through multivariate prediction tools, on the data acquired by a self-assembled prototype (Ragni *et al*., 2012). Even if TDR sensors are considered accurate and reliable, the equipment is still expensive compared to other electromagnetic methods, such as capacitive techniques or frequency domain reflectometry (Mane *et al*., 2024).

The principal advantages of the TDR method are related to the high accuracy coupled with the high temporal resolution, the safety, because hazardous radiations are not used, and the capability to obtain continuous and simple measurements. On the contrary, the TDR technique is more costly than other technologies used to measure soil conductivity and related parameters and has the disadvantage of a different calibration when different soil textures or compositions are analyzed (Jones *et al*., 2020). In addition, TDR cannot be put on mobile platforms or considered for contactless measurements as required to be inserted into the soil, changing also the compactness of the surface measured, with a possible increase in predictive errors.

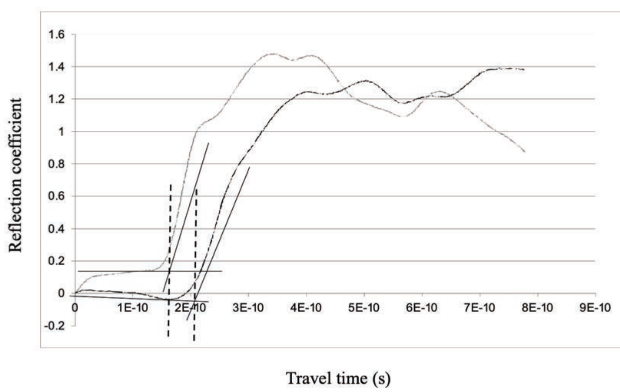

Figure 1. Examples of waveforms and tangent lines fitted to the waveforms for the identification of the travel time (dotted lines at the intersection points).

Table 1. Summary characteristics of radiofrequency and microwave sensors.

Radiofrequency and microwave sensors (Indirect)	CHARACTERISTICS AND MEASUREMENT PRINCIPLE	SOIL PROPERTIES MEASURED	DEPTH RANGE	DEVELOPMENT AND EVOLUTION	MOBILE/FIXED AND CONTACT/NON-CONTACT	COST
Time Domain Reflectometry	Electromagnetic, Permittivity. Need calibration.	Volumetric water content, salinity, bulk density, porosity, texture, pH.	A function of the probe placement	Final commercial instrument.	Not applicable on the go, sensor with contact.	High
Frequency Domain Reflectometry	Electromagnetic, Permittivity.	Volumetric water content, bulk density, salinity.	A function of the probe placement	Final commercial instrument.	Not applicable on the go, sensor with contact.	Low
Microwaves detectors	Electromagnetic, Permittivity.	Volumetric water content, bulk density, salinity.	Up to 30 cm	Prototype and commercial instrument.	Potential on-the-go application, proximity and non-contact sensors.	Low
Microwave satellite sensors	Electromagnetic, emissivity, backscattering.	Water content, temperature, surface roughness.	Up to few cm	Final commercial instrument.	Satellite sensors.	High

Frequency domain reflectometry

FDR sensors, or frequency domain fringing capacitors, estimate soil moisture content through dielectric permittivity by applying an electromagnetic wave between two or more electrodes inserted in the soil. Unlike TDR sensors, with FDR devices, indirect estimation of the physical parameter is assessed through the measurement of the charge stored in the capacitor or the resonant frequency of the oscillator circuit (IAEA, 2008; He *et al*., 2021).

These capacitive devices, operating at fixed frequency or by involving broadband measurements, received significant attention due to their low cost. However, since the operating frequencies (usually 20-300 MHz) are smaller than those at which the TDR devices work, the accuracy of the dielectric permittivity measurement is more affected by temperature and soil mineral components of the region immediately adjacent to the probe (Romano *et al*., 2014). Consequently, FDR needs specific calibration models considering different types of soil, the content of clay minerals, temperature, and field conditions (Linmao *et al*., 2012).

Microwaves detectors

The microwave devices (MD) can be inexpensive and measure soil at different penetration depths, giving a more comprehensive estimation. MD allows continuous monitoring but requires specific calibration models when applied to soil with different textures and compositions. Both contact and non-contact solutions were proposed with the aim of indirectly estimate soil moisture content through broadband spectral acquisitions.

Concerning the moisture content assessment by means of electromagnetic low-cost sensors, a different approach was used in research conducted by Luciani *et al*. (2017). The study aimed to explore the potential of a non-invasive technique (at the prototype stage) based on an open-ended waveguide combined with multivariate tools for the prediction of the gravimetric moisture content. Concerning traditional techniques exploiting the soil dielectric properties, the proposed solution can be considered a step forward in electromagnetic sensor development, especially for the use of a non-invasive probe. In addition, the combination with predictive techniques able to model the different types of soil spectra can allow overcoming the use of calibration equations for moisture estimation. The possibility of estimating the moisture content in layered soil profiles was also explored and discussed in the research work.

The system, set up by considering three different types of soils, silty clay loam, lightweight expanded clay aggregate, and river sand soils, is characterized by a rectangular aluminum waveguide (9.6 cm × 4.6 cm × 24.5 cm) positioned in contact with the soil surface. A transmitting and a receiving antenna are incorporated in the waveguide; the transmitted Tx (t) and the reflected Rx (t) waves (used frequency range: 1.5-2.7 GHz). The system returns gain and phase waveforms, which are influenced by the differences in the soil moisture levels. By detailing, Tx and Rx can be described by the following equations:

$$Tx(t) = A_{Tx}e^{j\varphi_{Tx}}e^{j2\pi ft} \qquad \text{(Eq. 1)}$$

$$Rx(t) = H(f)A_{Tx}e^{j\varphi_{Rx}}e^{j2\pi ft} = A_{Rx}e^{j\varphi_{Rx}}e^{j2\pi ft} \qquad \text{(Eq. 2)}$$

With A the wave amplitude, j the imaginary unit, f the frequency, t the time, φ the phase, and H (f) the transfer function between x and y, the soil impedance.
The relationship between A and φ of the two signals can be described through:

$$A_{Rx} = |H(f)|A_{Tx} \rightarrow \frac{A_{Rx}}{A_{Tx}} = |H(f)| = |Z_{soil} \qquad \text{(Eq. 3)}$$

$$\varphi_{Rx} = \langle H(f) + \varphi_{Tx} \rightarrow \varphi_{Rx} - \varphi_{Tx} = \langle H(f) = \langle Z_{soil} \qquad \text{(Eq. 4)}$$

The ratio between A_{Rx} and A_{Tx} is called "gain", while the difference between φ_{Rx} and φ_{Tx} refers to "phase" (Carlson and Crilly, 2010).

Starting from gain and phase spectral information, the moisture content was estimated through partial least squares (PLS) regression analysis, a bilinear data compression tool working through the extraction of new variables estimated by taking into consideration a linear relationship between dependent (moisture content, %) and independent variables (gain or phase spectrum) (Wold *et al*., 2001). Main results evidenced, in prediction, R^2 values up to 0.989 (river sand), 0.988 (lightweight expanded clay aggregate - LECA), and 0.941 (loam), and the highest accuracies in selected ranges of frequency, showing the highest relationships between spectrum and moisture content. The use of N- PLS where gain and phase waveforms are joined in a three-way array, resulted in a prediction improvement.

The validation of the non-invasive waveguide for the water content (%) assessment in a real environment was proposed by Franceschelli *et al*. (2020). The authors developed an affordable and portable prototype characterized by the PLS predictive model embedded in the system, while the measurement unit was composed of a data control and elaboration system and a gain/phase detector (Figure 2).

The validation was conducted on silty clay loam soil (moisture range: from 9% to 32%) characterized by a soil temperature ranging from 8 to 18°C. Soil temperature, as known, affected gain and phase spectral waveforms but the variability related to moisture content was higher and has driven the multivariate prediction of the moisture content (%).

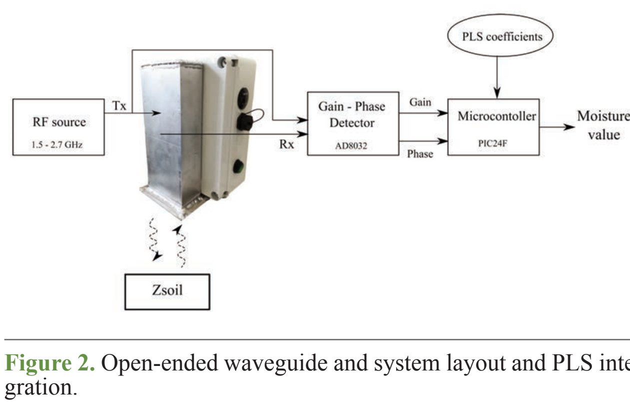

Figure 2. Open-ended waveguide and system layout and PLS integration.

The potentiality of a non-linear statistical tool for the soil moisture assessment was also explored by Berardinelli *et al*. (2018) applied to a microwave (1.0-2.7 GHz) transmitting and receiving dipole antenna located in a 170 mm long PVC sealed pipe. Always starting for gain and phase spectra, predictive models were based on linear PLS regression and nonlinear Kernel-based orthogonal projections to latent structures (K-OPLS) algorithms that can reduce the complexity by removing systematic variability in X (independent spectral variables, gain or phase) that is not correlated with Y (moisture content, %) (Bylesjö *et al*., 2008). The tested algorithm resulted in greatly increased prediction ability concerning the linear PLS algorithm independently of the kind of soil (R^2= 0.971 vs R^2= 0.513 for gain; R^2= 0.909 *vs* R^2= 0.553 for gain). Development of the proposed probe, with an array of dipole antennae, could be suitable for the determination of moisture at different depths.

More recently, a cheap and rapid prototype for the estimation of the gravimetric moisture content (%) in a real agricultural environment was proposed by Iaccheri *et al*. (2024) in the frequency range from 1.5 to 3 GHz. The solution, characterized by a miniaturized commercial Nano-Vector Network Analyzer (VNA) and a cavity antenna as a probe placed in contact with it, is combined with a PLS regression tool modeling both real (Re) and imaginary (Im) parts of the Scattering parameter S11:

$$|S11| = \sqrt{(Re(S11))^2 + (Im(S11))^2} \quad \text{(Eq. 5)}$$

The relationship between S11 and standing wave ratio (SWR), a measure of the impedance mismatch between the transmission line and its load (the higher the SWR, the greater the mismatch), is given by (Franceschelli *et al*., 2020):

$$SWR = \frac{1 + |S11|}{1 - |S11|} \quad \text{(Eq. 6)}$$

PLS multivariate models built starting from real and imaginary parts were characterized by R^2 values were 0.854 (RMSE 4.4%) for the S11 real part and 0.872 (RMSE 4.1%) for the S11 imaginary part (segmented validation).

The above cited research work shows that the penetration depth of the device can reach at least 28 cm, considering a soil characterized by a low moisture content (5%).

Microwave satellite sensors

Satellite sensors provide soil parameters and conditions in temporal and spatial variability. They are based on the analysis of soil electromagnetic radiation; thus, they are non-destructive, contactless, cover a large soil area, accurate, and cost-effective. On the contrary, some disadvantages regard the reliability of capturing the soil heterogeneity, the minimal soil depth, the scarce spectral and spatial resolution, and the limited accessibility.

Recently, a great effort was dedicated to studies involving soil moisture estimations through both passive and active satellite techniques. Even if satellite-based radiometer and radar microwave sensors have been used for four decades and commercial solutions are available, soil moisture metrology has gained attention in the last decade because of the influence on hydro-meteorological, climate, and agriculture (Karthikeyan *et al*., 2017).

Microwave satellite sensors are based on changes in soil dielectric properties. These changes can be assessed through the measurement of several parameters related to the emissivity and backscattering soil surface properties in the microwave region of the electromagnetic spectrum. Both passive (radiometer) microwave sensors assess the brightness temperature, T_b, or the microwave surface emissivity (e) in the L (0.39 - 1.55 GHz), C (3.9 - 5.75 GHz), and X (5.75 - 10.9 GHz) frequencies bands, even if the L-band is recognized to be the most suitable for moisture, the atmosphere and the presence of vegetation attenuate the signal at high frequencies (Li *et al*., 2021).

According to Planck-Einstein's relation, the energy emitted from the surface of the Earth is proportional to the frequency of microwave radiation. At frequencies associated with soil moisture, the natural emissions are very weak. In addition, microwave measurements refer to the top few centimeters of the soil layer (Feldman *et al*., 2023).

Empirical regression models have been replaced by physical approaches based on the use of the radiative transfer equation (RTE) and are based on two steps. The first one relates T_b to soil dielectric permittivity with the RTE (Ulaby *et al*., 1982), while the successive step links soil dielectric permittivity with moisture content by using mixing models such as those proposed by Hallikainen *et al*. (1985) and Dobson *et al*. (1985). Mixing models consider a mixture of three dielectric components: air, mineral particles, and water. If bound water is also considered, mixing models are characterized by four dielectric components (Robinson *et al*., 2003).

Temperature, surface roughness, vegetation, atmosphere, and cosmic background are recognized factors affecting the relationship between the emissivity of microwave signals and surface soil dielectric moisture (Choudhury *et al*., 1979; Wegmuller and Matzler, 1999). The vegetation effect is firstly considered in the τ-ω model proposed by Mo *et al*. (1982), a zeroth-order radiative transfer model characterized by the vegetation optical depth (VOD) parameter and the single scattering albedo.

Optical and radiometric spectroscopy

Soil infrared spectroscopy is a widely explored non-destructive technique for the rapid prediction of soil quality. Laboratory, proximal sensing, and remote sensing are the three types of Vis-NIR soil measurements that can be distinguished to map soil properties. Passing from laboratory to remote sensing, accuracy of the validation models decreases mainly due to the influence of uncontrolled atmospheric conditions and acquisition procedures. In the context of precision agriculture, some solutions have been installed to the subsoiler chisel or shank of a tractor to be used in movement (Christy, 2008). Recently, portable commercial solutions have been developed for in-field measurements. These tools are based on total reflectance (ATR) or Fourier transform (FT) spectrometers (Ji *et al.,* 2016).

The great number of reviews dedicated to the potentiality of the electromagnetic spectral region from 400 to 2500 nm in explaining the high soil variability, testifies the big role of the technique in the soil research panorama (Du and Zhou, 2009; Stenberg *et al*., 2010). Several commercial solutions, based on this technique, are available (e.g., Field spec A, Malvern Panalytical, NIR, FT-IR, and RAMAN Thermo Fisher Scientific). Soil spectral libraries at the regional, national, or even international level have been born during the past decades (Piccini et al., 2024), because the development of a consistent dataset for model calibration and validation is the most time-consuming part of NIR, MIR (Mid-Infrared) spectroscopy. The soil spectral libraries share spectral data, allowing a practical and economical approach useful for many users (Safanelli *et al*., 2021). The free platform Open Soil Spectral Library is an example of a spectra database (Hong *et al*., 2024), for conciseness, only continental and global libraries are reported in Table 2.

Spectral libraries are representative databases with properties depicted by reference methods and corresponding spectral data useful to compare, calibrate, or develop models of the interested properties. In the vis-NIR and range MIR, spectral soil libraries were respectively created by Viscarra Rossel *et al*. (2016) and by Terhoeven-Urselmans *et al*. (2010). The lab-derived libraries contain spectra from laboratory conditions, thus controlled and not properly considering the in-field influencing factors (Piccini *et al*., 2024). Particularly, moisture can be a factor affecting the model performance as it is mainly responsible for scattering phenomena in the considered spectral region of vis-NIR and MIR (Piccini *et al*., 2024). Overcoming this problem, libraries with in-field spectral data are developed and prove to be more realistic concerning the field application. The free consulting soil library was developed with spectral data of Brazilian territories and from the world to predict soil attributes all over the world (Demattê *et al*., 2022). Despite this, spectral variation between laboratory and in field conditions need to be addressed to be more reliable as possible and cover all the possible parameters of interest (Piccini *et al*., 2024). Other disadvantages of spectral library regard the availability of soil properties measured, the parameter of interest cannot be analyzed, or belongs to a different laboratory adopting different reference methods. Furthermore, soil sample variability produces also spectral variability that should be considered when a dataset needs to be downloaded by the libraries, accounting for a selection of a restricted group of spectra (Ge *et al*., 2011). Particularly considering the aim of precision agriculture practices, the use of different instruments and operative protocols could introduce significant differences in spectral data (Ge *et al*., 2011). However, all of these advantages can be reduced by sharing even more spectra at the global level, improving the time and cost of soil analysis. A summary of the characteristics of optical and radiometric spectroscopy is shown in Table 3.

Visible and near infrared reflectance

Visible and near infrared reflectance (Vis-NIR) applied to soil investigation is time-effective, allowing the *in situ* determination of a wide range of properties, such as biological, chemical, and physical, by correlating a spectrum per sample.

Starting from the first study conducted by Bowers and Hanks (1965) on the reflection of radiant energy from soils, a great effort has been dedicated to techniques for both qualitative and quantitative assessments (Ahmadi *et al*., 2021).

According to soil constituents, electromagnetic radiation involves the vibration (bending or stretching) of individual molecular bonds as a consequence of light absorption, and the energy quantum is related to the frequency. The shape of the relative absorption spectrum can be considered a characteristic of the sample under test and used for analytical purposes. Molecular functional groups can absorb in the mid-infrared, with overtones in a progressively weaker order (first, second, and third overtone) and a combination of fundamental vibrations (C-H, O-H, and N-H) detected in the NIR region. In addition to the presence of specific functional groups, environmental factors can influence the spectrum waveform. Band assignments for fundamental mid-infrared absorptions of soil constituents and their overtones and combinations in the Vis-NIR are well detailed in Viscarra Rossel and Behrens (2010). Diffuse reflectance spectra acquired in the Vis-NIR electromagnetic region are characterized by overlapping of soil constituent absorptions, and it is not possible to proceed with a direct spectral interpretation without mathematical spectral pre-processing tools able to correct non-linear scattering effects due to structural properties (Stenberg *et al*., 2010). Principal component analysis (PCA) and PLS are the most used tools for qualitative and quantitative soil assessments, in addition to data mining techniques such as artificial neural networks (ANN), multivariate adaptive regression splines (MARS), random forests (RF), boosted regression trees (BT), support vector machines (SVM) (Viscarra Rossel and Behrens, 2010).

Specific Vis-NIR spectral libraries have been developed by different research works considering different protocols for soil

Table 2. Vis-NIR and MIR soil spectral library at continental and global level.

Reference	Scale	Number of spectra	Spectroscopy technique	Data availability
Brown *et al*., 2006	Global	3768 (US) 416 (world)	Vis-NIR	Clay, OC, IC, Fe, CEC, mineralogy classes
Viscarra *et al*., 2016	Global	23,631	Vis-NIR	OC, IC, pH, CEC, Fe, Clay, silt, sand
Stevens *et al*., 2013	Europe	20000	Vis-NIR	Clay, silt, sand, pH, CEC, OC, IC, TN, P, K
Terhoeven-Urselmans *et al*., 2010	Global	971	MIR	pH, OC, CEC, Mg, clay, sand, Ca
Vagen *et al*., 2020	Africa	1900	MIR	OC, TN, pH, Mehlich-3 Al, Ca

OC, organic carbon; IC, inorganic carbon; CEC, cation exchange capacity; TN, total nitrogen.

spectral analyses together with national and international databases. Some examples are the world spectral library, including 3,794 samples from North America (Brown *et al*., 2006), the ICRAF-ISRIC spectral library containing 4,436 samples from five continents' soil profiles (CRAF-ISRIC, 2010), and the harmonized LUCAS soil database collected over 23 member states of the European Union (Eurostat, 2009). According to Ahmadi *et al*. (2021), up to 81 soil properties were predicted by Vis-NIR spectroscopy. Vis-NIR spectra have been used as independent variables to classify soil samples into different textural groups (Mouazen *et al*., 2005) or to predict clay, silt, and sand contents (Sörensen and Dalsgaard, 2005). Water molecules strongly absorb in the infrared bands near 1400 and 1900 nm, but weaker bands near 970, 1200, and 1780 nm can also be observed (Dalal and Henry, 1986). As illustrated in the review proposed by Shin *et al*. (2025), main results of the moisture predictive models, in terms of R^2 and RMSE, set up on acquisitions conducted in the laboratory or the field on samples characterized by different origins and water content variability, are shown by several works.

The soil pH has an indirect spectral response in the Vis-NIR range. Its prediction is due to co-variations with the buffering capacity and spectrally active soil constituents, mainly organic matter, clay, and mineralogy (Tümsavaş, 2017). In addition, the soil fertility index was also predicted through Vis-NIR spectra, as described in the research work conducted by Munnaf and Mouazen (2021).

The calibration and validation procedure related to the technique requires attention to avoid the scarce accuracy of NIR prediction. Robust calibration models are necessary, as well as a balanced validation data set to be reliable, which means acquiring, managing, and elaborating a huge quantity of data with all the potential variability concerning each parameter of interest. In this way, spectral libraries can have a crucial role in facilitating the creation of a comprehensive dataset based on different soil types, textures, and geological areas.

Colorimeter and machine vision systems

Soil classification systems, such as the UK soil Taxonomy, are based on soil color (Soil Survey Staff, 2014). The standard method for color assessment is based on Munsell Soil Color Charts (MSCC) and was intensely used to classify soils (Munsell Color Company, 2000). MSCC, proposed in 1920, is characterized by 238 standardized rectangular chip colors disposed of 7 charts by using three color coordinates: hue, value, and chroma. Soil scientists use these charts through visual comparison with the soil samples. In the work conducted by Wills *et al.* (2007), MSCC was used for the setting of predictive models of the soil organic content.

As is logical, the visual assessment of the method based on the charts is highly affected by the observer's experience and subjective illumination conditions. Standard laboratory colorimeter devices, able to give a reliable value of the color coordinates, are commonly used to replace the standard method (Fontes *et al.,* 2005).

In recent years, due to advances in digital image processing and statistical tools, great attention has been dedicated to predicting different soil parameters through the use of digital cameras and

Table 3. Summary characteristics of optical and radiometric spectroscopy.

Optical and radiometric spectroscopy (Indirect)	CHARACTERISTICS AND MEASUREMENT PRINCIPLE	SOIL PROPERTIES MEASURED	DEPTH RANGE	DEVELOPMENT AND EVOLUTION	MOBILITY	COST
Visible and Near Infrared reflectance	Electromagnetic, vibration of molecular bonds due to light absorption	Water content, soil constituents, soil organic carbon, soil texture, pH, fertility, heavy metals, petroleum contamination, microbial biomass, soil enzymes, and respiration.	Up to few mm	Final commercial instrument.	Applicated on the go, proximity sensor and non-contact sensors.	From low to high according to the sensor characteristics
Colorimeter and Machine Vision Systems	Electromagnetic, reflectance, light scattering	Colour, texture, morphology, organic matter, nitrogen content, and particle size.	Superficial	Final commercial instrument.	Applicated on the go, proximity and non-contact sensors.	Low
Ground Penetrating Radar (GPR)	Electromagnetic, Permittivity	Volumetric water content, soil texture, salinity, profile stratigraphy, organic horizons thickness.	Up to few m	Final commercial instrument.	Applicated on the go, proximity and non-contact sensors.	High
Optical Remote Sensing Technologies	Electromagnetic, reflectance, thermally emitted radiance, emissivity	Vegetation indices, soil degradation, and quality attributes, chemical composition as iron oxides, iron hydroxides, and iron sulphates.	Superficial	Final commercial instrument.	Applicated on the go, proximity and non-contact sensors.	High

computer vision systems. Soil surface features such as color and texture were successfully extracted from soil images by using a specific computer vision algorithm and a low-cost portable colorimeter (Stiglitz *et al*., 2017). In addition, smartphones, including good image acquisition tools, have been used during the last years in several research works for the assessment of both soil color and morphology (Han *et al*., 2016).

As shown in the literature, from the interpretation of soil color, several properties can be extracted in addition to mineral and organic content, such as the accumulation of pollutant substances (Chakraborty *et al*., 2017) and the soil-reduced conditions (Vaughan and Rabenhorst, 2006). In general, a dark surface is an indicator of high organic matter and nitrogen contents.

More recently, field-based colorimetric devices have been proposed. An example of these tools is the low-cost commercial NixProColorSensor (Hamilton, ON, Canada), characterized by an LED source and connected via Bluetooth to the smartphone for the extraction of color space data as RGB, CIEL*a*b*, XYZ (tristimulus values), HSV (hue, saturation, and value), CMYX (cyan, magenta, yellow, black). Color space models for soil sciences and relative scale transformations are well described in the work carried out by Viscarra Rossell (2007). The sensor accuracy in terms of soil organic content prediction was deeply investigated by scientists using also soil depth as an independent variable in addition to the color parameters (Stiglitz *et al*., 2017; Mukhopadhyay *et al*., 2020). This portable colorimeter was also tested for the prediction of total nitrogen N (Stiglitz *et al*., 2018) and in combination with other sensors based on diffuse reflectance spectroscopy (Mukhopadhyay and Chakraborty, 2020) and X-ray fluorescence spectroscopy (Mukhopadhyay *et al*., 2020).

Images captured through the smartphone or by a digital camera were also combined with a list of machine learning tools, such as neural network statistical (Aitkenhead *et al*., 2018), PLS multivariate image analysis (Morais *et al*., 2019), and random forest (RF) and convolutional neural network (CNN) algorithms (Swetha *et al*., 2020). Starting from different image features and their combinations, the main results evidence the potential of the color features in the prediction of soil textural parameters.

Machine vision data combined with soil electrical measurements and support vector machine (SVM) models was proposed by Meng *et al.* (2020) in a vehicle-mounted application. This combination produces up to 88.89 % of correct rate for sandy loam.

The possibility of using color information coming from high-resolution digital cameras for microscale mapping (down to 1 mm resolution) of soil organic carbon (SOC) (RMSE up to 0.14%, with HSV and full factorial regression) and free Fe contents (RMSE up to 0.14%, with HSV and full factorial regression) was also researched by Heil *et al.* (2020).

Finally, a portable microscope-based image acquisition system (200×) combined with a Bag of Visual Words (BoVW) computer vision algorithm was developed for surface soil particle size characterization (Qi *et al*., 2019). Main results evidence that sand, silt, and clay can be predicted with RMSE up to 5.92%, 6.01%, and 2.98%, respectively (leave-one-sample-out cross-validation, PLS).

Machine vision systems applied in soil research are fast, inexpensive, non-destructive, robust, and efficient, with some limits regarding the possible source of error due to environmental light variability, object identification, and environmental control. In addition, machine vision should be developed under specific conditions that become difficult to apply in certain situations.

Ground penetrating radar

Ground penetrating radar (GPR) is another technique based on the assessment of the dielectric properties of the soil to estimate water content.

Concerning the above-described point-based techniques, GPR explores a larger volume of soil and can be considered a middle ground between point-scale and measurement conducted using satellite solutions. GPR, designed to locate buried objects, has different applications in different sectors, from civil engineering to archaeological research (Liu *et al*., 2016). Remaining in the soil method studies, GPR was developed for soil texture, salinity, and profile stratigraphy, for organic horizons thickness estimation and non-pedological applications predominantly focused on tree roots automatic recognition and biomass, as reviewed by (Zajícová and Chuman, 2019). However, in the agricultural field and, as seen for TDR, a large number of research works are dedicated to GPR and the technique's ability in the water content measurement (Huisman

Table 4. Summary characteristics of radioactive techniques and X-ray fluorescence spectrometry.

Radioactive techniques and X-ray fluorescence spectrometry (Indirect)	CHARACTERISTICS AND MEASUREMENT PRINCIPLE	SOIL PROPERTIES MEASURED	DEPTH RANGE	DEVELOPMENT AND EVOLUTION	MOBILITY	COST
Radioactive techniques	Electromagnetic, neutron scattering, and gamma attenuation	Volumetric water content, vadose zone profile water content	Up to 30 cm	Final commercial instrument.	Not applicable on the go, static and contact/non contact sensor measuring a wide area.	Low
X-ray fluorescence spectrometry	X-ray fluorescence radiation, material emissivity	Soil constituents, pH, gypsum quantification, organic carbon and organic matter, soil contaminants, heavy metal, and soil cation exchange capacity.	Superficial	Final commercial instrument.	Not applicable on the go, portable instrument available. Non-contact sensors	High

et al., 2003; Klotzsche *et al*., 2018). In detail, GPR emits electromagnetic waves through a transmitting antenna and receives them from an antenna receiver. The transmitting antenna generates radar pulses that propagate into the soil. The reflected electromagnetic wave is related to changes in soil dielectric permittivity. A control unit with a computer and associated software and a display completes the device (Anbazhagan *et al*., 2020). GPR theory and numerous available measurement methodologies are well-reviewed by Daniels (2004). Advantages of GPR regard the non-destructive nature, the real-time data, and the high resolution of the technique for a wide range of soil constituents. However, the effectiveness can be reduced by different soil conditions, as well as a function of depth (GPR has a limited penetration depth capacity).

Optical remote sensing technologies

Optical remote sensing solutions mainly focus on hyperspectral imaging spectroscopy, multispectral, and thermal sensors.

Hyperspectral imaging devices can acquire images in many spectrally contiguous bands, and a reflectance spectrum in the Vis-Nir or MIR range is associated with each pixel. As described in the paragraph dedicated to infrared spectroscopy, reflectance spectra in the Vis-Nir electromagnetic range contain information related to several soil attributes. Wider spatial dimension acquisitions can be conducted with airborne or satellite sensors (Chicati *et al*., 2019).

As testified by literature, hyperspectral data are affected by several factors related to the distance between the soil surface and the device and the spatial and temporal variability of soils. In general, analytical approaches as flat field calibration, logarithmic residuals, and internal average reflectance are used to process the effect of light and atmospheric conditions (gas adsorption and water vapor) and to be comparable with ground-based spectra (Aspinall *et al*., 2002). Soil roughness, particle size, moisture content, and vegetation covering are the main properties that can vary in time and space (Wulf *et al*., 2015).

Multispectral sensors, recording data in fewer bands concerning hyperspectral devices involving in a reduced cost of the instrumentation compared to the hyperspectral one, have been deeply investigated for remote assessment of vegetation indices, soil degradation, and quality attributes. Some examples coming from the literature refer to discrimination between crop residues and soil, assessment of chemical composition as iron oxides, iron hydroxides, and iron sulfates, and discrimination between different mineral particle compositions (Mulder *et al*., 2011; Dewitte *et al*., 2012; Orlando *et al*., 2022).

Thermal infrared (TIR) bands (3-14 µm) are generally included in some multispectral sensors. Thermally emitted radiance is influenced by land surface temperature and the land surface emissivity. A traditional TIR parameter used to assess soil quality attributes is represented by the thermal inertia (TI). TI describes the resistance of the soil material to variations in the land surface temperature and is defined with a relationship that involves thermal conductivity (k, W m^{-1} K^{-1}), bulk density (, kg m^{-3}) and specific heat capacity (c, J kg^{-1} K^{-1}). From remote observations, TI is usually obtained through the diurnal temperature amplitude method by considering wind speed, air humidity, and surface roughness, or by introducing the use of phase angle information taken from the diurnal temperature variation. TIR potential has been combined with other spectral data to quantitatively assess moisture content (Verstraeten *et al*., 2006) and to qualitatively discriminate between different kinds of soils (Breunig *et al*., 2008). Respect to proximal optical techniques, the remote sensing ones have can have higher operating costs, lower temporal resolution, and can present a possible influence of the weather conditions. In contrast, these last are flexible, with a huge quantity of data in a short time, and the possibility to analyze large data archives.

Radioactive techniques and X-ray fluorescence spectrometry

The use of nuclear techniques for soil physical properties assessment has been tested since 1950, starting from laboratory investigations. Nowadays, the radioactive techniques can be found applied to commercial instruments for soil quality and health assessment (for example, Campbell Pacific Nuclear model 503DR, Troxler Electronics Laboratories model 4300), also coupled with imaging instruments. These techniques refer to neutron scattering and gamma attenuation methods. Undoubtedly, the main limitation of these techniques is related to safety regulations requiring licensing and training of users (IAEA, 2002).

A summary of the characteristics of radioactive techniques and X-ray fluorescence spectrometry is shown in Table 4.

Neutron probes

Neutron probes use a neutron scattering technique consisting of a source of fast neutrons (energy higher than 2 MeV) that, through collisions, become slow or thermal neutrons (energy lower than 0.025 eV). The hydrogen characterizing water molecules results in a good neutron moderator when in collision. By increasing soil moisture content, an increment in the number of slow neutrons in the presence of a source of fast neutrons can be registered. However, the number of thermalized neutrons can be affected by soil density and chemical composition, especially the presence of carbon (Grimaldi *et al*., 1994).

A neutron device generally includes a nuclear unit (neutron source and detector), a housing for the electronic receptors, and an instrument shield for safe shipping and handling. Probe geometry, the strength of the neutron source, and the type of neutron detector and electronics also influence the measurement (Stone, 1990). Neutron source, usually double stainless-steel encapsulation, is generally represented by the radioactive ^{241}Am. Source strength is in the range of 0.37 to 1.85 Giga Becquerel. The detector is a tube filled with ^{3}He or boron trifluoride (BF_3) gas and can absorb the thermal neutron by working in a reverse mode on the nuclear reaction, producing fast neutrons. In the middle of the detector is positioned a cathode wire charged to a large voltage concerning the tube wall. The alpha particles are driven to the wire and are responsible for an instantaneous voltage change, subsequently detected. These devices are available for both soil surface and profile assessments. Surface neutron meters, designed for nonintrusive measurements, acquire data from a soil depth of about 0.15 m, in the case of wet conditions, and of about 0.3 m for dry soils. On the contrary, profiling moisture meters are designed to indirectly assess moisture content for depths higher than 10 m and are characterized by a cylindrical probe, containing the source and the detector, connected through a cable to the readout and control unit. The cylindrical probe is lowered into an access tube transparent to neutrons.

An electronic counting system provides the value of the Count Ratio (), defined as the ratio of the count x measured during soil acquisitions to a standard count not influenced by the water content, *xs*. Starting from this indicator, a great number of calibration equations were obtained for different soil types by using linear regression tools for volumetric content estimations as reported in IAEA TECDOC (2000). These calibrations take into consideration the role of the geometry of the source, detector, and tube material, the soil type, the measurement depth, and the degree of spread in water content. A negative linear relationship between ambient temperature and standard counts was also shown.

The neutron probe technique is suitable for deep soil measurements, but it is useless within the first 15 cm of soil top, which is generally the typical depth of the active root of plants and thus the main interesting depth. The neutron probe is simple, cost-effective, non-destructive and it has an accurate measurement also considering the soil physical state, determining the elemental composition of soil. In addition, the neutron probe can detect nuclear materials. Radioactivity should be considered for safety reasons, even if the modern design of the shield and the probe allows a limited radiation exposure.

Gamma ray attenuation

Gamma-ray attenuation technique is another radioactive technique that was proven to be able to assess soil physical properties such as the bulk density and the volumetric moisture content. According to gamma-ray attenuation theory, described by Bertuzzi *et al*. (1987), the number of gamma photons passing through a soil mass per unit time (*C)* is related to the dry bulk density of soil (or, Mg m^{-3}) and to its volumetric moisture content (, m^3 m^{-3}). Methods to determine these mass attenuation coefficients are well-reviewed by Luo and Wells (1992).

The gamma ray technique is non-destructive and fast, and provides reliable measurements of different physical properties with a few millimeters' resolution. The greatest advantage remains the non-invasiveness compared to the traditional techniques. However, the gamma ray source can create risks for human safety and requires authorization from nuclear agencies.

X-ray fluorescence spectrometry

X-ray fluorescence spectrometry has been traditionally used in the laboratory for soil multi-element analytical approaches to replace standard and time-consuming methods for the assessment of soil composition (Towett *et al*., 2013).

In the last 20 years, the technology has evolved into field portable x-ray fluorescence devices (PXRF, ED-XRF, WD-XRF, and T-XRF Bruker.com) that have proven to rapidly and non-destructively analyze different materials in addition to soil, without the necessity of preparing the sample (Lemière, 2018). X-ray fluorescence can provide fast, accurate, and non-destructive measurements with simultaneous elemental characterization, but it is subject to normative restrictions and potential risks, like the other nuclear methods. In addition, concerning soil samples with high heterogeneity may result in a high level of uncertainty.

PXRF soil applications regard the assessment of numerous chemical and physical attributes and commercial solutions have been successfully proposed to quantify soil elemental composition (Borges *et al*., 2020). To improve the accuracy of the predictive models, data acquired by PXRF devices were also combined with those coming from other techniques such as electromagnetic induction, hyperspectral imaging camera, visible near-infrared diffuse reflectance spectroscopy, and color sensors (Andrade *et al*., 2020; Mukhopadhyay *et al*., 2020; Li *et al*., 2021).

Briefly, by using X-ray fluorescence, the elemental composition of a material is assessed through the action of high-energy X-ray photons. These last involve the ejection of an inner sphere electron from the atom, leaving a vacant space. Consequently, the electron from a higher shell moves to the inner shell and emits a secondary X-ray radiation (X-ray fluorescence) that is then detected. Each element is characterized by a specific fluorescence energy (Bruker, 2016).

PXRF excitation configurations include early radioactive isotope excitation sources (^{55}Fe, ^{109}Cd, and ^{241}Am) and recently miniature X-ray tube excitation dissipating a few watts. PXRF devices are based on an energy-dispersive principle. According to this principle, the dispersion of the entire spectrum occurs directly in the detector, a silicon PIN (P-type-Intrinsic-N-type) device, or a silicon drift detector in the energy domain. The acquired spectrum is characterized by peaks referring to a particular element, and the area under the peak is related to the element concentration (Willis and Duncun, 2008). Soil chemical properties have been extensively assessed via PXRF and mainly regard soil pH (Sharma *et al*., 2014), gypsum quantification (Weindorf *et al*., 2013), organic carbon and organic matter (Ravansari *et al*., 2021), soil contaminants (Li *et al*., 2021), heavy metal concentrations (Peralta *et al*., 2020), and soil cation exchange capacity (CEC) (Sharma *et al*., 2014). Soil moisture can affect the acquisition and if the content is higher than 20%, it is generally recommended to dry the sample. CEC, representing the total capacity of soils to bind exchangeable cations (Ca, Mg, K, Cu, Zn, and Fe), is the recognized indicator of soil fertility (Ross and Ketterings, 2011) while, the base saturation percentage (BSP), defined as the sum of four basic cations (Ca, Mg, K, and Na) relative to CEC at pH 7.0 or 8.2, has implications in soil taxonomic classification and soil fertility (Rawal *et al*., 2019). Main soil properties assessed by using PXRF devices are represented by soil texture (Silva et al., 2020) and microbiological indicators such as microbial biomass carbon, basal soil respiration, microbial quotient, and metabolic quotient, obtained starting from the assessment of soil elemental contents (dos Santos Teixeira *et al*., 2021).

Statistical processing: traditional and new tools

Electromagnetic sensors are indirect methods to estimate soil constituents and related statistical tools are essential to reach the information of interest. The estimations of soil constituents usually follow a two-stage calibration procedure: the first one regards the measurement of the physical parameter (e. g. the dielectric permittivity) that which is believed to be related to the soil constituent and the second one is focused on the setting up of predictive models relating the physical parameter to the soil constituent of interest, known as calibration. Mane *et al*. (2024) dedicated a review on dielectric soil moisture sensor calibration.

Before delving into spectral mining, preprocessing is usually applied to remove noise, to correct the baseline, and to emphasize sample features. Some of the main preprocessing methods used are: smoothing, light scattering correction, normalization, baseline correction, and mathematical transformation, such as the first and second derivatives, or the fractional-order derivatives (Hong *et al*., 2023).

The importance of calibration procedures is widely recognized, also considering the critical aspects of selecting representative samples (Adamchuck *et al*., 2004), one of the main concerns about data uncertainty (Li *et al*., 2023). Two types of models were developed for soil constituent estimation: laboratory and field calibrations. Both approaches concern limits and advantages, usually presenting a conflict between accuracy and price (Zhang *et al.,* 2011). Considering in-field calibration, it should be noted that, generally, it is difficult to identify several useful points for the model (different levels of soil properties). The extreme conditions of wet and dry soils are also challenging to obtain. On the opposite side, the laboratory is an optimally controlled environment (Stangl *et al*., 2009). These conditions can also influence the relationship between the dielectric permittivity and the parameters measured concerning linear or non-linear calibration models (Mane *et al*., 2024).

The most significant part of calibration models was developed to relate soil dielectric permittivity and its volumetric water content by also considering the influence of the various soil properties as soil bulk density (Topp, 2003), organic matter content (Park *et al*., 2019), orientation of the soil particles (Roth *et al*., 1990), salinity (Robinson *et al*., 2003) and texture (Szypłowska *et al*., 2019).

Starting from the calculation of the dielectric parameter, a considerable amount of inferential fitting models was developed and proposed for soil volumetric water content (q_v, m^3m^{-3}). Estimation is the first polynomial one obtained by Topp *et al*. (1980). In addition, some parameters related to soil physical characteristics, such as soil bulk density and soil electrical conductivity, can be taken into consideration in the equations (Topp, 2003). The proposed numerous calibration models take into consideration different typologies of soil, chemical compositions (Jacobsen *et al*., 1993; Malicki *et al*., 1996; Bittelli *et al*., 2008), organic matter (Herkelrath *et al*., 1991), and mixing models (de Loor, 1964; Dasberg and Hopmans, 1992). Electromagnetic mixing formulas were also proposed in the electromagnetic sensor panorama (Sihvola, 1989). These equations take into consideration the dielectric permittivity as a weighted sum of the dielectric permittivity of each soil phase.

Artificial neural networks (ANNs) tools were also tested for soil moisture. In detail, ANNs were used to calibrate TDR probes using the physical characteristics of soil (bulk density, sand, silt, clay, and organic matter contents) to estimate its moisture (Arsoy *et al*., 2013; Zanetti *et al*., 2015),

and to build 2D and 3D soil moisture profiles by relying on a grid of sensors (Francia *et al*., 2022).

Since dielectric permittivity varies according to temperature, its effect on the calibration models was also investigated according to the soil texture (Wraith and Or, 1999).

According to Berardinelli *et al*. (2018), models were based on both linear PLS regression and nonlinear Kernel-based orthogonal projections to latent structures (K-OPLS) algorithms. With respect to linear PLS and starting from gain and phase spectra, O-PLS models greatly improve the moisture content (%) prediction ability independently of the kind of soil.

The above-cited tools play a big role also in the field of digital cameras and machine vision sensors (Han *et al*., 2016, Gomez-Robledo *et al*., 2013, Gudkov *et al*., 2022). Images captured through the smartphone or by a digital camera were combined with machine learning to build calibration models. Neural network statistical tools (Aitkenhead *et al*., 2018), PLS multivariate image analysis (Morais *et al*., 2019), random forest (RF) and convolutional neural network (CNN) algorithms (Swetha *et al*., 2020, Hong *et al*., 2023) were successfully implemented to predict soil textural parameters and soil organic carbon (SOC).

In-field application of sensors based on electromagnetic wave interaction usually involves the contemporary application of several sensors based on different techniques and spectral ranges (Kayad *et al*., 2022). Recently, multi-source sensor fusion and deep learning have combined information from different techniques and the emerging field of multivariate statistics, drawing the most innovative approach in the field (Hong *et al*., 2023). Data fusion consists of the combination of the acquired spectral response from different sensors to build more robust calibration models (Li *et al*., 2023; Cevoli *et al*., 2024; Hong *et al*., 2023). This approach was previously used to combine Vis and NIR hyperspectral images to obtain more accurate and reliable models to estimate chicken meat quality (Li *et al*., 2023). In soil measurements, particularly considering field measurements, data fusion mining could help to reduce the variability impact due to all constituents' interferences. The fusion level can be variable, from a low level, passing through an intermediate level, and reaching a high fusion level. The data fusion low-level combines data collected from several sensors to obtain an extensive starter data set. The intermediate level is focused on selecting a feature from data sets to increase the potential information in data and limit the information containing noise. In the highest level of data fusion, for each data set, a model should be developed, and thereafter, the results are combined in a final unique response algorithm.

Soil organic carbon was estimated by applying two different sensors based on vis-NIR and MIR coupled with several data fusion strategies. Particularly, six approaches were considered, such as direct concatenation-partial least squares regression (DC-PLSR), outer product analysis-PLSR (OPA-PLSR), OPA-competitive adaptive reweighted sampling-PLSR (OPA-CARS-PLSR), sequentially orthogonalized PLSR (SO-PLSR), DC-convolutional neural network (DC-CNN), and parallel input-CNN (PI-CNN) (Hong *et al*., 2023). According to the results, CNN models, by capturing the nonlinearity, can be sourced from light interactions with soil and appear to be characterized by high values in terms of accuracy. In addition, authors show how combining multiple sensors and deep learning fusion techniques can improve model accuracy, particularly by using PI-CNN (RMSE=0.84%) and DC-CNN (RMSE=0.78%). However, differently from DC-CNN, PI-CNN is able to perform specific convolutions separately to extract the relevant features (vis-NIR and MIR) without enforcing the same kernel size for both problems related to spectral region size, vis-NIR, and MIR spectra. According to the authors, the PI-CNN model ability in terms of vis-NIR and MIR data fusion strategy for SOC prediction can be extended to other sectors of soil spectroscopy and properties (Hong *et al*., 2023).

Conclusions and future perspective

The potential of proximal and remote sensing technologies for a rapid and accurate assessment of soil quality attributes has been described, as well as the advantages and disadvantages of each technique. The high role of multivariate and machine learning statistical tools has been underlined, together with the improvements due to the possibility of integrating multiple sensing technologies.

Further steps may be expected in these fields and, in particular, in the development of tools able to quantitatively estimate soil physical, chemical, and biological properties. The spatiotemporal modeling of soil attributes should be improved to accurately transfer the information from a local to a global scale. In this context, machine learning algorithms can represent useful tools for data fusion matrices generated by using multiple integrating systems. Data fusion procedures can be considered a new perspective to improve statistical models' robustness and reliability for soil constituent estimation. These combined approaches can also be performed across various fields, improving the potential applications. In conclusion, it can be stated that the future trends go in the direction of a combination of sensors based on different principles and deep learning fusion methods to reach more accurate soil properties assessment. Furthermore, the global spectral libraries for vis-NIR soil data storing can be a reference model to apply this worldwide approach to a large amount of data, also belonging to other technologies, to create a harmonization, opening a future perspective to have more accurate and reliable data open for all users.

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