# Integrating Soil Spectral Library and PRISMA Data to Estimate Soil Organic Carbon in Crop Lands

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***Abstract*— The increasing demand for precise soil organic carbon (SOC) monitoring in croplands is crucial for food security (SDG 2), and has led to the exploration of fusing soil spectral libraries (SSLs) with hyperspectral sensing data for SOC estimation. However, the widespread adoption of SSL for SOC estimation faces challenges, particularly in developing nations, due to inconsistent calibration libraries and reliable estimation models. Furthermore, SSL rely on regular soil sample collection and spectral data recording using spectroradiometers, which is impractical in agricultural-predominant countries, such as India, with limited time for sample collection between crop rotations. To address this challenge, we developed synthesized SSL in laboratory conditions and integrated it with hyperspectral data using machine learning (ML) algorithms to bridge the gap between synthesized SSL and hyperspectral data for local-scale SOC mapping. This approach was tested by mapping SOC in Mysore, India, using spectroradiometer hyperspectral measurements and PRISMA sensor data. The proposed approach and synthesized SSL exhibited better performance prediction accuracies, $R^2$ of 0.92 and 0.79, and the RMSE values of 2.31 and 9.91 g/kg, respectively, for PRISMA and laboratory spectroscopy data. These results highlight the potential of synthesized SSL for SOC prediction in alluvial soils, leveraging local datasets, and hyperspectral data. Our future work will expand the synthesis approach to other study areas, particularly those with alluvial soil origins, further enhancing the applicability of this methodology for SOC estimation and aiding food security efforts.**

***Index Terms*— Hyperspectral remote sensing, India, machine learning (ML), PRISMA, soil organic carbon (SOC), soil spectral library (SSL), spectroradiometer.**

## I. Introduction

THE sustainable development goals (SDGs) for 2030 entail an initiative to safeguard the ecosystem and ensure food security [1]. Conversely, soil degradation in many parts of the world due to organic carbon decline impacts food production, environmental degradation, and carbon sequestration [2]. In the context of zero hunger (SDG 2), adequate levels of soil organic carbon (SOC) are essential to ensure nutrient availability and cycling, soil fertility and productivity, and water retention, which reduces the probability of crop failure [3], [4]. So, studies focused on mapping SOC in croplands are increasing to provide reliable and rapid inputs to farmers. Mapping SOC aids developing nations in accomplishing the SDGs and minimizes cultivation expenses.

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SOC has a slow temporal dynamic with high spatial variability in cropland [5], and continuous monitoring is required through collecting and analyzing a large number of samples throughout the crop period. Conventional wet laboratory techniques, such as the Walkley–Black method (titration and colorimetric method) [6], [7] and the dry combustion elemental analysis method [8], can accurately quantify SOC, but these techniques are expensive and time-consuming. Recent developments in Earth observation (EO) technology brought forward an efficient and rapid hyperspectral remote sensing tool for profoundly mapping and monitoring SOC. In this context, researchers rely on spectroscopic data collected using point spectroradiometers (laboratory spectroscopy) and imaging spectroscopy (airborne and spaceborne remote sensing) [5], [9], [10], [11], [12], [13], [14] in the visible (400–700 nm) and near-infrared (0.7–2.5 $\mu$m) portion of the electromagnetic spectrum. Using the ground-truth (GT) data, a relation between spectral reflectance signatures and SOC can be established using multivariate regression, advanced machine learning (ML), and neural network techniques. To achieve this, it is necessary to construct spectral libraries that mirror the variability of SOC in a target geographic area. This premise is not straightforward to fulfill, and to overcome this limitation, researchers proposed and employed techniques, such as data spiking, e.g., [15], [16], bottom-up approach, e.g., [17], [18], and a spiked bottom-up approach, e.g., [1], integrating the former two methods for estimating SOC locally using the GEOCRADLE soil spectral library (SSL) with simulated ENMAP and Sentinel-2 datasets. The construction of SSL at continental and national levels has substantially enhanced the effectiveness of these approaches, particularly for the local SOC estimation.

Despite considerable progress in developing spectral libraries, a significant obstacle to the widespread adoption of these approaches, especially in developing countries, is the lack of consistent calibration libraries and reliable SOC estimation models [19]. The diversity and lack of standardization in these libraries and models, stemming from variations in data quality, calibration methods, and model accuracy, are a notable challenge at present. Moreover, these approaches require regular soil sample collection and spectral data recording using spectroradiometers, which can be impractical in countries, such as India, with extensive agriculture and limited time for collecting samples between crop rotations. So, a novel methodology has been proposed to bridge the gap between data collection and the use of SSL to estimate SOC. The aim was to create a synthesized SSL of alluvial soils in laboratory conditions to mimic the variability in the SOC range observed in field conditions and achieve a better representation of high SOC values. Furthermore, the capability of synthesized SSL was tested using hyperspectral data for SOC estimation.

The study aimed to estimate SOC accurately using well-known ML techniques, including partial least square regression (PLSR), support vector regression (SVR), kernel ridge regression (KRR), random forest (RF), Gaussian process regression (GPR), and extreme learning machine (ELM), to address these issues. The algorithms were adopted to calibrate and validate predicted SOC values in assessing the synthesized SSL performance and its integration with PRISMA data.

## II. Materials

### A. Study Area

This work selected the alluvial-rich [20] Krishnaraj Nagar (KR Nagar) study region, located northwest of Mysore city, Karnataka, India. The dataset acquisition was carried out on March 22, 2022. Paddy, pulses, and ragi were the primary food crops cultivated in the study area. The Köppen–Geiger climatic classification system places KR Nagar in Zone Bsh, with an annual average rainfall of 1003 mm [21].

### B. Procurement of PRISMA Hyperspectral Data and Processing

RS data over the study area were acquired using the hyperspectral sensor PRISMA. The data were acquired on March 21, 2022, using the two hyperspectral cubes in VNIR (400–1010 nm) and SWIR (920–2500 nm) flown at an altitude of 615 km and a spatial resolution of 30 m. PRISMA collects data in 240 spectral bands with a field of view (FOV) of 2.45 and an SNR of 100–240. Atmospherically and geometrically corrected level 2-D products of PRISMA were downloaded (https://prisma.asi.it) [22]. Bands effected by atmospheric water vapor and incomplete spatial data were removed, and the remaining 153 bands were used for analysis.

### C. Preparation of Synthesized Soil Spectral Library and Validation Data

The introduced synthesized SSL was developed by using the soil of alluvial origin. Initially, a sample was preprocessed by following the steps in the order of oven drying, grinding, sieve analysis, and sample cleaning in typical laboratory conditions. Then, 159 soil samples were prepared by thoroughly mixing fixed proportions of soil and organic compost to obtain soil samples with specific SOC content. The proportions were designed to mirror the typical SOC levels found in croplands [23] while maintaining the C:N ratio within the range of 14:1–30:1 [24]. The spectral signature of each sample was recorded using a spectroradiometer in dark laboratory conditions using an ASD FieldSpec 4 spectrometer manufactured by Analytical Spectral Devices, based in Boulder, CO, USA. The data covered a wavelength range from 350 to 2500 nm, with precise 1-nm intervals. Artificial lighting (50 W at 2950 K) was employed for consistent illumination during the measurements at an incident angle of 40°–50°. The spectroradiometer was operated from a distance of 50 cm, using a pistol grip to target each soil sample. The spectroradiometer had an FOV with a radius of 3.5 cm, and the sensor had an angle of view (AOV) of 8°.

The spectral signature was resampled to the spectral resolution of PRISMA employing a relative spectral response (RSR) function that included center wavelengths and full-width at half-maximum (FWHM) as variables. This synthesized SSL was alone used for the calibration of ML models.

A local spectral library was prepared from 43 GT samples to validate ML models. The SOC of samples was determined to improve in wet laboratory conditions using a TOC analyzer. The spectral signature of a sample was obtained from the spectroradiometer and PRISMA data.

## III. Methods

This study seeks to evaluate the effectiveness of synthesized SSL in estimating SOC using a two-tiered approach. The specific procedures for both cases are depicted in Fig. 1(a) and (b).

### A. Case-I: Prediction of SOC Using Synthesized SSL and Laboratory Spectroscopic Data

The synthesized SSL undergoes spectral preprocessing, followed by the calibration of ML models. Top-performing models were selected for each step, and local SSL spectral data were used to predict SOC, which was then validated with SOC determined from chemical laboratory analysis.

### B. Case-II: Prediction of SOC Using Synthesized SSL and Spaceborne (PRISMA) Data

In case-II, the spectral data from the synthesized SSL were integrated with PRISMA data using spectral resampling. Resampled spectral data were preprocessed before being used to calibrate ML models. In order to estimate SOC, the top-performing model was then chosen and incorporated with spectral data from the PRISMA spaceborne sensor. Eventually, SOC determined by laboratory testing was employed for validation.

### C. Preprocessing of Spectral Data

Testing various preprocessing techniques that might improve absorption bands and perform scatter correction is typical in soil spectroscopy. A detailed summary of these techniques is published in [23]. The following frequently employed preprocessing strategies were investigated: 1) spectral reflectance (Ref); 2) continuum removal transformation of reflectance spectra (Ref + Cont); 3) smoothing of the reflectance spectra using a zero-order Savitzky–Golay filter and standard normal variate (Ref + SG0 + SNV); 4) first derivative of reflectance spectra (Ref + 1st Der); 5) second derivative of reflectance spectra (Ref + 2nd Der); 6) absorbance spectra (Abs);

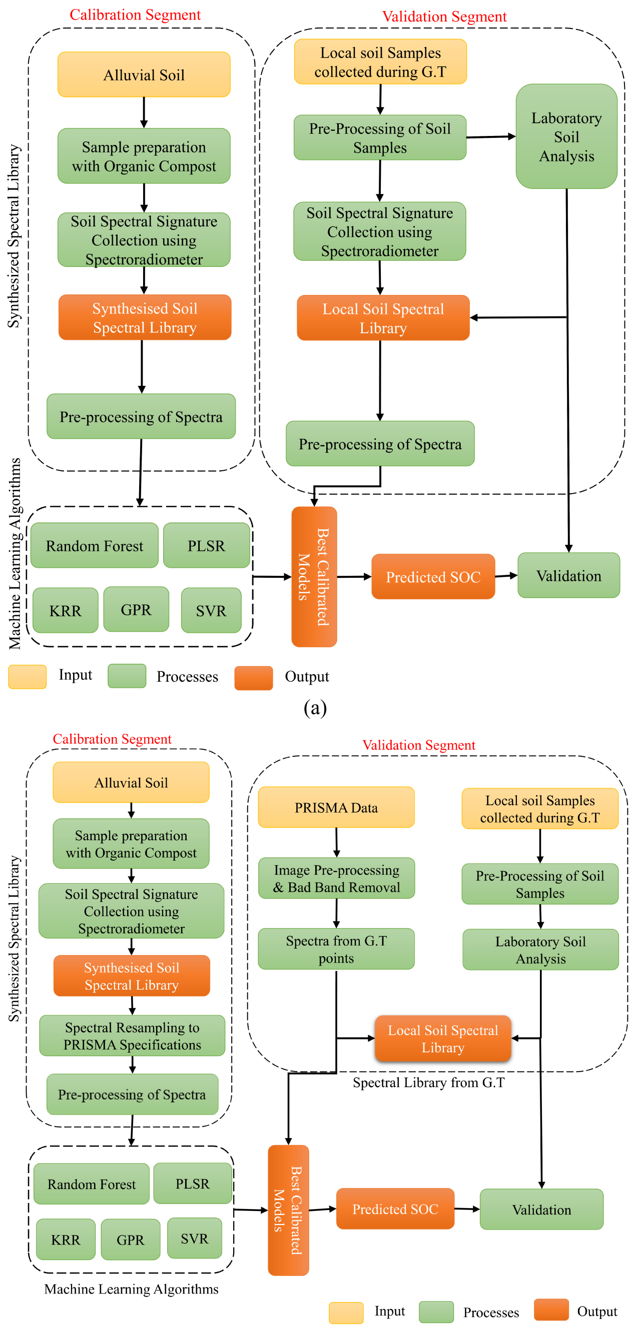


Fig. 1. (a) Methodology opted for case-I: prediction of SOC using synthesized SSL and laboratory spectroscopic data. (b) Methodology opted for case-II: prediction of SOC using synthesized SSL and spaceborne (PRISMA) data.

7) continuum removal of absorbance spectra (Abs + Cont); 8) smoothing of the absorbance spectra using a zero-order Savitzky–Golay filter and standard normal variate (Abs + $SG_0$ + SNV); 9) first derivative of absorbance spectra (Abs + 1st Der); and 10) second derivative of absorbance spectra (Abs + 2nd Der).

### *D. Integration of Synthesized SSL and PRISMA Data*

The integration was done by resampling the synthesized SSL spectra to the PRISMA hyperspectral data standards. We employed the weighted sum technique [25] using "(2)" to

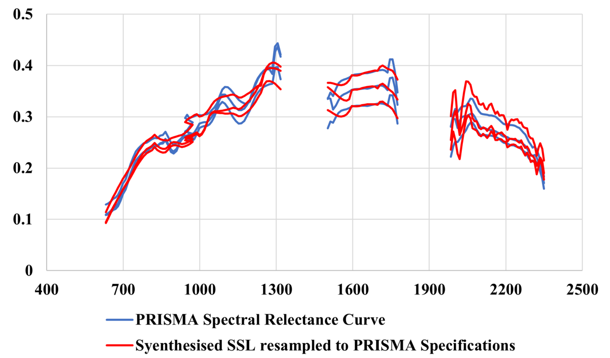


Fig. 2. Sample spectral reflectance curves for PRISMA data and synthesized SSL resampled to PRISMA specifications.

perform the resampling. This technique relies on the RSR of the PRISMA [26] and the spectroradiometer spectra as inputs. The RSR of PRISMA is defined by a Gaussian function in the following equation:

$$\mathrm{RSR}_\lambda = \frac{1}{\sigma\sqrt[2]{2\Pi}} e^{\frac{-(\lambda-\mu)^2}{2\sigma^2}} \tag{1}$$

where $\sigma$ is defined as follows:

$$\sigma = \frac{\mathrm{FWHM}}{2\sqrt{2\log(2)}}$$

where

1) $\lambda$ = sample wavelength of the sensor
2) $\mu$ = average wavelength
3) FWHM = full-width at half-maximum.

Resampled spectra (Fig. 2) can be calculated by the weighted sum of the spectral response of the PRISMA with the hyperspectral reflectance profile at each sampled wavelength, weighted by the respective RSR

$$\hat{f}_{\lambda j} = \frac{\sum_i^n S_{\mathrm{Prisma},i} \times f_{\lambda i}}{\sum_i^n S_{\mathrm{Prisma},i}} \tag{2}$$

where

1) $S_i = \mathrm{RSR}_{\lambda j}$
2) $f_{\lambda i}$ = spectral value of the input spectrum at wavelength $\lambda$ and band $i$
3) $S_i$ = spectral response function weight at $\lambda i$
4) $\hat{f}_{\lambda j}$ = spectral value of output spectrum at wavelength $\lambda$ and band $j$.

### *E. Validation and Verification of Results*

The initial local SSL developed in laboratory conditions (159 samples) was used for the calibration of ML models and also to validate the proposed methodology. The SSL was constructed using field data (43 samples) and used for validation. The predictive model's accuracy was subsequently determined by calculating the coefficient of determination ($R^2$) and the root-mean-square error (RMSE).

## IV. Results and Discussion

### *A. Overview of Soil Spectral Libraries*

The results of the chemical laboratory assessment of the SOC content of both synthesized and local SSL are summarized in Table I. The range of the local SSL SOC

TABLE I
SOIL ORGANIC CARBON (G/KG) DISTRIBUTION IN THE SYNTHESIZED SSL AT KRISHNARAJ NAGAR

| Dataset | Synthesised Library | Local Library |
|---|---|---|
| No. of Samples | 158 | 43 |
| Minimum | 0.5 | 4.9 |
| Maximum | 68.45 | 64.86 |
| Mean | 37.19 | 16.79 |
| Median | 37.03 | 12.68 |
| Std. dev | 15.15 | 3.18 |
| Coefficient of Variation | 41.71 | 25.07 |
| Skewness | 0.18 | 0.01 |

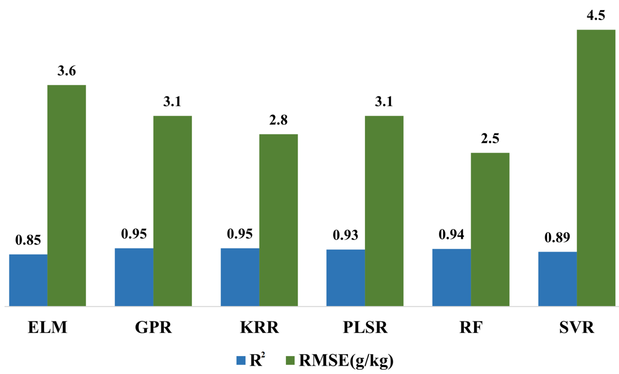


Fig. 3. $R^2$ and RMSE for best-performing case of each ML algorithm for case-I.

distribution was similar to that of the synthesized SSL SOC distribution and resembles a positively skewed pattern. This demonstrates the synthesized SSL appropriateness for determining the SOC contents of the local SSL.

### *B. Case-I: Estimation of SOC From Spectroscopic Data Using Synthesized SSL*

All the considered ML algorithms performed very well in the estimation of SOC. However, GPR ranked first with high $R^2$ and low RMSE. In Fig. 3, we provided an overview of the results from spectroscopic data validation. Notably, every spectral preprocessing technique and ML algorithm exhibited high performance, consistently achieving $R^2$ values exceeding 0.8 across major conditions. However, the significant variation became apparent within the range of RMSE, ultimately emerging as the determining factor for identifying the best-performing model. Regarding the preprocessing of spectral data, both reflectance and absorbance data showed effectiveness. In contrast, secondary preprocessing techniques, such as the first and second derivatives, had a detrimental impact on ML algorithm performance and SOC estimation. This thorough analysis emphasizes the practicality of employing synthesized SSL for SOC estimation in laboratory conditions. Abs + Cont outperforms other preprocessing techniques with an RMSE of 1.63 g/kg and an $R^2$ of 0.86.

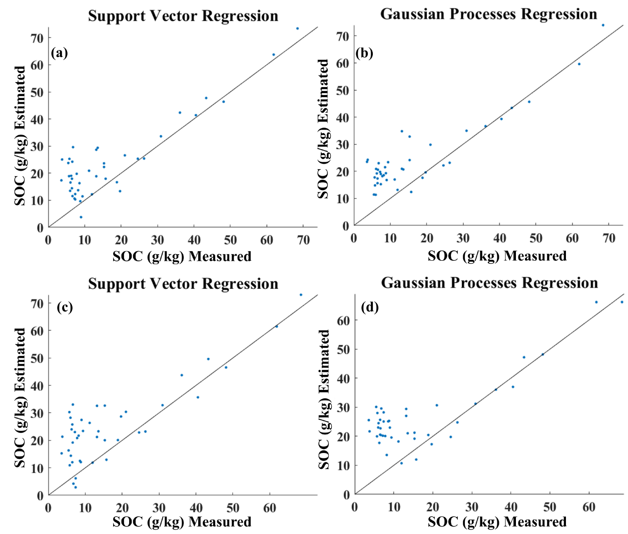


Fig. 4. Scatter plot between observed and predicted SOC for the independent set of soil samples from the local site for case-II. (a) and (b) Reflectance. (c) and (d) Reflectance + continuum.

TABLE II
ACCURACY METRICS OF THE PERFORMANCE OF THE DIFFERENT APPROACHES TO ESTIMATE SOC USING PRISMA DATA

| Machine Learning Algorithm | Reflectance | | Reflectance + Continuum | |
|---|---|---|---|---|
| | $R^2$ | RMSE (g/kg) | $R^2$ | RMSE (g/kg) |
| Support Vector Regression | 0.79 | 9.91 | 0.71 | 11.90 |
| Gaussian Process Regression | 0.75 | 10.58 | 0.70 | 13.03 |
| Partial Least Square Regression | 0.69 | 11.89 | 0.70 | 13.89 |
| Extreme Learning Machine | 0.49 | 12.04 | 0.60 | 14.25 |
| Kernel Ridge Regression | 0.77 | 9.54 | 0.49 | 14.75 |
| Random Forest | 0.26 | 20.86 | 0.37 | 20.28 |

### *C. Case-II: Estimation of SOC From PRISMA Data Using Synthesized SSL*

Furthermore, the study involved integrating PRISMA data with synthesized spectral libraries through ML algorithms to broaden the applicability of spectroscopic data for spaceborne sensors. From Table II, GPR, SVR, and PLSR performed well for predicting SOC, while RF exhibited lower effectiveness, possibly due to its tree-bagging approach not being well suited for handling noncontinuous spectral features of SOC. Marginal performance increase in ML algorithms was observed in comparing preprocessed and raw hyperspectral data used as inputs. The study also observed relatively high validation RMSE values for the SOC range 0–20 g/kg (Fig. 4), primarily due to the limited training samples. The results could potentially be improved by increasing the number of training samples in the range of 0–20 g/kg. The research suggests that the synthesized SSL offers an efficient alternative to the development of global and national SSL, particularly in developing countries with a need for new libraries. Prediction accuracy can be improved by including a more significant number of samples for calibration, especially within the SOC range of 0–30 g/kg. SVR and GPR were highlighted as robust choices due to their capacity to model uncertainty and effectively connect specific spectral bands, setting them apart from other ML algorithms.

## V. Conclusion

In this letter, a synthesized SSL was prepared to estimate SOC in cropland soils of alluvial origin using hyperspectral data. The synthesized SSL was prepared by mixing a fixed proportion of alluvial soil and organic compost to induce variability. PRISMA hyperspectral data and spectroradiometer data were utilized to test the capability of the synthesized SSL. In addition, synthesized SSL was resampled to PRISMA sensor characteristics to train ML algorithms. GPR, KRR, RF, SVR, PLSR, and ELM algorithms were employed to calibrate and predict SOC. The results showed that the synthesized SSL estimated SOC well using spectroscopic and PRISMA data. SVR performed better than other algorithms in both cases, with an $R^2$ of 0.92 and 0.79 and an RMSE of 1.63 and 9.91 g/kg, respectively. The proposed method showed that utilizing synthesized SSL could expedite the development of models with limited GT data for predicting SOC in croplands. This could prove beneficial to aiding farmers and tracking progress toward SDGs. Furthermore, considering the continuous advancements in hyperspectral technology, it is essential to investigate this approach further to understand its capabilities and constraints. The future scope of our work involves applying the designed synthesis approach to other study areas with different climatic conditions, particularly those with alluvial soil origins. Furthermore, future work aims to develop a synthesized SSL to estimate crucial soil parameters.

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