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Remote Estimation of Soil Organic Carbon via Reflectance Properties

S. Pozhilarasi[1] and Chuncha Laxmi Prasanna[2]

Abstract: -

One helpful soil characteristic that can be used to direct the application of chemical inputs in agriculture is the concentration of soil organic carbon (SOC). To make this possible, maps of surface SOC concentrations must be created using quick, easy, accurate, and affordable techniques. In order to quickly measure and track certain surface soil properties, including SOC, researchers have looked into estimates of soil surface properties from remotely sensed data. This paper's goal is to examine the possibilities and constraints of using remotely sensed data for SOC mapping and assessment. To examine the accuracy of such estimations, a number of statistical techniques have been applied to the data, including principal component analysis, geostatistics, the "soil line" approach, and basic regression models. A survey of the literature demonstrates that fresh regression models are needed for each scene and that prediction equations are not universal. The ability to provide a sample plan that may result in better representation of spatial variability in SOC is a significant advantage of remotely sensed data.

Introduction:

Understanding the mechanical and physical characteristics of soil, as well as how these characteristics vary geographically, is crucial to the precision agriculture idea. Differences in concentrations, fertilizer requirements, herbicide action, and crop yield within a field are caused by spatial variation in soil parameters. Accordingly, areas within a field that receive uniform soil treatment will either be over- or under treated. One barrier to the broad use of precision agriculture is the measurement of soil heterogeneity. Plant-soil interactions are significantly impacted by soil organic carbon (SOS). SOC content is closely

S. Pozhilarasi[1] and Chuncha Laxmi Prasanna[2]

[1]Ph.D Research Scholar, Department of Seed Science & Technology, TNAU, Coimbatore

[2]Ph.D Research Scholar, Department of Soil Science and Agricultural Chemistry, University of Agricultural Sciences, GKVK, Bangalore

associated with soil quality not only as a measure of soil erosion and degradation, but also as a regulator of various processes, including crop yield, pesticide behavior in soil, plant-available N, the soil's capacity to adsorb plant nutrients, and water holding capacity and permeability. It could be helpful to know its content in the soil, particularly if its spatial distribution could be precisely ascertained and affordably. Sampling strategies, such as those based on a grid or zones, have been employed to ascertain the within-field variation in SOC and other parameters. It is possible that the geographical variation in SOC occurs at a finer spatial scale than what can be achieved by physically sampling the soil and then analyzing it in a lab. To reduce the costs of creating maps of surface SOC concentrations to support precision agriculture, quantitative soil-landscape modeling, and global soil C monitoring, it is acknowledged that techniques that use the fewest number of soil samples possible must be developed. Reflectances in specific spectral bands have been linked to soil properties, according to recent research. These reflectances may offer low-cost predictions of the physical, chemical, and biological characteristics of the soil. The soil gets darker as SOC rises, and vice versa. The idea that electro-optical sensing of SOC would be possible was based on this broad observation. High resolution spectral sensors have been developed as a result of numerous researchers' attempts to use soil reflectance in the lab to determine SOC. Ancillary information on the soil can be obtained from the remotely sensed data produced by these sensors. Our comprehension of the site-specific variance of the soil's surface horizon may be enhanced by the capacity to estimate soil parameters from remotely sensed photographs. In order to create a model that can forecast soil organic carbon from reflectance values at any point on the field image, sampling areas are chosen using this method to cover the range of reflectances in the area of interest. Reflectance has been used to measure SOC in a number of methods throughout the last 30 years. This paper's goal is to examine the methods for identifying SOC content from remotely sensed data and look into its advantages and disadvantages. An outline of SOC's spectral characteristics is presented first, then techniques for estimating it from reflectances gathered by space and aerial remote sensing.

Spectral features of Soil organic carbon

In the electromagnetic spectrum, a material's reflectance or absorbance as a function of wavelength defines its spectral signature. The signatures are caused by vibrational stretching and bending of structural groupings of atoms that form molecules or crystals, as well as electronic transitions of atoms under regulated conditions. The energy levels at which molecules can reach higher vibration states are where fundamental characteristics of reflectance spectra appear. Overlapping bands from various mineral components and organic matter cause absorption features in soil. According to reports, the average R2 value for the visible (VIS), near infrared (NIR), and middle infrared (MIR) is 0.89, 0.79, and 0.74, respectively. The most popular approach, partial least-squares regression (PLSR), has produced the highest correlation coefficients.

The soil often exhibits reflectance spectra in the 1100–2500 nm range, with three major absorption peaks at 1400, 1900, and 2200 nm as well as a few minor absorption peaks between 2200 and 2500 nm. It is more challenging to identify the connection between spectral and physicochemical features when organic matter is present because it reduces the total reflectance and, consequently, the spectral contrast. The NIR (700–2500 nm) and VIS (400–700 nm) portions of the electromagnetic spectrum are dominated by the weak overtones and combinations of these fundamental vibrations caused by the bending of NH, OH, and CH groups. However, the fundamental features related to various components of soil organic matter typically occur in the mid- to thermal-infrared range (2500–25,000 nm). Around 410, 570, and 660 nm are significant bands in the VIS range for the prediction of SOC. Organic matter lowers reflectance in the 550–700 nm range. It also causes a concave curve for higher OM levels and a convex one for lower OM contents in the 500–1300 nm range. In the near-infrared spectrum, OM and reflectance are likewise highly correlated. The wavelengths that are most sensitive to OM levels include 1720, 2180, and 2309 nm and 1744, 1870, and 2052 nm. The MIR range offers more information on OC in soil than the NIR range does. Using the response of soil reflectance to OC, parent material, and other soil characteristics, Henderson et al. (1992) divided spectral bands. They discovered that the wavelengths between 2200 and 2500 nm were the most effective for detecting SOM. However, due to the influence of other soil characteristics that obscure soil reaction, the wavelengths between 2225 and 2255 and 2275 nm should be avoided. Henderson et al. (1992) also noted that the visible and near-infrared portions of the spectrum (400–1100) are where the effect of OC is most noticeable, and that certain regions of the SWIR spectrum (1100–2500) may be able to estimate SOC levels sampled across wide geographic areas on various parent materials.

Aerial and space remote sensing of SOC

Researchers have been looking into novel methods to improve the precision of determining SOC using remotely sensed (RS) data over the past thirty years. Regression, the "soil line," PCA, and geostatistics based models have so been put forth.

Simple regression models

The first airborne studies to examine the connection between OM and reflectance in the visible and near-infrared ranges were conducted by Baumgardner et al. (1970) and Al-Abbas et al. (1972).

Research was then conducted to determine whether remotely sensed data could be used to direct sampling, assess the status of SOC for agricultural and environmental activities and effectively distinguish between various soil properties and vegetation types. It can be predicted and expressed by soil reflectance, as evidenced by the significant association found between SOC and soil spectral reflectance. In order to identify the best wavelengths for assessing SOC, various spectra sections have also been examined. Abgu et al. (1990) demonstrated a substantial correlation between the soil's organic C content and just the red and green bands. Similar to McCarty's (2002) findings, Sullivan et al. (2005) demonstrated that 93% of the variation in SOC could be explained by the thermal infrared (TIR) index, with VIS and NIR spectra contributing less. The VIS, MIR, and TIR band ratios accounted for 38% of the variation in SOC in one of the fields under investigation. Similarly, at another site, 42% of the variation in SOC was explained by the TIR and VIS ratios. According to Bajwa et al. (2001), the red portion of the spectrum had the highest correlation. The link became less as the wavelength was reduced in the blue and green regions. When compared to the other spectral ranges, the NIR spectrum showed the least connection. Spectral mixing can have an impact on the associations by altering the spectra's slope and lowering the correlations. For instance, Galvao et al. (2001) found that the presence of non-soil residues on the soil surface resulted in modest correlation coefficients between reflectance and organic matter in the visible range. The maximum of these correlations occurred between 1200 and 2000 nm, after which they declined as the wavelength increased.

In more recent and thorough investigations, Chen et al. (2000 and 2005) used two distinct approaches to investigate the connection between the OC content in the top 15 cm of the soil profile and specific regions of the spectrum from the image. The surface SOC concentrations for every pixel were determined using an equation in the first technique, and the results were categorized into eight classes. The image was divided into 20 groups using the second approach, and the categorized result was then subjected to the aforementioned equation. Ultimately, eight classes were created by further grouping the initial 20 groupings. In every image, there was a high degree of agreement between the measured and anticipated values for both approaches. In order to calculate SOC, Chen et al. (2000) collected 28 soil samples from a field covering roughly 115 hectares, and then created maps using the information. This sample size is 10-40% of what would have been needed to create equivalent maps using grid sampling. At least 284 samples from this 115 ha area would be required for a grid sample at a scale of 0.405 ha. The main benefits of the SRM approach over grid sampling are its affordability and its capacity to provide a thorough and precise account of the geographical variation in soil organic carbon. When using grid sampling, 8–10 cores are usually collected in order to create a composite sample that represents an area of at least 0.405 hectares (1 acre). The composite sample offers little insight into the variation across the sample's covered region, even if the individual core samples accurately reflect the area sampled. On the other hand, surface SOC concentrations might be mapped at picture pixel size resolution using the SRM approach.

Geostatistical techniques

Local correlation between measured OM and spectral reflectance values at the same sites is used in multivariate regression-based spatial predictions. Spatial autocorrelation in OM is not taken into consideration in these projections. The implicit premise of regression is that values at one site are unrelated to those at nearby sites. In contrast, geostatistics models the spatial variance using spatial autocorrelation. Furthermore, some techniques have been demonstrated to enhance SOC estimates through the use of correlated secondary data, particularly when the latter is at a lower sampling density than the secondary variable. Both auto- and cross-correlation functions must be modeled using these techniques. The degree of spatial correlation in the variable of interest, sample size, and sampling design all have a significant impact on the accuracy of estimates in univariate mapping, according to sampling and geostatistics research. A number of geostatistical techniques can use secondary data, which is frequently more expensive and time-consuming to acquire than the primary soil variable. Cokriging, kriging inside strata, kriging with external drift, simple kriging with different local means, and regression kriging are some examples of these techniques. The assumptions made by these approaches vary with regard to the structure of the relationships between the primary and ancillary variables as well as the way in which the primary variable is estimated at unsampled locations using secondary data. Digital soil surveys, digital elevation models (DEM) and derived terrain indices, remotely sensed images of soil surface reflectance, apparent electrical conductivity

(ECa), and measurements of soil properties through on-the-go sensors are just a few examples of the ancillary variables that are available at the field scale. Given the close correlation between reflectances and SOC, as well as the affordability and real-time accessibility of pictures, remote sensing may be one of the most useful sources of secondary data. To enhance the forecasting of limited information from soil surveys, Kerry and Oliver (2003) proposed the inclusion of more extensive, less costly auxiliary data, such as aerial photos of bare soil. Even though the photos are from a typical survey archive and the coordinates (x and y) of the soil data and auxiliary information are not precisely at the same places, this was still advised. The use of supplementary data for kriging typically yields more accurate local forecasts if there is a significant connection between the primary and secondary variables. The degree to which SOC and secondary data were related determined how much better regression kriging was than standard kriging. Because kriging employs the spectrum data to determine the local mean or trend of any soil property, it produces more accurate estimates for soil variables that have a significant association to spectral data as secondary information. Nonetheless, secondary data ought to be included in the mapping prediction process whenever it becomes accessible. Techniques that use a moderately correlated secondary attribute to map the primary variable outperformed univariate approaches like standard kriging, even in cases where the secondary attribute is available, such as remotely sensed (spectral) data from aerial photographs. Regression and simple kriging have the highest mean squared errors (MSEs) among the various approaches, while the MSEs for the other geostatistical techniques that take into account secondary data, like spectral data, are lower. Due to the limited relationships between spectral values and soil properties, simple linear regression produced the worst forecasts. Compared to ordinary kriging, the MSE for basic linear regression plus ordinary kriging is lower.

Conclusions

Improved depiction of the spatial variation in the soil property of interest can result from estimates of soil surface properties derived from remotely sensed data. For the practical purpose of predicting SOC, simple regression models are sufficiently accurate. More general techniques like principal component analysis and the SLED methodology were created to guide soil sampling and enhance the depiction of within-field variation in surface organic matter content. Furthermore, it has been demonstrated that geostatistical methods that may make use of auxiliary data like that from sensors improve SOC prediction. These strategies do, however, have certain drawbacks. Regression models, for instance, are location- and even imagery-specific and cannot be applied in other contexts. The SLED technique ignores important relationships between other bands and OM content, etc., and only employs reflectance in the R and NIR bands. Studies have demonstrated a substantial correlation between bare soil reflectance and changes in parent material and soil surface conditions at the time of data collection (such as moisture, tillage, crop residues, crop cover, etc.). As a result, even while high resolution aerial or satellite photos are become cheaper, more accessible, and taken more frequently, their usefulness for mapping and tracking soil carbon stocks at the field scale might differ greatly. Nearly every researcher cited the primary benefit of remotely sensed data, which is that it can be utilized to create a sampling plan for mapping SOC with the fewest samples and the highest accuracy. Therefore, we suggest that rather than predicting soil attributes, future research should first concentrate on using remotely sensed data to guide sampling. PCA or the percentile approach of the soil line can be used for this. Future research should concentrate on the use of satellite data as secondary information in geostatistical analysis, as this has demonstrated the ability to enhance SOC forecasts. The majority of studies that have estimated SOC using remotely sensed data have done so in regions with high SOC contents and minimal interference from other soil characteristics. For example, no research has compared these methods in a region that is arid or semiarid. Large concentrations of $CaCO_3$ or $CaSO_4$ can significantly alter the spectral behavior of soil in these conditions. This might significantly impact how well the approaches are performed. Future studies are required to examine the potential of remotely sensed data to direct sampling and forecast SOC in settings with varying soil, parent material, and climate. The acquisition of more relevant data from fields could enhance soil surveys and evaluation.

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