

Estimation of soil organic carbon content using remote sensing and GIS techniques*

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Abstract

The depletion of Soil Organic Carbon (SOC) due to intensive agricultural practices poses a significant threat to soil health, impacting agricultural productivity, soil structure, and carbon sequestration. Remote methods to evaluate the surface SOC content will enhance efficient mapping and therefore, apply appropriate methods for remediation. A research study was developed to provide a cost-effective, non-invasive method for SOC estimation and mapping, contributing to sustainable agriculture and environmental conservation. The focus of the study included using remote sensing (RS), satellite imagery and Geographic Information Systems (GIS) software to estimate soil organic carbon (SOC) content through various vegetation indices (VIs). Statistical analysis included both descriptive statistics and multivariate analyses. The SOC data did not follow a normal distribution, necessitating the use of non-parametric tests. The study employed multivariate correlation, Spearman's rho as non-parametric tests, and ordinal logistic regression to create SOC estimation models. The transformation of SOC data into ordinal classes allowed for more robust regression analysis, improving the predictive power of the models. The results showed significant correlations between SOC and the VIs, particularly with NDVI, GNDVI, and SAVI, with correlation coefficients above 0.9, indicating strong predictive capabilities. BSI exhibited an inverse relationship with SOC, as expected. The distribution analyses of the indices highlighted varying vegetation health and density across the study area, confirming the suitability of these indices for SOC estimation. The study underscored the potential of RS and GIS technologies in providing reliable SOC estimates, promoting Precision Agriculture (PA) and sustainable land management. It also suggests further refinement and validation of the models using Unmanned Aerial Systems (UASs) equipped with multispectral cameras of high resolution, to enhance spatial resolution and accuracy. Additionally, future research should explore the integration of more environmental variables and advanced statistical techniques to improve SOC prediction models. In conclusion, the utilization of RS and GIS for estimating SOC through VIs is a promising avenue for enhancing soil management and conservation efforts. By leveraging advanced technologies and statistical methods, this study provides valuable insights into the complex interactions between vegetation and soil carbon dynamics, paving the way for more effective and sustainable agricultural practices. The study is under further validation in the same and other areas.

Keywords

Soil Organic Carbon, Remote Sensing, Vegetation Indices, GIS, Precision Agriculture, Sentinel-2, NDVI, GNDVI, SAVI, BSI

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1. Introduction

Soil organic carbon (SOC) are essential components of soil health and agricultural productivity, playing a pivotal role in maintaining the biological, chemical, and physical functions of soil ecosystems [1]. In agricultural terms, Soil Organic Matter (SOM) primarily consists of decomposed plant and animal residues that enhance soil structure, permeability, aeration, and nutrient retention, making it one of the three foundational elements of soil along with minerals and living organisms [2]. SOC, the measurable part of SOM, reflects the concentration of organic carbon in soil and provides a clear indicator of soil fertility and health, especially given the challenges in analyzing broader organic matter content [3]. High SOC levels benefit agriculture by improving soil structure, reducing erosion risk, and fostering microbial activity, which increases the availability of essential nutrients like nitrogen and phosphorus. Moreover, SOC plays a critical role in climate change mitigation by trapping carbon in the soil, preventing its release as greenhouse gases like carbon dioxide and methane [4]. However, unsustainable agricultural practices, including deep tilling and excessive chemical use, have led to a decline in SOC levels globally, threatening soil productivity and, in some areas, rendering soils nearly infertile [5]. The Industrial Revolution and recent decades of intensified land use have accelerated this degradation, highlighting an urgent need for SOC restoration to ensure sustainable agriculture [6]. Recognizing SOC loss as a global environmental crisis, various governmental bodies, including the European Parliament, the U.S. Congress, and COP conferences, have taken steps to address the issue. International efforts, such as the UN's initiatives and the EU's Green Deal and Common Agricultural Policy (CAP), aim to monitor and mitigate SOC depletion, promoting soil health and sustainability [7]. Remote sensing (RS) techniques, especially within the Visible-Near Infrared–Shortwave Infrared (VNIR–SWIR, 400–2500 nm) spectrum, present a promising solution for efficient SOC monitoring. These cost-effective, chemical-free methods enable precise SOC estimation, aiding scientists and farmers in sustainable soil management [8]. Automated RS processes, integrated with computer software, align with Precision Agriculture (PA) by providing rapid, data-driven insights into soil variability, enhancing resource efficiency, productivity, and sustainability. Through this synergy with PA, RS methods offer a valuable pathway to soil restoration and a more resilient agricultural future [9].

This study aimed to develop a custom model for estimating SOC levels using remote sensing (RS) techniques, building on insights from existing models and research. By creating a tailored system, the study intended to support Precision Agriculture (PA), sustainable monitoring, and soil carbon management in a controlled, smaller-scale context. The study employed QGIS, an open-source geographic information system software and JMP (Student Edition) for statistical analysis, among other tools, to complete project tasks and analyze data. By choosing accessible, cost-effective software, the study aimed to highlight a secondary objective, demonstrating that effective PA results can be achieved through careful planning, practical knowledge, and innovative approaches rather than reliance on high-cost technology.

2. Materials & Methods

The study, experiment, and design were conducted at the American Farm School of Thessaloniki and its affiliated areas, including Perrotis College, located in Thessaloniki, Greece. Research activities took place in an agricultural field on the campus's northeast side (Figure 1), and various laboratory facilities and university equipment were used to support different phases of the study. The study area's coordinates are 40.5710034° latitude and 22.9964484° longitude, at an altitude of 76 meters.

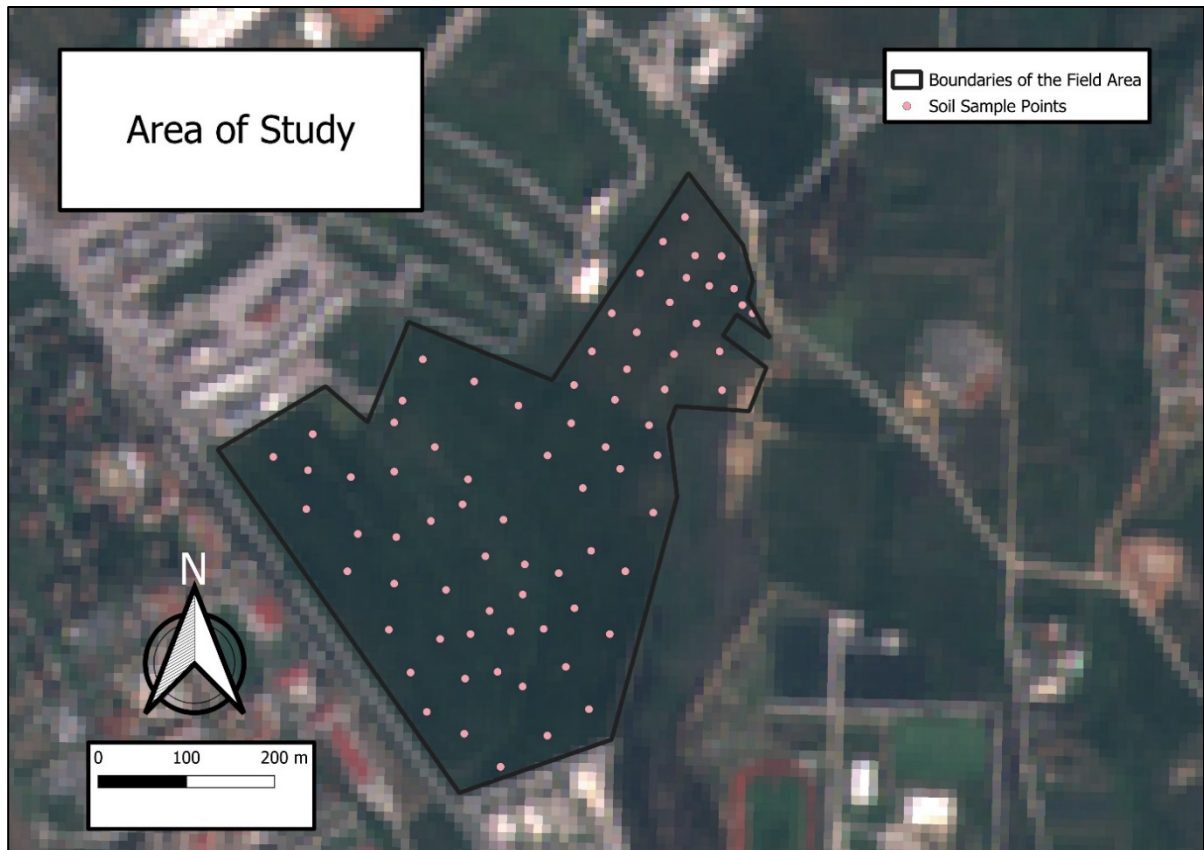


Figure 1: The Map of the Study Area is based on Sentinel-2 Spectral Bands and GIS. Source: Personal Collection & Creation (Karampetian Grigorios).

The study's experimental design was developed and refined over nearly a year, originating in fall 2022 and finalizing in summer 2023, with the goal of creating a SOC estimation model linking soil data with VIs from open-source satellite images. Once the design was established, the first step involved collecting soil samples from the field's top 15 cm. A small team used standardized equipment to gather and tag 73 samples, which were dried and processed for SOC analysis in the laboratory using a Dumatherm machine. This machine, known for its precision, enabled the analysis of soil carbon and nitrogen content through careful milling and measurement.

Following sample collection and processing, satellite data from the Copernicus Sentinel-2 database was accessed in January 2024. The imagery was carefully selected for minimal cloud cover and vegetative phases ideal for accurately assessing SOC-related VIs. Using QGIS software, the satellite data allowed the calculation of indices such as NDVI, BSI, GNDVI, and SAVI, each important for understanding soil characteristics. Soil sample coordinates were then added to QGIS, where each sample's VI values were recorded. Additionally, six maps were created within QGIS to visually represent the SOC study area, each VI, and the SOC ground truth data.

For statistical analysis, data was imported into JMP v18 (jmp.com) to assess relationships between SOC and each VI using multivariate methods and Spearman's correlation coefficients. To further explore these relationships, an ordinal logistic regression model was developed, providing insight into the predictive power of each VI. Results from each analysis were systematically documented in Word and Excel files, ensuring data integrity and supporting the study's overall goal of promoting accessible precision agriculture techniques.

3. Results & Discussion

In this study, the distribution analysis of Soil Organic Carbon (SOC) revealed a median of 0.85 and a mean of 0.8, indicating low SOC levels without significant outliers. Notably, the distribution

exhibited four distinct peaks, suggesting a complex, multi-modal structure and the potential presence of four distinct groups within the dataset. Traditional measures of central tendency may not adequately represent this data due to the clusters identified. The Shapiro-Wilk Test confirmed this non-normality, with a p-value below 0.05 leading to the rejection of the null hypothesis. As a result, the analysis was adapted to employ non-parametric tests, including multivariate correlation and Spearman's rho. The SOC data was also transformed into ordinal data, allowing for the use of ordinal logistic regression, detailed later in the study.

The distribution analysis of the Normalized Difference Vegetation Index (NDVI) indicated a median of 0.47 and a mean of 0.46, suggesting medium vegetative performance. The p-value from the Shapiro-Wilk Test for NDVI was again below 0.05, indicating non-normality and revealing a slight negative skewness. Similarly, the Bare Soil Index (BSI) had a median of 0.15 and a mean of 0.16, indicating low values and suggesting that much of the study area is covered by healthy vegetation. The Shapiro-Wilk Test p-value was also below 0.05, showing a slight positive skewness. The Soil Adjusted Vegetation Index (SAVI) exhibited a median of 0.59 and a mean of 0.57, reflecting moderate vegetation density. The analysis revealed a slight negative skewness, confirming non-normality. The Green Normalized Difference Vegetation Index (GNDVI) presented a median of 0.41 and a mean of 0.40, also showing medium-level vegetative health and a slightly skewed distribution.

Further analysis revealed strong associations between SOC and various vegetation indices (VIs). Correlation coefficients indicated a strong positive relationship between SOC and NDVI (0.9095), as well as between SOC and GNDVI (0.9143) and SAVI (0.9095). In contrast, the correlation with BSI was -0.9091, highlighting a strong negative relationship, consistent with existing literature. To further validate these findings, the non-parametric Spearman's rho test was employed, indicating strong correlations (coefficients around 0.9) between SOC and the VIs, while the coefficient for BSI was -0.9, suggesting a negative relationship (Figure 2).

Variable	by Variable	Spearman ρ	Prob> ρ
SOC	NDVI	0.9028	<.0001*
SOC	BSI	-0.9000	<.0001*
SOC	SAVI	0.9028	<.0001*
SOC	GNDVI	0.9084	<.0001*

Figure 2: Nonparametric: Spearman's ρ

Lastly, ordinal logistic regression results underscored the VIs' roles in SOC estimation. The "Effect Likelihood Ratio Tests" indicated that NDVI, BSI, GNDVI, and SAVI significantly affect SOC estimation, with p-values below 0.05. Specifically, the "Parameter Estimates" for NDVI, SAVI, and GNDVI were 78, 62, and 99, respectively, indicating strong positive relationships. In contrast, BSI had a "Parameter Estimate" of -77, signifying a strong negative relationship. The log odds imply an extraordinarily large odds ratio when exponentiated. That happens because the carbon classes are separated only by 0.1 units and simultaneously since VIs ranges from -1 to +1. Hence even small variations might be exaggerated in the model. While calculating "Odds Ratios" is typically recommended to assess the effect magnitude in ordinal logistic regression, the high "Parameter Estimate" values suggest a strong relationship between the VIs and SOC. These findings align with existing literature emphasizing the critical role of vegetation health in estimating SOC content.

4. Conclusions & Recommendations

In conclusion, SOC estimation can be effectively achieved through models based on vegetation indices (VIs). This study demonstrates that VIs have a significant relationship with SOC and can predict its fluctuations. Scientists, farmers, and stakeholders can leverage these findings to reduce costs associated with traditional laboratory SOC analysis, which often yields imprecise results. The

models proposed can provide a more comprehensive tool for SOC estimation, utilizing multiple VNIR and SWIR wavelengths to gather varied information about agricultural fields, their limitations, and SOC levels simultaneously.

Moreover, SOC estimation through remote sensing (RS) can enable instant global assessments without the constraints of time, chemicals, or labor. With just one ground-truth soil analysis to correlate SOC with VIs, farmers can access vital information remotely, facilitating informed decisions about their fields. This approach also reduces transportation costs and fosters a well-organized data environment for agricultural businesses, assisting policymakers in evaluating fields for subsidies or investments. Additionally, it can help identify fields at risk of degradation, allowing for appropriate interventions to promote sustainable practices.

SOC estimation via RS and VIs could create job opportunities for young scientists and farmers, fostering a sustainable working environment. Notably, the study highlights those essential tools, like GIS statistical programs, do not require substantial investment, rather, accurate data can be obtained through the application of knowledge and technology, saving time and resources.

However, the study has limitations, and further research is encouraged. Additional soil samples from similarly sized fields could lead to more precise maps and models. Although the results were satisfactory, a larger data pool might yield improved models with reduced errors. Future studies should develop SOC estimation models that incorporate multiple VIs simultaneously. While this adds complexity, it could result in more accurate models that effectively address the intricate factors influencing agricultural parameters, especially under climate change scenarios.

Lastly, the study suggests employing UASs equipped with VNIR–SWIR cameras, as satellite imagery offers limited pixel resolution, with each pixel from the Sentinel 2 database covering a 10m x 10m area. In contrast, UASs can capture spectral imagery with 4K resolution, yielding better data and minimizing errors from factors such as weeds, water, cloud cover, and wildlife, ultimately enhancing the accuracy of VIs and RS data analyses.

Declaration on Generative AI

The author(s) have not employed any Generative AI tools.

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