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REVIEW ARTICLE

Soil spectral libraries and their role in soil analysis

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Abstract

Soil Spectral Libraries (SSLs) play a crucial role for advancing soil testing by integrating soil spectroscopic tools. This article aimed to examines the development, utilizations and implications of the SSLs in soil science studies. The SSLs offer rapid and cost-effective quantitative estimation of different soil properties such as soil pH, salinity, nutrients, texture, organic carbon and others which is essential for environmental monitoring and precision agriculture. Furthermore, this article highlights the potentialities of the visible/near-infrared (Vis-NIR) soil spectroscopy for creating robust prediction models and demonstrating the necessity for large, variable reference datasets of the soil samples and their corresponding spectral reflectance data to enhance the applied prediction models' accuracy. Additionally, Open Soil Spectral Library (OSSL) aims to provide an access to the soil data and engaging the external communities in the soil data collection. There are many advantages of using the SSLs, but there are some challenges especially in predicting certain soil properties accurately; and the factors related to the used prediction models and soil types. There is a necessity for creating the SSLs in India due to its importance in achieving better soil monitoring, planning and management. The prospects for SSLs are promising whereas the applicability of the machine learning models for better estimation of soil properties can be enhanced globally through collaborative efforts and increased accessibility for stakeholders in developing regions. A key limitation of this study is that the accuracy of SSLs in predicting certain soil properties can be affected by the variability in soil types and the choice of prediction models, which may limit the generalizability of the results across diverse Indian soils. Thus, this review article comprehensive overview underscores the transformative potential of SSLs in soil analysis and their critical role in sustainable land management practices.

Keywords: modelling; precision agriculture; predictive; soil spectral libraries; soil analysis; spectroscopy

Introduction

Soil analysis is very crucial for assessing the status of the lands regarding their capability, productivity, suitability, fertility and other aspects (1). Determination of different soil properties such as soil organic matter, pH, calcium carbonates and salinity, macro and micronutrients are very important for decision-making regarding cultivating different crops for achieving optimal agricultural productivity. Moreover, soil testing provides insights about the current issues and limitations which can negatively affect the soil health as well as the land capability (2). These insights help in better planning and managing the land for a specific purpose. Soil testing is the main biller of the Precision Agriculture (PA) whereas understanding the spatial variability is based on the laboratory analysis. Some studies used different models and samples' sizes for accurate spatial variability mapping (3).

Soil analysis using the conventional methods is the most reliable approach but have several limitations. Soil testing is time consuming, laborious, hazardous to the environment as well as costly (4). In case of analysis huge number of soil samples, the conventional methods of soil testing are not efficient. Moreover, the soil analysis requires long process starting from surveying, sampling, preparation including samples' drying, grinding, sieving, extracting and measuring, which is limited to a small number of samples (5). Additionally, different analysis reports can be obtained when the same soil sample sent to various soil testing laboratories due to the experimental error occurs by the technicians, chemicals, instruments and the applied protocols. However, soil analysis requires large quantities of laboratory chemicals; for example, in soil organic carbon analysis in one gram of soil, the hundred grams of chemicals are utilized (6). Besides, the conventional soil surveying and analysis need to be repeated consequently for soil statuses updating which very difficult and costly in case of large, scaled areas (7). In India, soil health card project was issued in 2015 for analyzing and evaluating millions of soil samples using traditional methods of soil analysis. For achieving these project objectives, very tedious and costly soil surveying, sampling and analyzing processes were applied. For updating the developed database of this project, a massive budget is required for repeating these tasks every time (8). Therefore, there is a necessity for a new, rapid, accurate, eco-friendly technique for soil analysis which can cover unlimited number of samples in unlimited locations' areas (9).

Soil spectroscopy using reflectance data obtained from different sensors has proven a very effective performance in estimating soil properties. The reflectance data can be acquired from different kinds of sensors such as laboratory, field, airborne (10) or space borne sensors using various spectral ranges. These spectral ranges are such as ultraviolet, visible, near infrared, mid infrared and microwave. Among these spectral ranges, the visible and near infrared (vis-NIR) has been found to be a very effective for estimating a wide range of soil properties such as soil pH, salinity, cation exchange capacity, soil organic carbon, soil organic matter, calcium carbonates, clay, silt, sand, available macro and micro nutrients, total macro and micro nutrients, clay minerals, exchangeable cations such as sodium, calcium, magnesium and potassium as well as other soil elements such as chloride, sulfur and trace elements (11, 12).

Accurate estimation of the various soil properties depends on the quality of the spectral signatures collected from the soil samples. There are several studies evaluated the soil quality using the traditional protocols (13). The reflectance information collected from soil is a response of the different soil chemo metrics such as organic matter and clay minerals which appear as signals occurred by strong absorptions. However, there are two main soil chromophores which the first one is the direct chromophores (can be correlated directly to the soil properties); and the second is the indirect chromophores which are indirectly correlated to the soil properties and must be directly correlated with the direct chromophores. The main direct chromophores in soil are soil organic matter and soil minerals; while the indirect chromophores are such as other soil properties (pH, salinity and others) as described in many publications (14, 15).

Soil spectral library is a combination of different soil samples' reflectance data collected by a specific or same sensor in which the soil samples must be tested for their physical and chemical properties. Integration of soil properties' data and soil spectral data is very important for building the estimation or prediction models. These models are regression equations which include the two main factors (weighting of the soil property scores and weighting of the significant bands scores). However, these prediction models are helpful for quantitative estimation of the soil properties which unknown to the spectral library's datasets. There are some successive stories regarding creating soil spectral libraries and their potentialities against soil properties' estimations. Among them, the OSSL which have proven efficiency in estimating soil properties (16, 17).

For building such soil spectral library, good calibrations must be initiated using good quality spectral data as well as laboratory analysis. Integration of these data and Machine Learning (ML) as well as multivariate regression models is crucial for generating better quality SSL. Utilizing ML prediction models such as Partial Least Square Regression (PLSR), Artificial Neural Network (ANN), Support Vector Machine (SVM), Random Forest (RF), Multiple Adaptive Regression Splines (MARS) and other models are very effective for developing prediction models for estimating soil properties (18, 19). Previous research highlights significant advancements in integrating ML with SSLs, particularly in addressing India's diverse soil landscapes. Studies by the National Remote Sensing Centre (NRSC) demonstrated the efficacy of hyperspectral data combined with statistical transformations (e.g., PLSR) to predict soil pH, EC and nutrients, achieving high correlation with lab results in Kerala's Palakkad district. Comparative analyses of ML models reveal nuanced performance variations: Gradient Boosted Regression Trees (GBRT) showed superior accuracy over Random Forest (RF) for phosphorus prediction, though RF's stability and feature relevance make it viable for large datasets despite overfitting risks. Similarly, Support Vector Machines (SVM) outperformed K-Nearest Neighbour models in predicting properties like organic carbon and pH in Indian soils, emphasizing context-specific model selection. Globally, initiatives like the OSSL underscore the importance of harmonized datasets and collaborative calibration, though India's representation remains limited in existing libraries (e.g., only 104 Asian samples in a global library of 3768 soils). These findings stress the need for localized SSLs with region-specific algorithms to address India's soil heterogeneity, while advancements in ML-driven hyperspectral mapping (e.g., NRSC's national upscaling plans) promise scalable solutions for precision agriculture and nutrient management.

Accuracy assessment is mandatory for evaluating the performance of the applied prediction models as well as the accuracy of the soil properties' predictability. Therefore, some statistical parameters are commonly used for assessing the quality of predictions such as coefficients of correlation, ratio of performance deviation, root mean square error and others (20).

Although the advantages of the SSL for estimating soil properties, there are some limitations such as the applicability of the SSLs. That means, the successive SSL may give reasonable results in an area and not in another. Soil data uniformity and homogeneity is very important factor for achieving an accurate SSL. Sensor quality and precision is another main controlling factor as well as the applied prediction models; and the dataset's size (21).

Thus, this review aims to address the importance, applicability, necessity and limitations of developing soil spectral libraries for estimating soil properties.

Soil analysis

Soil analysis is important for providing a comprehensive assessment of soil properties and gain insights about soil chemical, physical and biological characteristics. It is also crucial for various applications such as in agriculture as well as environmental aspects whereas fully understanding of the soil composition is necessary for achieving sustainable practices (22). However, soil analysis in either laboratory or field is a determination of the different soil attributes such as measuring soil macro and micronutrients which are essential for plant growth and offer fertilization recommendations for farmers or stake holders. However, the total micronutrients content was analyzed using different methods (23). Additionally, determining the concentrations of the macro and micronutrients is very important for identifying the nutritional status of the cultivated crops and addresses the issues based on the nutrients' deficiencies (24). Other soil properties which are analyzed using the traditional methods of analysis are such as soil pH, salinity, contaminants, soil texture, cation exchange capacity, moisture, calcium carbonates, organic materials, clay minerals and others. Besides these advantages, soil analysis aims to minimize the costs required for the agricultural activities and maximize the benefits from the agricultural productivity as well as enhancement of the soil health, which are parts of the precision agriculture objectives (25). On the other hand, soil testing is useful for providing exact information and recommendation against specific crop or growing plant which include water and nutrients' requirements. Literature mentioned the water assessments using the traditional methods of analysis (26, 27). Soil analysis is important also for assessing the possible issues such as land degradation, contamination, desertification and others. The obtained insights from the soil analyses can be taken in account by the stakeholders regarding achieving better land management and planning (12).

Soil analysis advantages and disadvantages

Soil analysis is crucial for achieving optimal agricultural practices as well as land management which can provide essential observations of the soil health and its fertility. There are many advantages of soil analysis such as nutrient management whereas accurately evaluating of essential nutrients' levels like nitrogen, phosphorus and potassium is useful for farmers who can optimally uses the fertilizers to fulfil the exact need of the growing crops (28). Therefore, this advantage not only enhances the crop productivity but also reduce the risk from the intensive fertilization which can make another problem such as pollution (29) and degradation. Another advantage is achieving a part of the environmental sustainability's goals whereas soil analysis aims also to reduce the used fertilizers which harm the environment. With achieving the 4Rs (right 'source', 'rate', 'time' and 'place'), the farmers will be able to manage the agricultural inputs. Moreover, continuous soil analysis helps in monitoring the soil health and their controlling parameters such as soil pH and organic matter which are very crucial for sustainable agriculture and soil fertility. This advantage can contribute to saving costs whereas optimizing fertilizer use to improve crop's management based on soil analysis, can improve the overall farmer's profitability (30).

There are some disadvantages of soil analysis using the traditional methods of determination. Among these disadvantages, the high costs associated with laboratory analysis starting from surveying, sampling, shifting, preparing, analyzing and interpreting. These processes consume money and cannot be feasible for the farmers in case of large-scale areas which can be done by new technology even using the low-cost smartphone services. Another drawback is the temporal limitations whereas the soil properties changes because of climatic conditions as well as the crop rotations and human land practices (31). Therefore, repeating the long, costly and tedious processes of surveying, sampling and analysis is very difficult. Several studies used the traditional methods for studying the long-term effects of the agricultural activities on the soil capability and suitability (32). Moreover, obtained results of the soil analysis are complex and need experience for interpretation and give right decisions which may not be available in many farmers (33).

Need for new advances techniques

There is a strong need for new advanced, cheaper, faster and clean techniques for soil analysis. This need is because of the disadvantages of the traditional soil testing methodologies as well as the increasing complexity of the agricultural practice day by day. The required technique must be able to avoid the limitations of the conventional methods of soil analysis for achieving better and sustainable land management (34). As the traditional methods of soil analysis has many limitations such as time and costs' consuming, laborious, destructive and limited accuracies; new techniques are needed. There are some advanced techniques which play crucial role in supporting soil analysis. These techniques are such as Artificial Intelligence (AI), ML and RS. However, these techniques are rapid, cost-effective, eco-friendly and accurate for real-time and robust soil properties' estimations (35). For example, the AI algorithms analyze large sized datasets which collected from different sources (wet-chemistry analysis and spectral reflectance data) to predict and quantitatively estimate the different soil properties. By using these AI algorithms, quick and efficient decisions can be taken regarding the agricultural practices. Moreover, ML utilizations provide accurate prediction models based on soil laboratory data as well as environmental attributes. The ML models such as RF and SVM help in predicting soil properties in unknown soil samples to provide spatial overview against soil status (36). Remote sensing (RS) tools provide large-scale monitoring and characterizing of soil properties with minimal requirements of ground-based soil sampling. However, acquiring soil spectral reflectance data using different sensors such as ground-based sensors or even satellite imagery, much soil attributes can be characterized. Previous study viewed the soil characterization and classification using the conventional methods of soil surveying, sampling and analysis (37). By using high-resolution monitoring technique, soil variability can be detected in field to reducing the inputs of agricultural activities. Integrating AI and RS for analyzing soil properties has promising and potential future whereas further efforts must be given for improving the accuracy, as well as cost-effectiveness of these new and advanced technologies in different geographical scales even farm scale (38, 39). Besides establishing standard protocols for each step (data collection, preparation, calibration and analysis) can enhance the reliability of the outputs in different regions and contexts (40).

Remote sensing (RS)

The RS is acquiring information of any object without physical contact using different kinds of sensors or cameras. Specifically in agriculture, the RS techniques employ aerial or satellite imageries for acquiring spectral data of vegetation and soil with reasonable speed, accuracy and data size for large, scaled areas (41). There are many applications of RS in agricultural sector such as crop health monitoring whereas RS data are captured for the vegetation cover to detect the nutrients' deficiencies as well as stress conditions. The visible and near infrared range of spectra can be used as RS tool for detecting the crop's changes employing various spectral analyses. The outputs of these analyses can be helpful for farmers to take suitable decisions in suitable times regarding the irrigation, fertilization and pest-controlling (42). The multispectral and the hyperspectral RS are used for identifying the plant requirements of the nutrients as well as other agricultural practices. Additionally, RS is used for crop's yield estimation using time-series spectral data of each growth stages of the plants which essential for planning harvest logistics and optimizing storage utilization. Furthermore, RS can detect the quantities of soil moisture in different soil types and agricultural climatic regions, which this information is necessary for irrigation scheduling (43). Not only these mentioned applications of RS, but also environmental monitoring can be done using different spectral aspects to detect various climatic factors such as air quality, weather patterns and climate change. The RS is utilized effectively for detecting and mapping land use and land cover and their changes by using different images and suitable prediction models (44).

There are many applications of RS in soil studies based on the soil testing methods. Soil properties mapping using RS data can be done for different soil properties such as texture, organic matter content and nutrients to overview the spatial variability distribution in detail. By utilizing the RS data, soil moisture can be detected and assessed to evaluate the drought conditions and manage the irrigation more efficiently (45). Moreover, the RS data can be employed in detecting soil erosion through analyzing the changes in the land cover by the time to allow better soil conservation strategies for protecting the soil health and improve the agricultural productivity (46). An integration of the RS data and soil measurements is mandatory for achieving the objectives of precision agriculture which enhance the decision-making process.

Soil spectroscopy

Soil spectroscopy is an interaction of electromagnetic radiation and soil matrix aims to estimate soil properties like nutrient content, organic matter, moisture, salinity, pH and others. Detecting soil attributes is based on the molecular vibrations as well as electronic transitions occurred when soil chromophores interact the incident light (47). This can be acquired by collecting soil spectral signature using the spectral range between the visible, near infrared or mid infrared which can be correlated with the soil analysis' data (48).

Moreover, there are many applications of the soil spectroscopy techniques in soil testing purposes, whereas one of the main advantages is the ability for providing fast and reliable evaluations soil properties using single scan (49). Soil spectroscopic technology is employed in effective estimation of key macro nutrients (nitrogen, phosphorus and potassium) and micronutrients (iron, manganese, copper and zinc) using real-time data for providing exact insights about the soil nutrients availability for farmers to take a suitable decision. Additionally, soil spectroscopy provides the capability of monitoring the content of the soil organic matter and other fertility and quality parameters (37). These modern techniques are also engaged in precision agriculture practices which allow the Site-Specific Nutrient Management (SSNM) and mapping their spatial variability. Soil spectroscopy plays a vital role in evaluating the environmental factors such as soil, air and water contaminants and detecting the land use and land cover changes in soil which reflected by the different agricultural practices (48).

Machine Learning (ML) and Artificial Intelligence (AI)

The Ml and AI techniques transform the conventional soil analysis to be economic, faster, more accurate and robust for detecting, estimating and assessing various soil properties and their conditions. These techniques provide quick processing of big soil data obtained from the laboratories, fields and sensors to estimate the soil parameters. Moreover, ML prediction models such as multivariate regressions and other models can integrate the soil chemistry data and the soil spectral signatures for achieving better estimations for unknown samples (50). Furthermore, the AI helps in monitoring soil quality and fertility using many specific algorithms as well as being used for smart irrigation. Not only these applications cut also the soil spectroscopy and AI models can be employed in soil classification based on various soil properties such as soil texture, cation exchange capacity and clay minerals using RF, ANN and XGBoost prediction models (51).

The best ML prediction models for soil estimations

The ML prediction models are mainly based on statistical relations between independent and dependent variables for selecting better predictions. However, the ML models are crucial for soil properties' estimations which provide faster solutions and good alternative to the conventional techniques of soils' data processing and interpretation (52). There are three main kinds of the prediction models (regression, ML and deep learning 'DL') whereas the regression models are such as multivariate regression which are publically utilized in establishing relationships between soil samples' analysis and their corresponding spectral signatures. Another type is the ML models such as RF, ANN, SVM and others which can deal with very large and complex datasets as well as the non-linear relationships (53). For example, there are many studies employed these models for estimating soil properties such as soil pH (54), salinity (55), cation exchange capacity (56), calcium carbonates (57), organic carbon (58), nitrogen (59), phosphorus (60), potassium (61), iron (62), manganese (63), copper (64), zinc (58) and clay minerals (65). Among these ML models, ANN is effective in modeling complex relationships for the soil properties' data and developing accurate estimations. The DL approaches such as Long Short-Term Memory (LSTM) networks can be utilized for soil moisture estimation to achieve continuous monitoring of the moisture content to take an action regarding irrigation or selecting suitable crops which can be adapted in the soil (66).

However, these ML and DL models have many advantages regarding their utility in soil estimations. These advantages are such as reducing the time needed for soil determination. Moreover, these models are cost-effectiveness which provides farmers better and cheaper solutions for their business. These models offer quick possibility for making suitable decisions regarding the various agricultural activities such as irrigation, fertilization and pest-controlling. Additionally, predictive models including geo-statistical approaches for interpolating the unknown soil attributes based on the developed datasets can be an optimal option for proximal soil estimations (67).

Soil properties' predictabilities

The vis-NIR spectroscopy and ML models together can estimate the soil properties in rapid, cost-effective and eco-friendly way the most predictable soil properties include soil organic matter, moisture, texture and minerals. The soil organic matter can be accurately predicted because the strong correlation between organic matter and strong specific absorption features (spectral functional groups) in the NIR spectral range (58). The total nitrogen can be also accurately detected using the vis-NIR and ML due to the captured data of the strong absorptions associated with nitrogen compounds. Moreover, the ML and vis-NIR can predict soil texture and its fractions (clay, silt and sand) but with variable accuracies whereas clay is more accurately predictable than silt or sand. Soil pH predictability varies from study to another because it depends on the soil organic matter content as well as the nature of the soil minerals. The most predictable soil parameter is the soil moisture content which there is some functional groups help in accurate estimation of soil moisture in 1400, 1900 and 2200 nm (48). Furthermore, the soil calcium carbonates can be also estimated based on the ML and vis-NIR integration due to carbonates related spectra of soil minerals.

The sensitive spectral bands for estimating each soil property

In the spectral range of the vis-NIR between 350 and 2500 nm, the different soil properties can be individually estimated. Each soil parameter can be detected based on some significant or sensitive spectral bands or wavelengths (Table 1). However, soil organic matter can be estimated accurately in the wavelengths of 1400 and 1900 nm which are associated with the absorption features of C-H bonds (58). Total nitrogen can be detected using the spectral band of 2100 nm which correlated effectively with the nitrogen compounds (59). Regarding the soil texture fractions, spectral bands of 1800, 2000 and 2100 nm can be used for estimating clay, while the band of 1400 nm is used for sand (48). Moreover, the spectral bands around 1700 nm are associated with soil pH (54); while soil moisture functional groups are exactly in 1400, 1900 and 2200 nm (48). Furthermore, calcium carbonates can be detected in the range between 400 to 2500 nm with high accuracy (57); and salinity expressed by the electrical conductivity can be estimated using the 2100 nm wavelength (55).

Soil Spectral Library (SSL)

The SSL is a soil samples' database which includes chemistry analysis' data as well as spectral data collected in a specific spectral range (i.e. vis-NIR) using one sensor. Based on this database, many soil properties can be estimated like soil organic carbon content, texture, moisture, mineral composition and others (68). In this process, integration between these databases and AI models occurred. The scientific base behind the SSL is that the reflectance or absorbance patterns of soil samples cab be matched with some soil attributes which called chromophores had spectral functional groups. These outputs can be correlated with other indirect soil properties or spatial locations for larger detection or mapping purposes. However, the SSL has proven efficiency in estimating soil properties using the collected data from field or laboratory sensors which is rapid, cost-effective and eco-friendly (69). The SSL is employed also in digital soil mapping whereas large, scaled areas can be easily mapped with reasonable accuracy and resolution. For example, digital soil mapping can be done for the carbon sequestration as well as land degradation levels and soil health (70). However, these maps can be considered as guide for decision makers and stake holders for better land management and planning. The Global Soil Spectral Library (GSSL) which was created by Food and Agriculture Organization (FAO) include soils' data collected worldwide can be employed for national and international mapping of the soil properties (16). By using this GSSL, soil health monitoring and characterizing can be easily and continuously done.

Role of SSL in soil estimations

The SSL is crucial modern analytical tool for soil analysis which offers robust and efficient protocol for comprehend understanding and estimating soil parameters using the vis-NIR spectral data (69). Moreover, the SSL save the time and cost compared to the conventional methods of soil analysis in laboratory without using any chemicals or other further instruments. As previously mentioned, the SSL is combination of soil chemical analysis' data and the soil spectral signatures which are modelled using the ML prediction models. The most common uses of the SSL are for predicting and mapping soil organic carbon and soil minerals without field surveying, sampling or laboratory analysis. Furthermore, integration between SSL, GIS and digital soil mapping offer a great opportunity for estimating and mapping the different soil properties in accurate way. These opportunities may save costs of fertilization, irrigation, pesticides and other agricultural practices (16).

SSL creation

Creating SSL is a systematic criterion which starting with collecting soil samples, preparing and determining against their physical and chemical properties as well as spectral signatures. However, the detailed criteria (Fig. 1) include soil surveying which aims to understand the soil variability and types in the proposed sites which can be different in the soil texture, colour, elevation, organic materials, oxides, minerals, lime, gypsum, or other main factors. Afterwards, soil mapping units are developed to know the number of soil types or samples which can be represented or collected from the area (71). The sampling process depends on the purpose of samples collection as well as the soil properties needed to be determined whereas disturbed soil samples can be collected for chemical tests, while undisturbed or core soil samples are obtained for physical determinations. However, in most cases, surface soil samples are collected for building SSLs because of their possibility to be matched by other remotely sensed data

Table 1. The soil properties predictability and their corresponding sensitive spectral bands

Soil property	Predictive wavelengths (nm)	Typical correlation coefficient
Soil organic matter	1400, 1900	High (varies by study)
Total nitrogen	2100	Moderate to high
Soil texture	1400, 1800-2000	Sand (positive), Clay (negative)
Soil pH	1700	Variable
Soil moisture content	1400, 1900	Negative
Calcium carbonate	2100	Very high
Soil salinity	2100	High

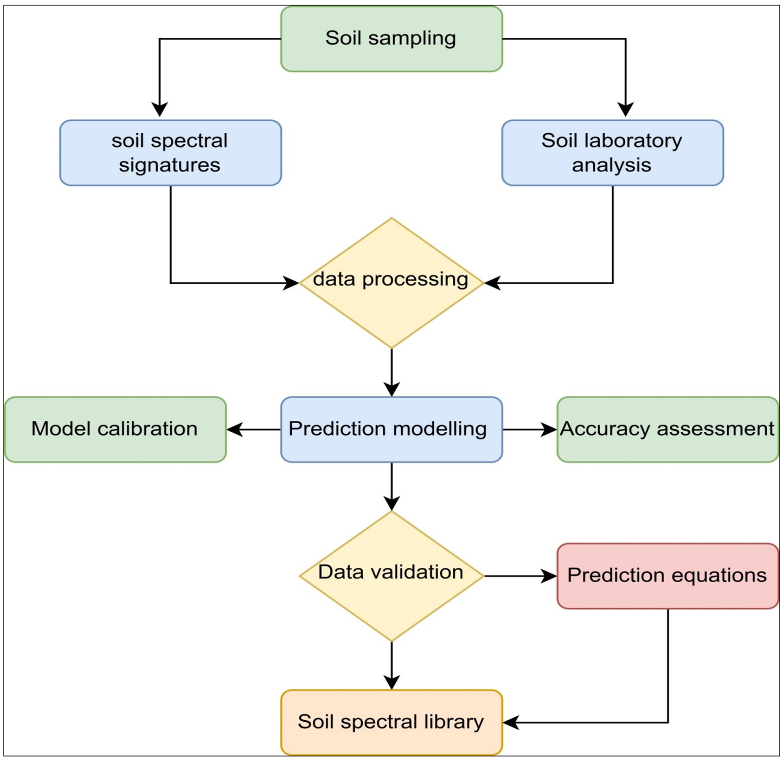

Fig. 1. The criterion of creating the SSL.

sources such as air-borne, or satellite-based sensors. All possible observations are collected and recorded in the field while soil samples are collected such as soil labels, date, depth, area's name, latitudes, longitudes, altitude and others (72).

Accordingly, soil samples are shifted to the hyperspectral remote sensing laboratory which is a dark or black room designed especially for acquiring soil spectral signatures without any external effects of any light source except instrumental. However, the soil spectral data in the spectral range between 350 and 2500 nm are collected using specific sensor or spectroradiometer. The spectral formatted files are converted to text files to be easier for sharing and processes using several kinds of software. Moreover, these soil samples are prepared to be analyzed for their physical or chemical properties whereas air -dried, crushed and sieved as well as kept in suitable storing containers. Soil physical properties such as colour, bulk density, particle density and soil texture as well as soil stricter and aggregates' stability can be determined; while the soil chemical properties are soil pH, salinity, calcium carbonates, soil organic matter, gypsum, oxides, minerals, cation exchange capacity and others. Other soil properties can be measured such as the soluble, exchangeable, available and total contents of several soil properties such as potassium, sodium, calcium and magnesium; as well as available and total contents of the macro and (48, 72).

After the soil spectral and chemical analysis done, data integration and calibration can be done whereas in one excel sheet, the soil chemical properties and the spectral reflectance data are combined (50). These prepared data are processed using many steps including data normalization (all values are between zero and one); data randomization (selecting data in either calibration or validation datasets is random); data sorting (distributing high, moderate and lower values equally between the two datasets of calibration and validation); removing outliers (using suitable data transformation method to eliminate odd values which are either much higher or lower than the dataset's mean). Afterwards, applying the suitable models for predicting or estimating different soil properties is conducted. These models are such as PLSR, ANN, RF, MARS, SVM, or others which all depend on the ideation of data rotation and cross-validation techniques (51).

Consequently, model's evaluation of accuracy or performance is conducted using statistical parameters such as R-squared, RMSE, RPD, or others to understand the predictability of each soil property as well as the performance of the applied prediction model. There are many factors affects the accuracy and the predictability such as the soil samples' variability, preparation, number, colour, type, collection method, analytical method, scanning protocols, etc. However, after developing the prediction models and knows the accuracy of each soil property to be estimated by the different kinds of prediction models, the SSL is ready to be created using suitable software. Moreover, other spectral processing techniques can be employed for selecting the sensitive spectral bands as well as developing the regression or prediction equations to be used in other areas. It must be mentioned that the SSL generated based on a specific calibration dataset may work in a specific area and not for another due to soil variability and other environmental or experimental factors (58).

Success stories of the SSLs

Several SSLs have been successfully implemented worldwide such as the GSSL which succeeded in estimating soil properties like organic carbon, clay content and pH. The GSSL facilitated large-scale digital soil mapping to monitor the soil health and productivity (72). The second example is the Africa Soil Information Service (AfSIS) which aimed to improve the African soil health and fertility based on analyzing thousands of soil samples to help farmers to take correct and suitable decisions regarding their farms. The AfSIS contributed to increasing the agricultural productivity and food security in degraded regions (73). Another example is the Brazilian Soil Spectral Library (BSSL) which developed from various soil types (included thousands of soil samples) of Amazon rainforest, Cerrado savanna and Atlantic Forest. The BSSL is employed in mapping the LULC as well as different agricultural practices (74). European Soil Spectral Library (EUSSL) was initiated under the LULC Area frame Statistical Survey (LUCAS) program which represented different countries' samples to achieve accurate estimation and mapping of soil organic carbon, texture and pH (68). Another library is the Australian Soil Spectral Library (AuSSL) which aimed to create high resolution datasets and maps for the unique soil challenges in Australia such as soil salinity, erosion and nutrient depletion (75). China Soil Spectral Library (CSSL) was developed in large-scale to map soil properties across the country, including areas affected by pollution and degradation (76). It has also supported the development of precision agriculture technologies. Additionally, Soil Health Card Scheme in India (SHCS) which issued to analyze soil samples and provide farmers with personalized recommendations for fertilizer and crop management quickly and cost-effectively (77).

Advantages and limitations of the SSLs

The SSLs have several advantages for soil analysis and management such as are rapid and Non-destructive (73). The SSLs offer quick evaluation of soil parameters utilizing spectroscopy compared to the conventional methods which are very useful in case of large, scaled regions. The conventional soil analysis' methods were briefly discussed in previous works (78). Moreover, the SSLs are cost-effective tools for estimating new soil samples which can analyze unlimited number of soil samples in limited time for regional, national and global scales. The SSLs are high resolution and eco-friendly option for environment as an alternative to traditional soil testing methods. Furthermore, the SSLs are capable to estimate a wide range of soil properties like organic carbon, salinity, texture, pH, moisture and nutrient content utilizing single spectral measurement. Regarding the data integration and sharing, SSL offers a standardized platform for these purposes across regions and institutions which encourage the collaboration and enhances the global understanding of soil systems (74). Additionally, SSLs support the precision agriculture's objectives for saving the agricultural production's requirements such as fertilization, irrigation and crop selection to monitor of soil health, land use as well as mitigate climate change impacts. Fig. 2 displayed the several factors affect the SSL (77).

There are also some limitations of the SSLs such as dependence on reference data collected from laboratory to develop the accurate calibration models which can be expensive and time-consuming for large number of soil samples in large-scaled projects. The SSLs are specific for actual regions and may not perform well in another due to differences in soil compositions, climates as well as environmental conditions (68). However, this limitation can be ignored by specific regional calibrations including homogenous soil samples' datasets. The soil spectral variability is another limitation which can be affected by factors such as moisture content, particle size and surface roughness, which can introduce variability and reduce

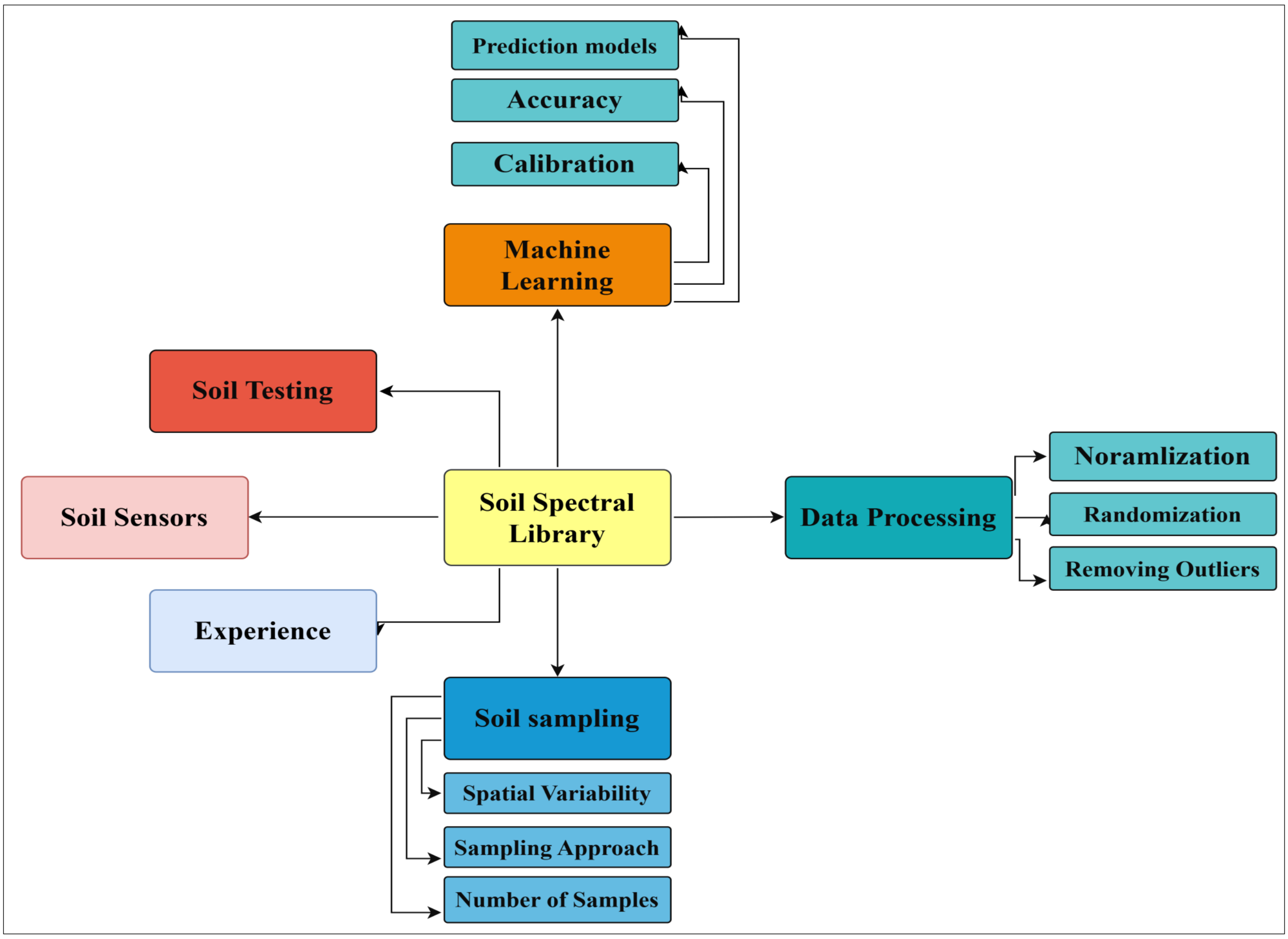

Fig. 2. The several factors affect the SSL.

prediction accuracy by the different models or data analytics' tools. The complexity of using the prediction models and different data processing and transformation tools are also challenges face the applicability of the SSLs. Moreover, the SSLs are limited in their accuracy for some soil properties whereas micronutrients' content and specific mineral types are not accurately detectable by the soil spectroscopy. As soil is a dynamic and complex matrix, the SSLs cannot be an optimal method for estimating soil properties accurately over time due to the continuous management practices, climate and biological activity. Therefore, the SSLs need to be regularly updated to remain accurate and relevant which is difficult whereas the instrumental measurements and soil analysis are expensive (75).

Necessity of the SSLs in India

As the SSLs are vital for modern agriculture specifically for soil analysis and estimations, India need such technique because of its diverse agro-climatic zones, extensive agricultural activities and land uses. The SSLs enable quick and non-destructive soil estimation utilizing spectroscopic tools which is efficient compared to traditional methods. Moreover, the SSLs offer large-scaled soil mapping, monitoring soil health, fertility and degradation over different regions as well as support the precision agriculture's objectives by providing detailed data related to soil macro and micronutrients, moisture content and texture fractions (clay, silt and sand), optimizing resource uses as well as productivity (77). Additionally, the SSLs help in detecting soil health changes over time to address the various challenges such as degradation, salinity and erosion and mitigate climate change impacts. Besides these applications, the SSLs are cost-effective compared to traditional methods of soil analysis whereas provide the Government initiatives such as the SHCS as well as help in the sectors of research and development. SSLs offer significant advantages over traditional soil assessment methods in the Indian context. Unlike conventional laboratory techniques, which are often time-consuming, labor-intensive and require expensive reagents and skilled personnel, SSLs enable rapid, non-destructive and cost-effective estimation of multiple soil properties from a single spectral measurement. This is particularly beneficial for India, where there is vast heterogeneity in soil types and a pressing need for timely, large -scale soil health assessments to support sustainable agriculture and resource management. SSLs also facilitate the use of hyperspectral remote sensing, allowing for efficient mapping and monitoring of soil attributes across diverse landscapes, which is crucial given India's scale and diversity. Additionally, by centralizing high-quality reference data, SSLs help overcome limitations of inconsistent laboratory standards and limited local capacity, making advanced soil analysis more accessible to regions with fewer resources. This accelerates decision-making in agriculture, land use and environmental management, supporting India's goals for food security and climate resilience. Regarding the global cooperation, the SSLs offer enhances for international collaboration. However, there are some limitations may face India for implementing and creating such SSLs such as developing infrastructure, training personnel, integrating spectral data with existing databases and ensuring accessibility for smallholder farmers (79-84).

Conclusion

SSLs have emerged as transformative tools, enabling rapid, cost-effective and scalable soil property assessment that supports precision agriculture and sustainable land management. Their integration with advanced machine learning models and open, collaborative initiatives such as the OSSL has significantly improved the accessibility and reproducibility of soil data, especially when libraries are regionally tailored to capture local soil diversity. However, limitations remain prediction accuracy for certain soil properties (such as total sulfur, extractable sodium and electrical conductivity) is still suboptimal and the effectiveness of SSLs depends heavily on the diversity and representativeness of reference datasets. In India, the development of comprehensive, geographically representative SSLs is particularly critical given the country's vast soil heterogeneity and currently limited spectral databases.

Future research should prioritize expanding regional and national SSLs, standardizing data collection and calibration protocols and developing robust, property-specific prediction algorithms. Additionally, efforts should focus on integrating hyperspectral remote sensing with ground-based SSLs, fostering open data sharing and building local capacity to ensure that SSL technology can be effectively leveraged for large-scale soil monitoring, agricultural planning and environmental management in India and beyond.

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Authors' contributions

ARAM and EAAS contributed equally to all aspects of this review, including literature search, analysis, synthesis and manuscript preparation. Both authors have read and approved the final manuscript.

Compliance with ethical standards

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