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Can Soil Spectroscopy be a Strong Alternative to the Conventional Methods of Analysis?

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ABSTRACT

Soil is considered as the source of life on the globe. Although, numerous research studies, the soil is not completely understood whereas it is dynamic complex matrix include many simultaneous processes. The conventional methods of soil testing are the most reliable for assessing the land productivity and management. Unfortunately, these methods are time consuming and laborious as well as costly and hazardous to the environment. Therefore, the soil spectroscopy technique provides the functions of detecting, characterizing, quantifying and mapping several soil properties based on the uses of different kinds of the sensors (ground-based, airborne-based, and satellite-based). An integration of soil spectroscopic data, data processing, and modelling is considered as an effective tool for estimating soil parameters. Although these advanced techniques able to predict the majority of soil properties, there are some of these properties require more experiments for building accurate calibration models for estimation. Moreover, creating accurate soil spectral libraries (SSLs) for specific areas or soil types is very crucial for saving time, effort, expenses of soil surveying, sampling, and analysis. The application of these SSLs has a big limitation of the continuous variability of the soil properties over time. Thus, establishing extensive spectral libraries is important and mandatory for covering the small scaled areas' variabilities as well as available soil types. Till now, the soil spectroscopy is not entirely replacing the conventional testing methods of soils because these techniques need future applications to be trusted and guaranteed of their effectiveness.

Keywords: Remote sensing; spectroscopy; soil prediction; soil analysis

1. INTRODUCTION

Soil is an important and essential environmental resource to produce the food and regulate the Earth's life, whereas soil plays crucial functions of water move management, metals and nutrients filtering, and storing the carbon for helping in global warming mitigation. These functions are affected by soil structure and composition as well as physical, chemical, and biological properties. Moreover, these soil properties differ spatiotemporally [1]. Furthermore, the soil is a dynamic complex matrix consists of organic and inorganic compounds which is hardly to be understood [2]. Therefore, there is a global need for a good technique which able to explain the soil details because there is a dramatic increase of the human needs of food with the limited available land resources. Moreover, the need of the extensive spatial soil data is crucial to achieve the precision agriculture goals (El-Sayed et al., 2024). There is a big challenge in the qualitative and quantitative soil parameters' estimation, whereas estimating different soil properties is essential as well to enhance the land production of food and mitigate the climate change impacts [3]. However, there are global efforts from scientists and researchers in different scales (regional, continental, and global) to create different soil databases for helping in improving agricultural and environmental practices. Therefore, soil surveying is needed for morphological studies and detecting the soil sampling locations; and more samples is better for detailed land management (Moursy and Thabit 2022a). Therefore, using of the conventional methods of soil analysis has many drawbacks such as consuming time and costs, laborious, slow, and destructive to the environment. These methods are limited to the number of the soil samples and tested soil properties, thus are not suitable for big land reclamation projects [4]. For example, assessing the soil health in a regional scale, requires huge number of soil samples to be collected, prepared, and analyzed. Therefore, there is a strong need for rapid, cost-effective (cheap), eco-friendly (non-destructive), and accurate approach for soil analysis which able to analyze many soil properties in the same time as well as having a potential for utilizing spatial information of the soils [5]. Thus, the soil spectroscopy has been found as a promising and effective tool for estimating soil properties which is faster and less-expensive compared to the conventional soil testing methods [6]. This technology provides visible-near-infrared (vis-NIR), and mid-infrared (MIR) hyperspectral ranges between 350 and 2500; and between 2500 to 25000 nm, respectively which are suitable for predicting majority of the soil parameters [7]. The soil spectroscopy detects the sensitive spectral bands from the soil properties which have strong vibrations and these parameters are called 'chromophores'; and other soil properties which don't give absorptions are called 'non-chromophores' [8]. There are several types of the spectral sensors which can be used for soil estimation such as field, laboratory, airborne and satellite sensors. However, many studies utilized the spectral data collected from various sensors for estimating and predicting the soil parameters like soil organic matter (SOM), texture, clay minerals, soil nutrients, structure, and biological parameters [9]. An example of soil spectroscopic advantages, the soil spectroscopy is ten times cheaper than conventional methods in estimating SOM [10]. Therefore, this technique is an optimal option large land projects like African Soil Information System (AFSIS), and others [11].

This review article aims to overview the different applications of soil spectroscopy for estimating and predicting soil parameters, and answer a question of 'can these advances techniques be as an effective and potential substitution to the conventional methods of testing?'

2. SOIL SENSORS

There are many hyperspectral sensors such as filed, laboratory sensors which are handheld; airborne sensors which are attached on airplanes or unmanned automated vehicles (UAVs) or drones; and satellite sensors [12]. Under NASA's auspices, the imaging spectroscopy (IS) is developed whereas many satellite and airborne sensors were created for research purposes. Among these sensors, an Airborne Imaging Spectrometer (AIS) and the Airborne Visible Infrared Imaging Spectrometer (AVIRIS) were created to study the Earth surface in details regarding geology, vegetation, soil and minerals [13]. The Thermal Infrared Multispectral Scanner (TIMS) and the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) spacecraft sensor are produced by NASA and utilized for the thermal imaging and mineral identifying [14]. The TASI, MASI, HySi, and other sensors were developed also for thermal studies for the minerals and geophysical research. Over more than three decades, the spectral range of 350 to 2500 nm in the vis-NIR region is widely used for studying soil [15]. Therefore, several sensors like GERIS, DAIS, hyperspectral mapping (HyMap), Compact Airborne Spectrographic Imager (CASI), and Shortwave Infrared Full Spectrum Imager (SFSI) were developed [16]. Various hyperspectral cameras such as HySpex were developed for research purposes. Regarding the spaceborne or satellite sensors such as MERIS, MODIS, and ASTER covering more than hyperspectral hundred narrow bands with less than thirty meters of spatial resolution [17]. The recent sensors of NASA are HyspIRI and EnMAP which has been found to provide spatiotemporal data of the globe [18]. According to the HI, Airborne Visible and Infrared Imaging Spectrometer - Next Generation (AVIRIS-NG) has been initiated by NASA's Jet Propulsion Laboratory (JPL) to cover significant sites over the world for studying geology, soil, water, and vegetation [19].

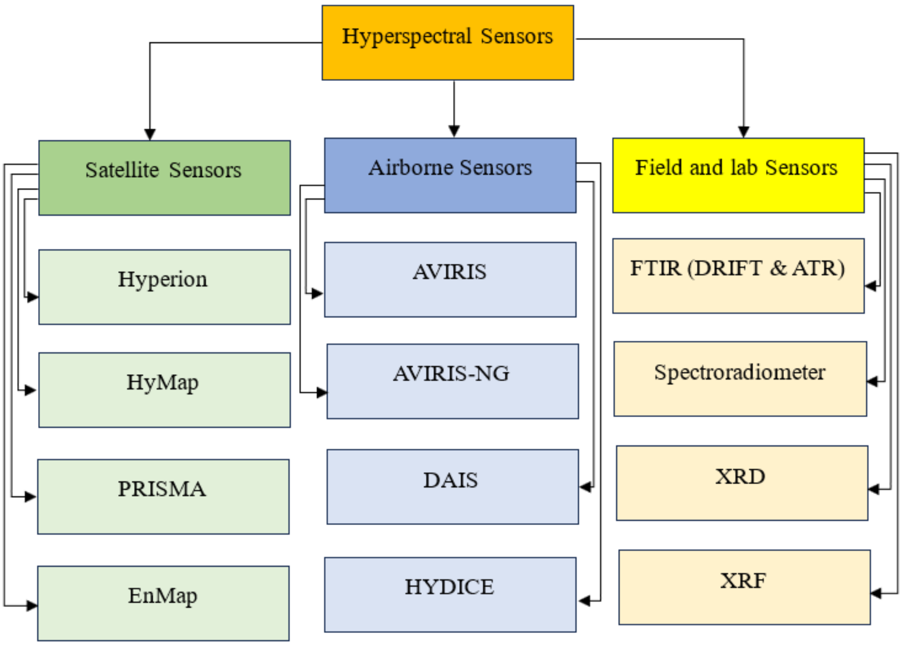

Fig. 1. Types of hyperspectral sensors

Multispectral remote sensing (MSS) typically involves a limited number of spectral bands (ranging from 5 to 10) with wide bandwidths (50 to 400 nm) [20]. In contrast, hyperspectral remote sensing (HSS) utilizes narrow bands (1 to 10 nm) and can encompass a much larger number of bands (100 to 500). HSS offers several advantages over MSS, including the ability to detect multiple features—such as soil, rocks, vegetation, and snow—simultaneously [21]. the HSS provides a direct correlation with surface chemical structures and allows for approximate estimations of present materials [22]. HSS capability is particularly valuable for developing spectroscopic instruments aimed at both qualitative and quantitative soil assessments [23]. Recently, a variety of handheld HSS devices have emerged, including Snapshot, Nano-Hyperspec, and Micro-Hyperspec. These imaging spectrometers provide centimeter-level spatial resolution and can be mounted on UAVs, airplanes, robots, and ground-based vehicles. NASA's satellite-based mission, the EO-1 Hyperion sensor, offers valuable datasets sampled globally. However, it is important to note that the Hyperion sensor has a relatively low signal-to-noise ratio [24]. In India, numerous applications of Hyperion sensors have been conducted, particularly in agriculture, where they have been used to study mustard crop diseases, as well as in geological studies in Dongargarh, Rajasthan [25].

3. SOIL SENSORS' APPLICATIONS

There are many applications of the soil spectroscopy which focus on the sensitive bands which are related to the soil properties. For selecting these bands, the most absorbance vibrations represent the sensitive wavebands. Moreover, the spectral behavior of the soil is unique, whereas water absorption bands are distinguished in 1400, 1900, and 2200 nm wavelengths [26]. Furthermore, this behavior depends on some soil factors such as soil constituency, structure, concentration, and content of other nutrients or organic materials as well as the clay minerals. The soil spectra are differed from the plant whereas the plant spectral absorption is mainly affected by the pigment's concentration or content in visible region (Miao et al., 2024). Additionally, the plant spectral behavior depends also on leaves' structure, length, size, shape, pores, and water interfaces. These features can be detected within the vis-NIR spectral region as the vegetation spectral signature include the green peak which can be identified between 500 and 600 nm as well as chlorophyll absorption (400 - 600 nm), red-edge (680 - 750 nm), plateau and water absorption (NIR region) as described by [27]. Moreover, the vegetation chemical properties can be predicted at of 480, 620, and 840 nm wavebands; and also, several spectral vegetation indices can be applied such as normalized difference vegetation index (NDVI), normalized difference water index (NDWI), water band moisture stress index (WBMSI), and normalized difference infrared index (NDIRI) as mentioned by [28]. Therefore, the hyperspectral sensing between 350 and 2500 nm is very important in early detection of the plant biotic and abiotic stresses. By using this spectral information, the decision makers can take suitable actions in a suitable time [29]; as well as identifying the affecting factors related to soil such as soil moisture, salinity, alkalinity, and nutrients status. Consequently, other sensors such as the ground, airborne, and spaceborne hyperspectral sensors are used to get detailed spatial information related to plant responses in its local ecology status in order to detect several environmental stresses which affect the agricultural production negatively [30]. An example for the airborne sensors is an AVIRIS-NG which used for detecting crop varieties, types, and for mapping. This sensor is also used for detecting, identifying, characterizing, analyzing and mapping several soil properties (physical, chemical, biological, others) as studied by [31]. Not only hyperspectral data but also multispectral remote sensing data such as LANDSAT images are used for soil and vegetation studies with a good resolution and spatial information.

Abdulraheem et al. [32] reviewed the quantitative remote sensing of soil properties, providing comprehensive insights into HSRS and its applications in soil studies. Furthermore, many studies have focused on developing accurate protocols and standard methods for predicting and estimating soil parameters using various ground and air-based hyperspectral sensors, often integrating multiple data processing techniques. There are also numerous methodologies for processing data obtained from sensors (soil spectra) and traditional soil laboratory analyses. These methodologies are such as data transformation (using logarithms, box-cox, arcsine, etc), data randomization, data sorting, data dividing, etc.

4. SOIL SPECTRAL LIBRARIES (SSLs)

Despite the significant potential of spatial variability assessment through geostatistical approaches and the quantitative evaluation of soil attributes using spectral reflectance models, substantial knowledge gaps remain. Soil spectral libraries (SSLs) play a crucial role in predicting soil parameters in unknown samples by accounting for various types of variability in reflectance spectra [9]. Additionally, mid-infrared (MIR) spectroscopy serves as a rapid and reliable analytical tool for predicting several soil parameters using global SSLs (Wang et al., 2023). Historically, there is a very rapid progress in the field of sensors especially for the soil sensors whereas this progress started when the first relation between soil spectral information and corresponding soil characteristics was explored till creating the first soil spectral library (SSL). Recently, the expression of ‘chromophores’ be common in the soil spectroscopic community, whereas it is used in an interpretation of the soil spectral behavior. However, the comprehensive understanding of this relationship is mandatory for achieving better accuracy and predictability of the soil parameters (i.e. SOC, and carbonates) are categorized under the well-predicted parameters while other soil properties performed a lower predictability because of the weaker spectral responses as well as the correlations between the soil chromophores and the SSL [33]. There are several applications of the SSL in soil studies whereas it is used as standard references for the obtained data in different scales and sensors such as field, laboratory, airborne, and space-borne. These SSLs are integrated with advanced data analytics approaches as well as statistical and mathematical models for predicting and estimating the soil parameters [34]. An advantage of the SSL is that the limited number of soil sample is not a barrier in creating these libraries as mentioned by several studies such in [35]. On the other hand, many researchers used SSLs which include numerous numbers of soil samples’ data such as an ASTER SSL of clay minerals which consists of more than 2400 spectra in the spectral range between 400 and 15400 nm [36]. Another SSL is created the United States Geological Survey (USGS) which include a wide variety of clay minerals and helps many researchers to estimate the cay minerals as well as the relation between these minerals and other several soil properties using an automated prediction model [37]. Moreover, the free SSLs such as SPECCHIO, DLR, ASTER, and USGS are used for detecting, characterizing, classifying and mapping the soil properties. In SSLs usage, there are several issues related to the spectral images’ classification like unmixing problem whereas one pixel can include different responses from different objects (i.e. soil, water, vegetation, mineral, etc.). Therefore, using SSL created from pure soil spectra has more helpful for identification and estimation the soil properties [38]. Furthermore, there is a new expression called ‘spiking’ which means using the spectra of unknown sample to estimate it using the SSL without analyzing it in the wet chemistry laboratory [39]. Although, there are many examples of using the SSLs in different applications of soil, there is an increasing need for a global SSL that include all soil variabilities including types, classes, and properties. As the soil is a very complex matrix, and hardly to be understood, the needed SSL is differed from the clay library. However, the global SSL has more than 10000 samples and spectra data which collected from the soil variations over the world. Another SSL is created by the ICRAF-ISRIC which consists of 4438 soil samples which are collected from 785 soil profiles in 58 countries; while an Australian SSL included 21500 spectra collected from more than 4,000 profiles. The US SSL contained 145000 spectral data obtained from 32000 profiles; and a European SSL includes 20000 spectra acquired from the surface soils and tested for different 13 different soil parameters; and used for develop SSL of New Zealand [40]. Lobsey et al. [41] created SSL which include 18000 soil spectra collected from 92 countries and focused on SOC estimation. Moreover, the Chinese SSL (CSSL) is created of 4000 samples; while Brazilian SSL included 223 soil profiles’ spectra [42].

5. APPLICATIONS OF SSLs

As discussed previously that the SSLs are important tools for estimating various oil properties using the untested samples. For that, using the hyperspectral data collected by the satellites or airborne sensors are not highly accurate and not suitable for estimating the soil parameters except few. Thus, the ground sensors (fled or laboratory) are recommended to be used as they are accurate and suitable for creating the SSLs because they are used in estimating the majority of the soil parameters. However, these SSLs are efficient in estimating soil properties in any research studies such as a very recent study of Wang et al. [43]. They concluded their study with that the accuracy of the USGS SSL is similar to the field and lab data in estimating the limonite mineral and in selecting the sensitive bands of 500, 620, 930, 1410, and 1800 nm. They also used this SSL for comparing their findings with the AVIRIS-NG sensor, whereas a strong correlation between the two datasets was recorded in the 460 and 540nm wavebands for the limonite mineral. Spectral libraries are effective tools for estimating various important soil parameters, soil classification, and digital mapping. Rossi and Gholizadeh [44] emphasized that spectral libraries must include sufficient soil spectral signatures representing spatial diversity, with carefully collected, prepared, stored, and scanned soil samples. Calibrations should be established using reference data from accurate and trusted analyses. Large SSLs developed on regional, national, continental, or global scales are used for predicting soil parameters. Many soil parameters, such as sand, silt, clay, CEC, pH, organic carbon, total organic carbon, calcium, nitrogen, potassium, manganese, kaolinite, gibbsite, montmorillonite, and iron oxides, can be estimated using hyperspectral remotely sensed data such as reviewed in Yang et al. [45] study. The MIR region of spectra, with a range between 2500 and 25000 nm, has proven to be a good technique for estimating some soil parameters, such as organic carbon, total nitrogen, and soil texture [46]. Partial least squares regression (PLSR) models have been used to estimate SOC, clay, sand, and CEC based on SSLs. The boosted regression trees (BRT) models are applied for estimating SOC on the basis of vis-NIR global SSL data. There are different results obtained when comparing between several prediction models, whereas Egeonu and Jia [47] pointed out that the artificial neural networks (ANN) demonstrated better performance than the PLSR model in predicting the soil parameters using the MIR SSL. In contrast, El-Sayed et al. [48] demonstrated that the PLSR was more accurate than ANN in estimating soil pH and moisture. Goydaragh et al. [49] applied PLSR and Cubist models to predict SOC, clay and CEC based on the MIR spectral data and concluded that the Cubist was better. However, these applications can be more accurate by using a wide global SSL as well as more data analytics and prediction approaches.

6. DATA ANALYTICS OF SOIL SPECTRA

Fig. 2 illustrates the overall methodology for predicting and mapping soil properties using various types of sensors. Data analysis techniques based on soil spectral variables involve several processes suitable for qualitative analysis, such as discriminant analysis, band ratios, and classification methods [50]. These processes are most appropriate for satellite imagery acquired over bare soils. One challenge is that soil spectral signatures collected in the field or laboratory can be noisy and difficult to evaluate. Data preprocessing is used to clean these noises and develop fit soil spectral curves [51]. Spectral transformation plays a crucial role in correcting non-linear measurements, noisy spectra, and variations in soil samples. Spectral smoothing methods, such as Savitzky-Golay, mean-median filtering, and running average, are commonly used to suppress soil spectral noises. The first derivative and second derivative are widely used to account for viewing geometry, solar angle, and enhance outputs [52]. The continuum removal (CR) technique is used to identify and quantify material absorptions in specific spectral ranges, excluding other material absorptions around the studied range. Santra et al. (2009) successfully applied spectral data transformation methods, including CR factors integrated into the prediction model, to estimate soil hydraulic conductivity parameters using an ASD spectroradiometer and Landsat satellite imagery [53]. Principle component regression (PCR) calculates principal components of data and uses them as predictors in a linear regression model. Partial least squares (PLS) uses both known property data and spectral data during principal component calculation, reducing wavelength selection and removing spectral noises [54].

Partial least squares regression (PLSR) is a popular technique in chemometrics for quantitative estimation of hyperspectral reflectance data, particularly when many highly collinear predictor variables are present. Artificial neural networks (ANNs) are another statistical and mathematical method recently used for estimating soil parameters integrated with Vis and NIR hyperspectral reflectance data. Linear discriminant analysis (LDA) minimizes within-class scatter to between-class scatter ratios, while multivariate adaptive regression splines (MARS) develop non-parametric regression models. Random forests (RF) and boosted regression trees (BRT) divide data into multiple predictor trees, with RF being suitable for hyperspectral data and few soil samples, robust to noise, and with low bias [55].

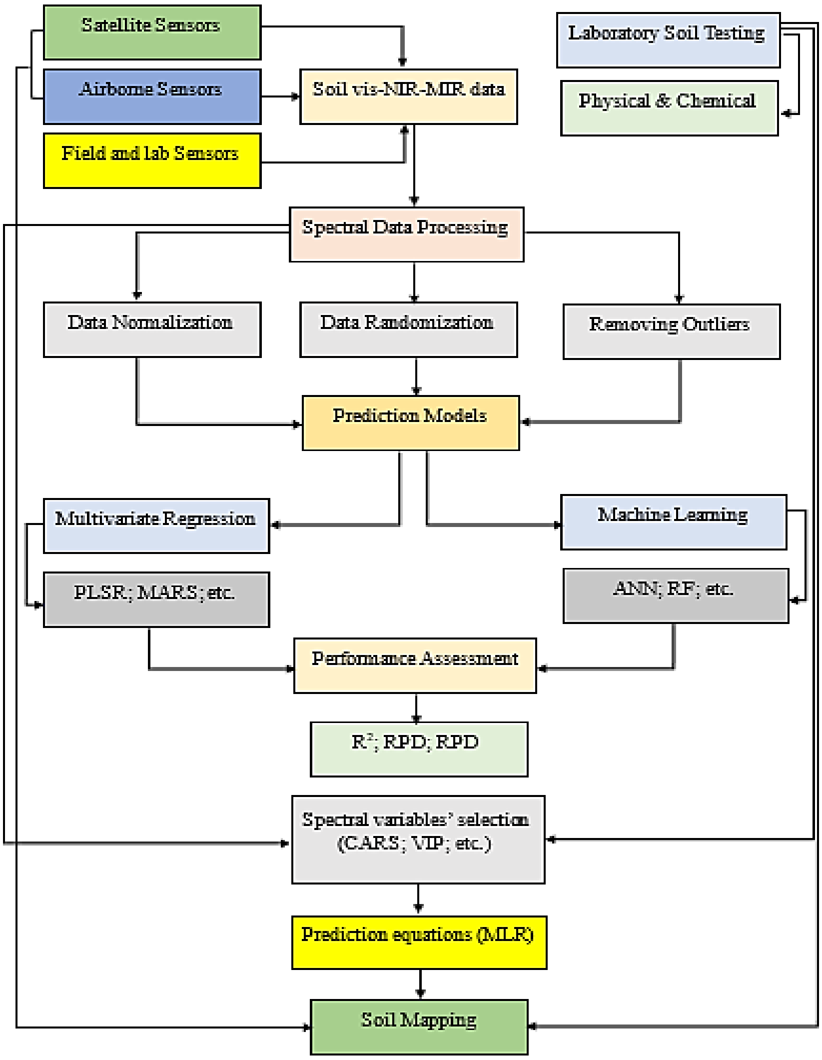

Fig. 2. Predicting and mapping of soil parameters using hyperspectral sensors

Other machine learning algorithms, such as relevance vector machines (RVM), are similar to support vector machines (SVM), using a linear combination of calibration datasets to produce real predictions, unlike SVM's pseudo-outputs. Root means square error (RMSE) is used to assess the accuracy of calibration and validation models, estimating prediction error from soil estimations and corresponding soil spectra [56]. The regression coefficient (R^2) is another statistical parameter used to evaluate model performance, representing the square of the correlation between observed and predicted values of the targeted soil parameter. The R^2 and RMSE statistical parameters can be not sufficient for evaluating the accuracy of the prediction model in calibration and validation, because the insufficient dataset size, specifically when the soil samples have wide variability.

7. SOIL CHARACTERISTICS' MODELING

Several studies applied the multivariate regression models for estimating different soil properties, whereas this process starts with the soil spectral data processing and transformation to enhance the models' accuracy. Afterwards, the data normalization, randomization, removing outliers, and sorting processes are applied. Liu et al. [57] used the principal component analysis (PCA) for estimating and spatial variability mapping of the soil parameters. Song et al. [58] suggested the use of wavelet analysis (WA) for smoothing the soil spectral data to improve an accuracy of prediction. Vaudour et al. [59] used the BRT model for estimating different soil parameters on the basis of global SSL; and they mentioned that soil complexity can prevent the prediction model from well performance.

Moreover, several research studies revealed good results of predicting soil properties using the vis-NIR-MIR spectral data or SSLs. For example, Karray et al. [7] employed partial least square regression (PLSR), locally weighted regression (LWR), and support vector machine (SVM) prediction models to estimate soil nitrogen. Rossel et al. [60] successfully predicted soil parameters using a local regression model integrated with hyperspectral data based on SSL. Shen et al. [61] recommended PCA and PLSR algorithms to extract soil information regarding various properties from spectra in the range of 350 to 2500 nm. Abdellatif et al. [62] used ASD spectroradiometer reflectance data to predict soil properties through PLSR multivariate techniques. Li et al. [63] focused on predicting soil properties such as carbon, phosphorus, and nitrogen for soil fertility assessment, noting that qualitative predictions heavily rely on reflectance spectroscopy and infrared reflectance. Karray et al. [7] achieved quantitative predictions of soil parameters using the PLSR algorithm and suggested that more accurate predictions could be made using MIR data. Lee et al. [64] utilized ASD spectroradiometers to obtain soil spectra and applied the PLSR model to effectively predict soil organic matter in certain Korean soils. Safanelli et al. [65] estimated various parameters in Italian soils by collecting spectra in the vis-NIR-MIR regions, applying the PLSR model to predict sand, silt, clay, soil organic carbon, and total nitrogen. Mustafa and Moursy [66] concluded that integrating soil reflectance with the PLSR model enhances the estimation of total carbonate and soil electrical conductivity in the Mugan Plain area. To select the most accurate model for predicting soil properties, several comparative studies have been conducted. Mariz and Soofastaei [67] compared two prediction models, NN-PCR and PLSR, and recommended NN-PCR for estimating soil properties. Miloš et al. [53] assessed the PLSR efficiency for mining the spectral data in order to estimate soil clay, SOC, and pH. They suggested that MARS, RF, SVM, and NN are efficient data mining tools for predicting these soil parameters. Chang et al. [68] applied the NIR-PCR approach using four processing steps: pretreatment, calibration and validation dataset development, application of PCR, and prediction-validation assessment; and they classified spectral range of 350 to 2500 nm into three main classes based on statistical parameters, including the ratio of performance deviation (RPD). Class "A," with RPD > 2.0 and R^2 = 0.80 - 1.00, includes parameters such as total soil carbon, total nitrogen, soil moisture content, sand, silt, exchangeable calcium, and cation exchange capacity. Class "B," with RPD ranging from 1.4 to 2.0 and R^2 from 0.50 to 0.80, includes parameters like clay, pH, available iron, potassium, magnesium, and manganese. Class "C" encompasses parameters with R^2 < 0.50 and RPD < 1.4, such as available copper, phosphorus, zinc, and exchangeable sodium. This technique can also estimate soil minerals like kaolinite and montmorillonite [69].

8. SOIL MAPPING

There is no doubt that the soil maps play vital role in understanding the soil status, types and achieving better management, whereas these maps were started as aerial photographs for soil surveying purposes till now as high-resolution soil maps represent mandatory, effective, accurate, and cheap tool for soil monitoring and management. However, these soil maps are crucial for land capability, suitability, fertility, degradation and productivity evaluation in order to achieve the agricultural sustainability goals and reduce the environmental impacts. Therefore, different governments work on developing the soil databases as well as the soil maps for improving the agricultural practices management [70]. On the other hand, the spatial variability evaluation of the soil properties is important for the precision agriculture activities whereas accurate detection of the crop and soil requirements of fertilization, irrigation and pest-control can be achieved easily using the digital soil maps [71]. These new advanced technologies of soil mapping such as using the hyperspectral satellite or areophane imageries are found as a very good alternative to the conventional methods of mapping. The traditional method are consuming time, cost and effort as well as laborious and destructive. Therefore, remote sensing (RS) and geographic information systems (GIS) are utilized for mapping the soil properties very efficiently in the time and cost [72]. For the RS technology, understanding and evaluating the spatial variability distribution of the different soil properties can be done through developing the corresponding maps. Moreover, imaging spectrometers (IS) which cover several spectral ranges (vis; vis-NIR; NIR; vis-NIR-MIR) offer the hyperspectral interval of 1nm for generating very high-resolution maps. Furthermore, ground-based sensors such as portable spectroradiometers can be used for generating soil properties' models through the machine learning algorithms (ML) which can be used for mapping the soil properties' spatial variability based on the hyperspectral airborne or satellite sensors' imageries [13]. For examples, using the AVIRIS-NG sensor for mapping different soil properties, minerals and earth's surface objects [73].

9. SSLs DRAWBACKS

Utilization of SSLs has some limitations such as the soil parameters applicability can be suitable for one area but not for other areas, whereas the African SSL successfully predicted some soil properties such as clay and SOC in the same areas while not suitable for predicting the same soil parameters in other areas. On the other hand, many researchers proved that the applications of the SSLs are effective and important. For example, Tziolas et al. [74] revealed that creating the SSLs is useful for stablishing reliable estimation models for soil monitoring and management using various sensors or platforms. The uniformity of the soil samples as well as soil data in order to create a precise SSL; and also, the unknown samples must be under the same soil type or region. Furthermore, the heterogeneity of the soil samples (database) may lead to improper calibration of the soil properties' prediction models. Another drawback of the SSL is the various effects on the soil spectra such as soil roughness and moisture content variabilities, as well as the atmospheric effects and sensor characteristics like spectral and spatial resolution which can impact the accuracy of the SSL. Moreover, in situ acquiring the soil spectral reflectance is affected by the sunlight, while soil roughness and microrelief cause non-Lambertian reflectance behavior. Thus, the filed instruments must be calibrated through the available conditions for generating an accurate SSL [11,50].

10. SOIL SPECTROSCOPY CHALLENGES

It is essential to know the behaviors of the soil spectral reflectance data to understand the disadvantages of the soil spectroscopy. There are different factors which affect the vis-NIR performance and calibrations such as sampling and preparation like drying, grinding, and sieving; and instrument conditions such as lighting effects as well as the surrounding noises. Unfortunately, there is no a standard protocol for soil sampling, preparation, collecting spectra, data processing, modelling and many other factors which affect the predictability of the soil parameters [50]. Grinding soil samples can significantly affect the obtained spectral signatures, particularly in clay-rich samples, where reflectance tends to increase. A similar increase in reflectance has been observed when drying soil samples, which also reduces absorption in the 1400, 1900, and 2200 nm bands [11]. The impact of grinding can be minimized through data transformation or correction. Rossel et al. [60] noted that air-drying soil negatively affects predictions of SOC and total nitrogen. Kouakou et al. [75] compared ground soils (<0.2 mm and <2 mm) and found that finer soils yielded better predictions of soil parameters. Conversely, some studies have indicated that grinding does not significantly affect the estimation of micronutrients using hyperspectral techniques. Despite the advantages of spectroscopy in soil analysis, several issues can affect its performance and accuracy. Soil fractions influence the obtained spectral signatures, and the protocols used for collecting soil spectra can vary between laboratory and field conditions. The type of instrument used also plays a role, as different laboratories may employ different equipment. Currently, there is no standardized protocol for obtaining soil spectral signatures or for soil preparation prior to spectral collection. Additionally, there is no fixed approach for data processing or for establishing calibration and validation models. As a result, building SSLs is challenging and requires standardization through a reliable protocol. Utilizing a standard protocol for soil sample preparation, spectral data collection, and modeling can help reduce errors. To further minimize analysis errors, it is advisable to send the same soil samples to multiple trusted soil testing laboratories. This approach can also be applied during soil spectral data collection to enhance accuracy. Relying on spectral data collected from a single laboratory (with one spectroradiometer) can lead to higher error rates [11]. Both ground-based and airborne sensors have drawbacks. One significant external error affecting soil spectral data acquisition is atmospheric attenuation, which is particularly problematic in imaging spectroscopy techniques, as some soil chromophores may not correlate with the obtained spectra. In multispectral remote sensing, this issue is less pronounced because the broader spectral bands tend to mitigate atmospheric noise. Atmospheric noise arises from solar radiation and natural atmospheric gases, necessitating atmospheric data correction to improve spectral accuracy. Such corrections require substantial expertise and technical skills.

Another challenge researchers face is the high cost of spectroradiometers and scanning instruments. Estimating soil properties utilizing several algorithms side by side of different calibration and validation models provide a proficiency of the statistical analysis and software. Advanced techniques and methodologies suggested must be followed to enhance the outputs. There is no doubt that the soil spectroscopy is crucial for fast analysis but this technique still empirical and need to be guaranteed; and the researchers have to continue their efforts by using more prediction models and data transformation techniques as well as different kinds of soil spectral data.

11. FUTURE DIRECTIONS

For over 40 years, soil spectroscopy and integrated tools have been studied for their applications in the quantitative estimation of various soil parameters. In the past two decades, a significant number of research papers have been published utilizing these techniques, with findings strongly recommending the use of visible-near-infrared (vis-NIR) spectroscopy for estimating soil properties. The data obtained from these studies are directly applicable for mapping and land-use management. Additionally, diffuse reflectance spectroscopy (DRS) has proven to be an effective method for accurately estimating soil parameters such as pH, organic carbon, clay content, exchangeable cation capacity, and soil mineralogy [60]. Despite these advancements, the technique remains empirical, and there is a pressing need for the development of reliable theoretical calibrations and trusted protocols. A deeper understanding of the behavior of soil spectral signatures in relation to different soil chromophores is essential for building effective soil spectral libraries (SSLs). The demand for a standardized method for obtaining spectra, whether in the laboratory or the field, is increasing due to the inaccuracies that can arise from using spectroradiometers. Factors such as soil surface roughness, structural complexity, and chromophore interactions must also be understood. To address these issues, high-quality spectral libraries should be used to standardize methods applied in both laboratory and field settings. Furthermore, a comprehensive collection of soil spectral signatures on a global scale is necessary to represent the diversity and variation of soils effectively. The selection of appropriate data treatment methods is crucial in establishing these protocols. With the right approach, significant progress can be made in creating new standards for assessing soil parameters. In summary, while ground-based spectrometers provide reliable data, they can be costly, making satellite data essential for larger-scale applications. Several spectral databases, such as NASA's Terra spacecraft imagery collected in 2016 and the European spectral database covering parts of Europe and North America from 2011 to 2013, offer freely accessible resources. NASA has been a leader in sharing spectral data, with various platforms making this information available to the public. Looking ahead, conditions for using space-borne data include ensuring uniform spatial resolution that matches ground-based sensor data and obtaining cloud-free data. The integration of multisource data is anticipated to become more common. Certain soil parameters, including soil texture, clay minerals, soil organic carbon, and moisture content, have been accurately estimated using the visible and near-infrared spectrum in conjunction with advanced modeling techniques. However, other parameters, like soil pH and nutrients, may not always yield accurate predictions due to varying correlations with soil chromophores. For instance, soil pH is indirectly correlated with chromophores but directly correlated with buffering capacity. Therefore, parameters with indirect correlations should not be assumed to provide guaranteed results. More research is needed to apply hyperspectral data alongside laboratory data to develop robust prediction models for estimating unknown soil parameters. Currently, this technique is particularly effective for estimating soil moisture content and clay minerals, while results for other parameters, such as available macro- and micro-nutrients, remain less reliable. Field measurements using handheld spectroradiometers are essential for enhancing this technique. While field spectral measurements of soil parameters, such as minerals and moisture content, are recommended, they do face limitations. For example, artificial noise from plant residues, gravels, and other materials can contaminate data acquisition. Additional studies focusing on field spectral measurements are necessary to reduce time and costs associated with soil surveying and analysis. The data obtained from such studies are invaluable for large-scale mapping and improving land use management such as in Moursy et al., [76].

12. CAN THIS TECHNIQUE SUBSTITUTE TRADITIONAL METHODS?

After examining the advantages and effectiveness of diffuse reflectance spectroscopy

(DRS) in estimating soil parameters, a critical question arises: Is this technique promising? The answer hinges on the body of evidence supporting the efficiency of DRS for soil parameter estimation. Many studies advocate for the use of soil remote sensing sensors as viable alternatives to traditional laboratory analysis, utilizing field-acquired data. That DRS is emerging as a strong alternative to conventional soil analysis methods, albeit with some limitations. That various remote sensing techniques, including mass spectroscopy, nuclear magnetic resonance, and visible-near-mid-infrared spectroscopy, could serve as surrogates for routine soil analysis. Key soil parameters of interest that influence soil fertility include soil texture, organic carbon, and nutrient levels. No single sensor can estimate all soil parameters effectively. Furthermore, most previous studies have utilized laboratory sensors under controlled conditions, which may not accurately reflect actual field situations. Another reason for the technique's perceived immaturity is that a prediction model for a specific soil parameter may yield accurate results in one region but not necessarily in another. To minimize data collection errors, a universal soil sensor should be employed across all studies. A potential solution is to gather a large number of soil spectral signatures along with corresponding soil testing data to develop a universal spectral library and prediction model. This would enable the estimation of unknown soil samples with reasonable accuracy [77]. Using a global spectral library allows for the effective testing of several soil parameters, including moisture content, organic matter, cation exchange capacity, salinity, pH, and electrical conductivity. There are some key factors contributing to variability in results when employing this technique, such as soil genesis diversity and mineralogy, which can lead to discrepancies in soil reflectance data and reduced accuracy of prediction models [78,79]. Thus, creating a spectral library with a comprehensive range of soil spectra is recommended to address soil diversity and enhance the use of vis-NIR spectroscopy. A necessary step in developing spectral libraries is establishing calibrations that relate near-infrared spectra to analytical data. Currently, DRS should at least be considered a cost-effective alternative to more expensive soil parameter analyses, such as measuring soil organic carbon, which typically requires complex procedures like dichromate digestion with large amounts of acid. Therefore, DRS is a valid method for estimating soil organic carbon. Using mid-infrared (MIR) spectral data combined with PLSR is suggested for accurate quantitative estimation of soil pH. While the ability of DRS to estimate other soil parameters remains empirical and requires further evaluation, it is particularly effective for estimating soil moisture content and clay minerals, where reliable results have been achieved. However, the technique's effectiveness for estimating other parameters, such as available nutrients, is still under investigation. Field measurements using handheld spectroradiometers are essential for enhancing the application of this technique. Although field spectral measurements of soil parameters, including minerals and moisture content, are recommended, they do have limitations. For instance, artificial noise from plant residues, gravel, and other materials can contaminate data acquisition. More studies focusing on field spectral measurements are needed to reduce the time and costs associated with soil surveying and analysis. The data obtained from such studies are crucial for large-scale mapping and improved land use.

13. CONCLUSION

The integration of hyperspectral reflectance data with multivariate regression and machine learning models has proven to be an effective technique for estimating various soil parameters. This approach is eco-friendly, rapid, non-destructive, and both time- and cost-effective, allowing for in situ analysis of soil samples. Additionally, it enables the simultaneous estimation of multiple soil parameters. Several mathematical and statistical methods have been successfully applied to achieve reasonable and acceptable efficiencies in estimating different soil properties. Both ground-based and airborne sensors have demonstrated high efficiency in estimating various soil parameters. Hyperspectral remote sensing, particularly in the visible and near-infrared (vis-NIR) ranges, has emerged as a promising alternative to traditional laboratory analysis. Studies have shown that this technique can effectively estimate key soil parameters, including soil texture, organic carbon content, and nutrient levels. Despite its advantages, the technique is still considered empirical, and there is a need for improved theoretical calibrations and standardized protocols. Understanding the behavior of soil spectral signatures in relation to different soil chromophores is essential for building reliable soil spectral libraries (SSLs). The demand for a common standard method for obtaining spectra in both laboratory and field settings is increasing, as inaccuracies can arise from various factors, including soil surface roughness and the complexity of soil structure. To address these challenges, it is recommended to create extensive spectral libraries that encompass a wide range of soil types and conditions. By acquiring a large number of soil spectral signatures and corresponding soil testing data, researchers can develop universal spectral libraries and prediction models. This would facilitate the estimation of unknown soil samples with improved accuracy. Furthermore, studies have shown that using a global SSL can yield good results for estimating various soil parameters, such as moisture content, organic matter, cation exchange capacity, and soil pH. However, variability in results can occur due to differences in soil genesis and mineralogy, which affect soil reflectance data and the accuracy of prediction models. In summary, while hyperspectral reflectance data combined with multivariate regression and machine learning models offer a promising approach for soil parameter estimation, further research is needed to refine these techniques and establish standardized protocols. The integration of diverse data sources and the development of comprehensive spectral libraries will enhance the reliability and applicability of this technology in soil science.

DISCLAIMER (ARTIFICIAL INTELLIGENCE)

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc) and text-to-image generators have been used during writing or editing of manuscripts.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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