ESTIMATION OF SOIL NUTRIENT CONTENT OF HYPERSPECTRAL IMAGE USING MACHINE LEARNING ALGORITHM

A PROJECT REPORT

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This is to certify that this project entitled **“ESTIMATION OF SOIL NUTRIENT CONTENT OF HYPERSPECTRAL IMAGE USING MACHINE LEARNING ALGORITHM”** submitted by

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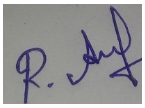
in partial fulfillment of the requirements for the award of the **Degree of Bachelor of Technology** in **ELECTRICAL & ELECTRONICS ENGINEERING** is a bonafide record of the work carried out under my guidance and supervision at Amrita School of Engineering.



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This project report was evaluated by us on...............

INTERNAL EXAMINER

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Abbreviations

SOC	–	Soil Organic Carbon
PLSR	–	Partial Least Square Regression Algorithm
RF	–	Random Forest
GDBT	–	Gradient Boosting Decision Trees
SOM	–	Soil organic matter
HSI	–	Hyperspectral Imaging
CARS	–	Competitive Adaptive Reweighted Sampling
FS	–	Field Spectroradiometer
PCA	–	Principal Component Analysis
SVM	–	Support Vector Machines
ANN	–	Artificial Neural Networks
LOI	–	Loss-on-ignition
CNN	–	Convolutional neural network
TSS	–	Temporal Spatial Spectral
PAL	–	Probabilistic Active Learning
SSL	–	Soil Spectral Library
ANN	–	Artificial Neural Networks
LOI	–	Loss-on-ignition
CNN	–	Convolutional neural network

Abstract

Estimation of soil nutrient content of Hyperspectral image using Machine learning algorithm reports on how the search for new possibilities of improving soil nutrient assessment with a strong emphasis on the main soil nutrients can be supported by advanced remote sensing technologies: SOC, nitrogen, phosphorus, and potassium. Comprehensive spectral information through hyperspectral imaging, in tandem with machine learning models, offers a non-invasive, efficient, and scalable method to analyze soil nutrient variability. Thus, it is a really good return towards sustainable agriculture in places like Tamil Nadu in India.

The project focuses on the application of various regression models and optimization techniques to identify the important spectral bands and predict the levels of nutrients with high accuracy. The developed approach will cover hyperspectral data collection from the soil samples, noise removal by preprocessing, and ensemble machine learning algorithms such as Random Forest (RF), Partial Least Squares Regression (PLSR), and Gradient Boosting Decision Trees (GDBT) to develop prediction models. Data used in this work were collected from the Radhapuram region, Tirunelveli, and is the basis of training and validation for the model. Some methods of optimization are used to improve the spectral data by trying to reduce the redundancy and select relevant bands, which may result in good predictions.

The present study proposes a robust framework for comparison of various machine learning techniques to perform real-world soil analysis for improving productivity. The project highlights the critical contribution that hyperspectral imaging and machine learning will make toward the prediction of nutrient deficiencies in soils and, therefore, land management with the aim of optimizing crop yields in tropical regions.

Chapter 1

Introduction

1.1 Preface

The knowledge of soil contents is necessary in agricultural regions for the proper maintenance and in order to plant the right crops for the specific land/soil. Hyperspectral imaging technique is used in this case in order to determine the various characteristics of the soil, i.e., the components of the soil such as soil carbon, nitrogen, potassium contents etc [1]. The advantages held in place by the Hyperspectral Imaging method over the traditional soil sample method is that it maintains the quality of soil. There is no need to take live samples from Oxisols which would eventually lead to damaging the soil nature. Through a properly trained ML model or Neural network, we can accurately obtain the soil organic content with the help of Hyperspectral Images. Hyperspectral Imaging is a technique used to capture images from the entire bandwidth of electromagnetic waves. The organic contents in the soil interact differently with each wavelength of light. Although the changes may not seem significant with successive wavelengths, the SOC can be determined through specific bandwidths of light [2].

1.2 Objective

- To design an efficient algorithm that can identify the relevant bands using optimization techniques.
- To design an algorithm that finds the set of minimal non-redundant bands to maintain the regression error intact.
- To apply the developed algorithm for the real-world soil data and achieve the best regression model to predict soil nutrients.

1.3 Organization of the Project

Project Phase 1

- Literature Review and Domain Identification
- Data preprocessing and Band selection
- Feature Extraction and Regression
- comparision of Results
- Project Report Writing

Project Phase 2

- Preprocessing of Hyperspectral Satellite images
- Deploy band selection Techniques to preprocessed images
- Prediction of soil nutrient content

Chapter 2

Literature Review

2.1 Introduction

Hyperspectral imaging is a powerful tool importantly used in agricultural and environmental sciences, where one of its applications is to determine the soil's organic content from the degree of reflectance of the organic matter interacting with the various bands of electromagnetic waves falling on it. Each and every organic matter such as carbon, nitrogen or potassium etc., interact differently to a specific wavelength of light, thus providing us with abundance of data when the imaging of the piece of land is done.

Conventional methods of soil sampling techniques, although may be more accurate than using ML, it is labor intensive and costly, whereas hyperspectral imaging technique is much faster, convenient, and more efficient. The vast majority papers make use of supervised learning. The dataset made use is of soil samples taken from a local region and through conventional soil sampling techniques, it is processed through various bands of light, we are able to create a dataset pertaining the reflectance of the organic content.

Various ML and deep learning networks are used in order to select the specific bands that are most suitable for the prediction of the SOC in the soil. This is done to reduce the redundancy in the features used in training the dataset, therefore possibly reducing the possibility of overfitting. Screening algorithms are used to select the best bands that produce the most optimal solution or data for specific organic content in the data. The best out of the screening algorithms are chosen by Partial Least Square Regression (PLSR).

2.2 Literature Survey

Spectroscopic measurements and imaging of soil colour for field scale estimation of soil organic carbon. The study used a digital camera and Sentinel-2 remote sensor to estimate soil organic carbon (SOC) through soil color analysis. The method offers cost-effectiveness, efficiency, accurate predictions, and convenience compared to traditional spectroscopic methods. However, it lacks the ability to determine soil components not influencing the visible spectrum and requires further research to validate its effectiveness. The motivation is to provide a convenient alternative to traditional spectroscopic methods for improved soil management practices. Comparing laboratory and airborne hyperspectral data for the estimation and mapping of topsoil organic carbon: Feature selection coupled with random forest. This study compares the use of airborne hyperspectral images and proximal laboratory Vis-NIR spectral data for estimating and mapping bare topsoil soil organic carbon (SOC) [1]. Random forest and advanced feature selection algorithms were used to optimize prediction models. Advantages include improved spectral information extraction, enhanced accuracy, and potential for quantitative estimation. Drawbacks include discrete sampling, point-to-point data, and external factors affecting model robustness. Combination of efficient signal pre-processing and optimal band combination algorithm to predict soil organic matter through visible and near-infrared spectra. This study uses 233 soil samples, nine spectral pre-processing methods, and an optimal band combination algorithm to improve soil organic matter (SOM) prediction accuracy [2]. The Savitzky-Golay filter is found most effective. However, it faces limitations in accurately representing complex soil composition, sensitivity to environmental conditions, and applicability in specific soil types or regions. Hyperspectral imaging for high-resolution mapping of soil carbon fractions in intact paddy soil profiles with multivariate techniques and variable selection. The study explores the potential of hyperspectral imaging (HSI) spectroscopy in mapping soil carbon fractions in paddy soil profiles [3]. It compares linear and nonlinear multivariate techniques and applies a spectral variable selection technique, competitive adaptive reweighted sampling (CARS), to simplify models. The CARS-SVMR model's accuracy and robustness may need validation in other regions. The study aims to improve processing speed and efficiency in HSI spectroscopy applications.

Comparison of field and imaging spectroscopy to optimize soil organic carbon and nitrogen estimation in field laboratory conditions [4]. The study compares two hyperspectral sensors, SVC HR-1024i field spectroradiometer (FS) and Specim IQ imaging spectrometer (IS), to estimate Soil Organic Compound (SOC) and Soil Nutrient (SN) content using 157 soil samples from Taita Hills, Kenya. Results show better predictive accuracy in the full wavelength and shortwave-infrared regions, suggesting FS with the SWIR region is best for SOC and SN estimation. The research aims to contribute to regenerative agriculture initiatives. Regional soil organic carbon prediction model based on a discrete wavelet analysis of hyperspectral satellite data. The study proposes a noise removal method for hyperspectral satellite soil data, using discrete wavelet transform to reconstruct original and first derivative reflectance [5]. It then selects objective, accurate spectral inputs and builds regional-scale soil organic carbon (SOC) prediction models. The method improves SOC prediction accuracy compared to multispectral data. However, limitations include limited sample size, spatial resolution, and transeferability. Hyperspectral Estimation of Soil Organic Matter Content using Different Spectral Preprocessing Techniques and PLSR Method. The study uses 54 spectral pretreatments to preprocess soil spectral data, including denoising methods, data transformations, and dimensionality reduction methods. The spectra are then used to construct Partial Least Squares Regression (PLSR) models for predicting soil organic matter content. The accuracy of the SOM content estimation model based on SWDR was higher than that of NDR and PCADR. However, the study could improve data quality and accuracy by using appropriate preprocessing methods.

Exploring Appropriate Preprocessing Techniques for Hyperspectral Soil Organic Matter Content Estimation in Black Soil Area [6]. The study used denoising methods, fractional derivatives, and dimensionality reduction techniques to improve soil organic matter (SOM) estimation in black soil areas. The Svitzky-Golay filter denoising, fractional derivatives, and principal component analysis (PCA) method yielded the highest predictability, achieving a maximum RPD of 2.60. This approach enhances efficiency and accuracy, enhancing ecological and agricultural protection in black soil areas. However, potential drawbacks include complexity and specific parameters. The study aimed to improve SOM estimation efficiency.[9] Detection of soil organic matter using hyperspectral imaging sensor combined with multivariate regression modeling procedures. This paper uses hyperspectral imaging to determine soil characteristics, including carbon, nitrogen, and potassium content. It uses multivariable regression modeling to predict organic matter in Paraná, Brazil, using samples from oxisols. The research gap is estimating soil organic matter concentration at various depths, rather than examining the presence of different organic compounds. The study aims to improve agricultural practices.

Estimation of Soil Nutrient Content Using Hyperspectral Data. This paper uses hyperspectral imaging to monitor soil nutrients for agricultural sustainable development [7]. Techniques like PLSR, PCC, LASSO, and GBDT are used to find the optimal screening algorithm for estimating total nitrogen, total phosphorus, and total potassium contents in soil. The optimal results were found for TN and TP, and TK for the latter. Linear and non-linear machine learning techniques are also employed. [11] Usage of Airborne Hyperspectral Imaging Data for Identifying Spatial Variability of Soil Nitrogen Content Soil being a significant part of agriculture, it is important to get an estimate of organic contents such as nitrogen in the soil for agricultural development. Hyperspectral imaging is performed to get the spatial and spectral imaging information for detecting physical, chemical and biological attributes. This paper aims to perform the above-mentioned on two pieces of land in the Czech Republic, using laboratory and handheld spectrometers. This paper is considering only soil nitrogen content as a testing parameter. Other organic matters such as potassium, phosphorous and carbon are not considered in this paper's scope.

A regional-scale hyperspectral prediction model of soil organic carbon considering geomorphic features. The accuracy and transferability of regional-scale hyperspectral prediction models of soil organic carbon (SOC) can be significantly improved by considering geomorphic features, incorporating soil physical properties, and using advanced algorithms. Factoral order derivatives and stable denoising methods can also enhance predictive accuracy. Mid-infrared spectroscopy, preprocessing techniques, and multivariate methods have proven successful in predicting SOC content [8]. Semi-supervised DNN regression on airborne hyperspectral imagery for improved spatial soil properties prediction

Deep learning models, including transfer learning, self-supervised learning, and hybrid

CNN-RNN models, have shown promising results in predicting soil properties from airborne hyperspectral imagery. These models use spectral reflectance data, derived features, and pre-trained weights to improve accuracy and overcome challenges like small data sizes and overfitting. Mapping soil organic carbon stock by hyperspectral and time-series multispectral remote sensing images in low-relief agricultural areas. Agricultural land contributes to 8%-10% of global soil carbon storage, supporting crop growth and reducing emissions. Hyperspectral and multispectral images are used for digital soil mapping, with PLSR and ELM models predicting soil organic carbon stock and properties [9]. Improving the accuracy of soil organic carbon content prediction based on visible and near-infrared spectroscopy and machine learning. Vis-NIR diffuse reflectance spectroscopy is a rapid and nondestructive method for estimating soil organic matter distribution and properties. It saves time and reduces costs in collecting soil sample information. Various calibration methods, including partial least-squares regression, support vector machines (SVM), and artificial neural networks (ANN), have been used to predict SOC content. A study in southern Hangzhou Bay, Zhejiang Province, China, compared the performance of different calibration methods and preprocessing approaches for SOC estimation. SVM regression combined with first derivatives of reflectance provided the best prediction results. Hyperspectral technology, particularly Vis-NIR-IR hyperspectral technology, has emerged as a rapid, accurate, economical, and non-destructive method for soil analysis. Hyperspectral Estimation of Soil Copper Concentration Based on Improved TabNet Model in the Eastern Junggar Coalfield. The study used soil samples from the Eastern Junggar coalfield in China, enhancing data with Deep Learning techniques and Principle Component Analysis. The results showed improved TabNet and CNN regression predictions, indicating the use of NIR hyperspectral imaging for heavy metal pollution identification. However, the limited sample size may limit generalizability.

Estimation of soil organic matter content using selected spectral subset of hyperspectral data. Loss-on-ignition (LOI) is a reliable method for determining soil organic carbon (SOC) content in soil samples. Two variable selection methods, Genetic Algorithm and Variable Importance in the Projection (VIP) score, were used to select spectral bands. The method improved accuracy and generalization, but may not capture the full complexity of soil spectral signatures. The method may require rigorous preprocessing and atmospheric correction, which can be time-consuming and introduce uncertainties. The results suggest that estimating SOC content using informative spectral subsets is a promising approach [10]. Using soil library hyperspectral reflectance and machine learning to predict soil organic carbon: Assessing potential of airborne and spaceborne optical soil sensing. The study uses a public soil spectral library and machine learning algorithms to predict soil organic carbon (SOC) concentration. Techniques like vector normalization, continuum removal, and first-order derivative were used. The study highlights the potential of remote sensing data and ML algorithms for accurate SOC quantification. However, limitations include the DESIS sensor's lack of shortwave infrared wavelengths and potential biases. Satellite hyperspectral missions and multispectral data can enhance global SOC monitoring.

An advanced soil organic carbon content prediction model via fused temporal-spatial-spectral (TSS) information based on machine learning and deep learning algorithms. The study uses a discrete wavelet transform based on regional energy weighting (RW-DWT) to fusion temporal, spatial, and spectral data from multi-temporal multispectral data, topography data, and satellite hyperspectral data. Three prediction models are used: Partial least square regression (PLSR), Random forest (RF), and Convolutional neural network (CNN) [11]. The Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) module is used for radiometric calibration and atmospheric correction. The study found that improved data fusion of temporal spatial spectral information improves image products, eliminates noise in satellite hyperspectral images, and reduces the risk of overfitting in machine learning and deep learning models. [20] Regional soil organic carbon prediction models based on a multivariate analysis of the Mid-infrared hyperspectral data in the middle Indo-Gangetic plains of India. The study used preprocessing techniques to enhance spectral data for soil organic carbon (SOC) prediction. Four multivariate methods were used to develop predictive models, with higher RPD values indicating better performance. MIR spectroscopy is quick, accurate, and consistent across different laboratories. However, it has high incentive costs and can exhibit high spectral variability due to soil composition and moisture content. The study suggests expanding spectral libraries to include a wider range of soil types and conditions, combining MIR data with GIS and remote sensing technologies, and developing miniaturized, low-cost MIR sensors for continuous monitoring. Retrieval of carbon content and biomass from hyperspectral imagery over cultivated areas.The study uses a hybrid approach combining Radiative Transfer Modeling (RTM) and machine learning regression algorithms to estimate plant carbon content and biomass from EnMAP data [12]. Principal Component Analysis (PCA) is used to reduce dimensionality of full-range spectral information. Hyperspectral images are obtained using AVIRIS-NG. The Probabilistic Active Learning (PAL) approach optimizes the training sample pool, resulting in lightweight and efficient models. The method has practical implications for environmental monitoring and commercial use, but has high time complexity compared to Gaussian Process Regression (GPR).

Integrated Use of Hyperspectral Remote Sensing and Geostatistics in Spatial Prediction of Soil Organic Carbon Content. The study used Ordinary kriging and Cokriging geostatistical techniques to predict soil organic carbon (SOC) content. Hyperion hyperspectral image and spectral indices were used as auxiliary variables. Atmospheric correction was done using ENVI's FLAASH module. The integrated approach improves SOC prediction reliability by providing more accurate and detailed maps. However, limitations in spatial resolution and coverage and assumptions about spatial autocorrelation structure may affect predictions. Soil Moisture, Organic Carbon, and Nitrogen Content Prediction with Hyperspectral Data Using Regression Models. The study evaluates machine learning techniques for predicting soil content using band selection and feature transformation. Different regression models are compared, and Principal Component Analysis is applied to improve accuracy [13]. Hyperspectral imaging (HSI) is used to capture spectral and spatial data for accurate soil properties estimation. Traditional methods like thermogravimetric and mass loss on ignition are also discussed. However, limited access to high-quality hyperspectral data may limit the application of these methodologies.Integrating Soil Spectral Library and PRISMA Data to Estimate Soil Organic Carbon in Crop Lands The study created a soil spectral library (SSL) to represent soil organic carbon variability, using hyperspectral data from the PRISMA satellite [14]. Machine learning models were used for prediction. SOC predictions were validated using ground-truth samples using metrics like R^2 and RMSE. The method reduces field sampling, shows strong prediction accuracy, and can be applied to different regions and soil types. The study uses the EnMAP spaceborne imaging spectroscopy mission to monitor soil properties in Amyntaio, Greece, and Demmin, Germany. The data is processed to remove atmospheric effects and smooth reflectance spectra, mapping soil properties like SOC, clay, and carbonate content. The research aids global soil protection and carbon sequestration initiatives, but requires extensive ground data, limited monitoring ability, and is affected by vegetation cover and moisture.

The Tehra project uses PRISMA satellite hyperspectral data to estimate soil properties for sustainable agriculture and environmental monitoring. It addresses soil variability, soil moisture, and crop residues, and integrates multi-temporal PRISMA data with proximal soil sensing techniques. This approach enhances soil property estimation accuracy, aiding in precision farming and environmental policy enforcement. However, it requires advanced techniques, relies on satellite data quality, and can be affected by soil moisture and crop residues [15]. Improving Leaf Area Index Estimation With Chlorophyll Insensitive Multispectral Red-Edge Vegetation Indices.Researchers used the PROSAIL model to simulate canopy reflectance and collected data on leaf area, chlorophyll content, and reflectance. They identified red-edge bands that are sensitive to leaf area and least affected by chlorophyll content. These bands improve LAI estimation accuracy and are less influenced by chlorophyll content [16]. However, they may require specialized satellite data and new methods (Vegetation Indices) to effectively utilize the red-edge data. High-Resolution Mapping of Soil Organic Matter at the Field Scale Using UAV Hyperspectral Images with a Small Calibration Dataset. The study used UAV hyperspectral imaging to map soil organic matter (SOM) in a low-relief black soil area in Northeast China. The data, covering 400-1000 nm, was collected over a 20 ha field. Machine learning models, particularly the Random Forest model, were applied to predict SOM from the preprocessed spectra, achieving a spatial resolution of 1 m. UAV technology offers fine spatial resolution, is more accessible and economical, and can quickly capture data for soil conditions assessment [17]. However, UAVs have restricted flight times and coverage areas, and data quality can be affected by factors like soil moisture and atmospheric conditions.Calibration Dataset.

Chapter 3

Methodology

The figure 3 illustrates a workflow for analyzing hyperspectral data to develop prediction models. Here is a step-by-step explanation. Ground Truth Hyperspectral Spectroradiometer Data from Tirunelveli district: The process starts with collecting hyperspectral data from the ground, specifically using a spectroradiometer. The data is obtained from the Tirunelveli district, which likely includes spectral signatures or reflectance values across a wide range of wavelengths. The next step involves taking spectral reflectance measurements of soil samples. This reflects the unique spectral characteristics of the soil, which can help identify various soil properties such as organic carbon content, moisture, and mineral composition. Once the spectral reflectance data is obtained, optimization techniques are employed to select the most relevant spectral bands. This step aims to identify the specific wavelengths or range of wavelengths that are most informative or significant for predicting the soil properties of interest. Regression trees are used to further refine the band selection process. This step involves using decision tree algorithms to identify the most significant spectral bands that contribute to accurate predictions of soil properties [16]. The regression trees help in determining the relationship between the selected spectral bands and the soil properties being studied. Finally, prediction models are developed using the significant bands identified in the previous step. These models aim to predict soil properties based on the hyperspectral data. Different machine learning or statistical modeling techniques may be used, such as regression analysis, neural networks, or support vector machines. Overall, the figure depicts a systematic approach to process and analyze hyperspectral data to develop reliable prediction models for soil properties.

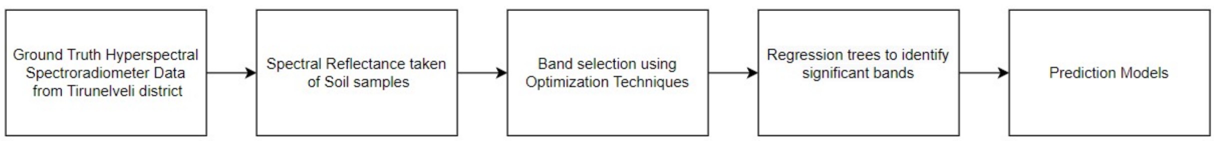

Figure 3.1: Proposed Methodology

3.0.1 Materials and Methods

- The ground truth data has been obtained from Radhapuram, Thirunelveli.
- The spectral reflectance of the soil samples are recorded into a dataset which is to be processed with the help of ML models
- Various optimization techniques are used to reduce the number of redundant bands from the dataset.
- Regression trees are used to select significant bands.
- The resultant algorithm obtained is used to predict the soil organic content from any soil sample.

Chapter 4

Results and Discussions

The table 4.1 provides a classification framework for evaluating soil nutrient levels based on specific thresholds. It categorizes four key soil nutrients: Organic Carbon, Nitrogen, Phosphorus, and Potassium, into three distinct levels—Low, Medium, and High—based on their respective concentrations. These classifications are essential for assessing soil health and fertility, which can significantly impact crop growth and agricultural productivity. For hyperspectral data analysis, this table serves as a reference to correlate spectral reflectance measurements with nutrient content. By identifying the spectral bands most sensitive to variations in these nutrient levels, researchers can use hyperspectral imaging techniques to estimate and map soil nutrient content over large areas. The spectral data, processed through optimization and regression models, can help predict whether a soil sample falls into the Low, Medium, or High category for each nutrient.

In practical applications, such classifications enable precision agriculture practices, allowing for tailored fertilizer application and soil management strategies. Using hyperspectral data to remotely sense these nutrient levels can reduce the need for extensive soil sampling and laboratory analysis, leading to more efficient, cost-effective, and sustainable agricultural practices.

Table 4.1: Soil nutrient levels for spectroradiometer data

Soil Nutrients Levels	**Low**	**Medium**	**High**
Organic Carbon	<0.5 %	0.5 - 7.5%	>0.75%
Nitrogen	<240Kg/ha	240- 480kg/ha	>480Kg/ha
Phosphrous	<11.0 Kg/ha	11 – 22 Kg/ha	>22 Kg/ha
Pottasium	<110Kg/ha	110-280Kg/ha	>280Kg/ha

4.0.1 Datasets Description

The figure 4.1 shows hyperspectral spectroradiometer data collected from Radhapuram in the Tirunelveli district of Tamil Nadu. The map highlights specific locations where data was gathered, indicated by numerous small dots. These dots likely represent sampling points where the spectral properties of the soil were measured. The x-axis of the graph is labeled "Wavelength," ranging from 350 to 2500 nanometers, and the y-axis is labeled "Spectral Reflectance," ranging from 0 to 0.4. The graph shows how different levels of soil nutrients, such as phosphorus, affect the reflectance measured by the spectroradiometer.

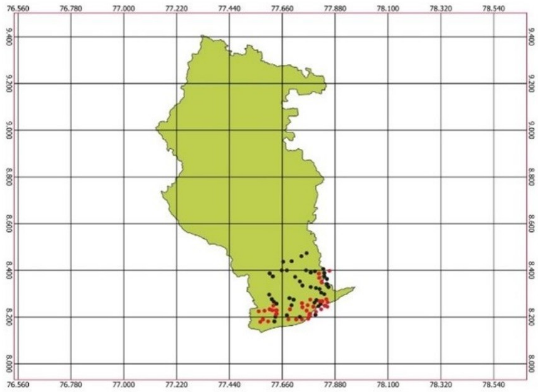

Figure 4.1: Hyperspectral Radiometer dataset Locations

This data is crucial for understanding the soil's optical properties and how they vary with nutrient content. By analyzing the spectral reflectance, researchers can infer soil characteristics over large areas without direct sampling. This information is valuable for precision agriculture, allowing for better land management decisions and optimizing agricultural productivity. The distinct patterns of reflectance for different nutrient levels suggest that hyperspectral remote sensing can effectively monitor soil health and fertility, providing essential insights for sustainable farming practices.

4.0.2 Organic Carbon with different levels

The figure 4.2 illustrates the spectral reflectance of soil with varying levels of organic carbon content across different wavelengths, ranging from 350 to 2500 nanometers. The graph features three distinct lines: a solid blue line representing low organic carbon, a dashed orange line for medium organic carbon, and a dot-dashed yellow line for high organic carbon. The y-axis, labeled "Spectral Reflectance," ranges from 0 to 0.4, indicating the proportion of incident light that is reflected by the soil. The x-axis, labeled "Wavelength," shows the range of wavelengths measured. The data reveals that soils with higher organic carbon content generally exhibit lower reflectance values across most wavelengths compared to soils with lower organic carbon content. This pattern is significant in the context of hyperspectral soil spectroradiometry, as it highlights how organic carbon levels influence the soil's optical properties. Such information is crucial for remote sensing applications, where spectral data can be used to infer soil characteristics over large areas without direct sampling. By analyzing the spectral reflectance, researchers can develop models to estimate soil quality, monitor changes over time, and implement precision agriculture practices. This approach enhances the ability to manage soil health and optimize agricultural productivity efficiently.

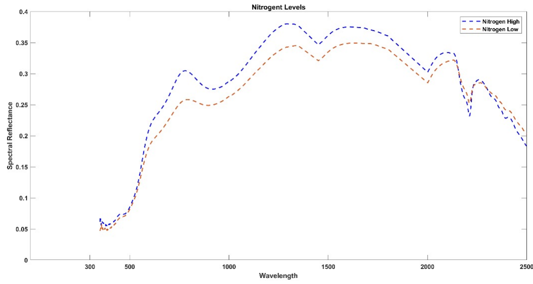

Figure 4.2: Organic Carbon with different levels

4.0.3 Nitrogen Levels

The figure 4.3 illustrates the spectral reflectance of soil with varying nitrogen levels across different wavelengths, ranging from 350 to 2500 nanometers. The data reveals that soils with higher nitrogen content generally exhibit different reflectance patterns compared to soils with lower nitrogen content, with noticeable peaks and troughs across the spectrum. This pattern is significant in the context of hyperspectral soil spectroradiometry, as it highlights how nitrogen levels influence the soil's optical properties. Such information is crucial for remote sensing applications, where spectral data can be used to infer soil characteristics over large areas without direct sampling. By analyzing the spectral reflectance, researchers can develop models to estimate soil health, monitor changes over time, and implement precision agriculture practices. This approach enhances the ability to manage soil fertility and optimize agricultural productivity efficiently.

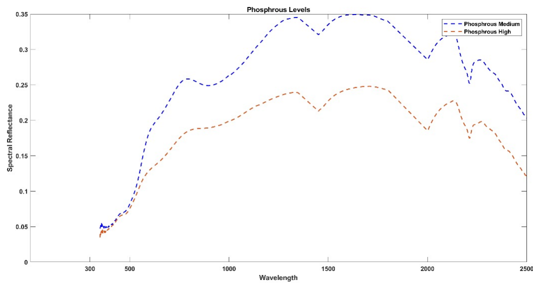

Figure 4.3: Nitrogen Levels

4.0.4 Phosphrous Levels

The figure 4.4 illustrates the spectral reflectance of soil with varying phosphorus levels across different wavelengths, ranging from 200 to 2500 nanometers. The graph features three lines: one representing low phosphorus content, another for medium phosphorus content, and the third for high phosphorus content. The y-axis, labeled "Spectral Reflectance," ranges from 0 to 1.35, indicating the proportion of incident light that is reflected by the soil. The x-axis, labeled "Wavelength," shows the range of wavelengths measured. The data reveals that soils with different phosphorus levels exhibit distinct reflectance patterns, with noticeable peaks and troughs across the spectrum. This pattern is significant in the context of hyperspectral soil spectroradiometry, as it highlights how phosphorus levels influence the soil's optical properties. Such information is crucial for remote sensing applications, where spectral data can be used to infer soil characteristics over large areas without direct sampling. By analyzing the spectral reflectance, researchers can develop models to estimate soil health, monitor changes over time, and implement precision agriculture practices. This approach enhances the ability to manage soil fertility and optimize agricultural productivity efficiently.

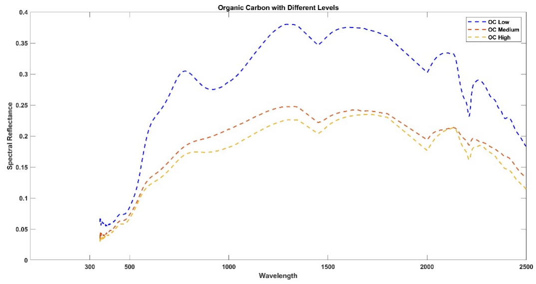

Figure 4.4: Phosphrous Levels

References

[1] D. Datta, M. Paul, M. Murshed, S. W. Teng, and L. Schmidtke, "Soil moisture, organic carbon, and nitrogen content prediction with hyperspectral data using regression models," *Sensors*, vol. 22, no. 20, p. 7998, 2022.

[2] A. Gholizadeh, M. Saberioon, R. A. V. Rossel, L. Boruvka, and A. Klement, "Spectroscopic measurements and imaging of soil colour for field scale estimation of soil organic carbon," *Geoderma*, vol. 357, p. 113972, 2020.

[3] S. Xu, M. Wang, and X. Shi, "Hyperspectral imaging for high-resolution mapping of soil carbon fractions in intact paddy soil profiles with multivariate techniques and variable selection," *Geoderma*, vol. 370, p. 114358, 2020.

[4] X. Meng, Y. Bao, J. Liu, H. Liu, X. Zhang, Y. Zhang, P. Wang, H. Tang, and F. Kong, "Regional soil organic carbon prediction model based on a discrete wavelet analysis of hyperspectral satellite data," *International Journal of Applied Earth Observation and Geoinformation*, vol. 89, p. 102111, 2020.

[5] A. S. Reis, M. Rodrigues, G. L. A. A. dos Santos, K. M. de Oliveira, R. H. Furlanetto, L. G. T. Crusiol, E. Cezar, and M. R. Nanni, "Detection of soil organic matter using hyperspectral imaging sensor combined with multivariate regression modeling procedures," *Remote Sensing Applications: Society and Environment*, vol. 22, p. 100492, 2021.

[6] Y. Peng, L. Wang, L. Zhao, Z. Liu, C. Lin, Y. Hu, and L. Liu, "Estimation of soil nutrient content using hyperspectral data," *Agriculture*, vol. 11, no. 11, p. 1129, 2021.

[7] V. Pechanec, A. Mráz, L. Rozkošnỳ, and P. Vyvlečka, "Usage of airborne hyperspectral imaging data for identifying spatial variability of soil nitrogen content," *ISPRS International Journal of Geo-Information*, vol. 10, no. 6, p. 355, 2021.

[8] S. Wang, K. Guan, C. Zhang, D. Lee, A. J. Margenot, Y. Ge, J. Peng, W. Zhou, Q. Zhou, and Y. Huang, "Using soil library hyperspectral reflectance and machine learning to predict soil organic carbon: Assessing potential of airborne and spaceborne optical soil sensing," *Remote Sensing of Environment*, vol. 271, p. 112914, 2022.

[9] A. Ghosh, K. M. Hati, N. K. Sinha, N. Mridha, B. Sahu, *et al.*, "Regional soil organic carbon prediction models based on a multivariate analysis of the mid-infrared hyperspectral

data in the middle indo-gangetic plains of india," *Infrared Physics & Technology*, vol. 127, p. 104372, 2022.

[10] S. Chabrillat, R. Milewski, K. Ward, S. Foerster, S. Guillaso, C. Loy, E. Ben-Dor, N. Tziolas, T. Schmid, B. van Wesemael, *et al.*, "Monitoring soil properties using enmap spaceborne imaging spectroscopy mission," in *IGARSS 2023-2023 IEEE International Geoscience and Remote Sensing Symposium*, pp. 1130–1133, IEEE, 2023.

[11] Y. Yan, J. Yang, B. Li, C. Qin, W. Ji, Y. Xu, and Y. Huang, "High-resolution mapping of soil organic matter at the field scale using uav hyperspectral images with a small calibration dataset," *Remote Sensing*, vol. 15, no. 5, p. 1433, 2023.

[12] D. Chambers and D. Simon, "Analyzing the influence of emotional intelligence on investor behavior in developing regions: A prisma systematic review," *International Journal of Management and Humanities*, vol. 8, no. 12, pp. 19–22, 2022.

[13] D. Roshani, R. Ramazanzadeh, F. Farhadifar, A. Ahmadi, S. Derakhshan, S. Rouhi, S. Zarea, and F. Zandvakili, "A prisma systematic review and meta-analysis on chlamydia trachomatis infections in iranian women (1986–2015)," *Medicine*, vol. 97, no. 16, p. e0335, 2018.

[14] A. Raju and R. Subramoniam, "Assessing soil nutrient content and mapping in tropical tamil nadu, india, through precursors iperspettrale della mission applicative hyperspectral spectroscopy," *Applied Sciences*, vol. 14, no. 1, p. 186, 2023.

[15] R. Casa, R. Bruno, V. Falcioni, L. Marrone, S. Pascucci, S. Pignatti, S. Priori, F. Rossi, A. Tricomi, and R. Guarini, "Topsoil properties estimation for agriculture from prisma: the tehra project," in *IGARSS 2023-2023 IEEE International Geoscience and Remote Sensing Symposium*, pp. 3209–3212, IEEE, 2023.

[16] Y. Peng, L. Wang, L. Zhao, Z. Liu, C. Lin, Y. Hu, and L. Liu, "Estimation of soil nutrient content using hyperspectral data," *Agriculture*, vol. 11, no. 11, p. 1129, 2021.

[17] M. M. Chitale and S. Kundapura, "High-resolution mapping of soil properties using aviris-ng hyperspectral remote sensing data—a case study over lateritic soils in mangalore, india," *Trends in Civil Engineering and Challenges for Sustainability: Select Proceedings of CTCS 2019*, pp. 735–751, 2021.