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ANALYSIS OF SPECTRAL REFLECTANCE AND ABSORPTION PATTERNS OF SOIL ORGANIC MATTER

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ABSTRACT

As remote sensing technology is advancing into 1-m resolution and hyperspectral imaging, there is a corresponding interest in the detailed analysis of spectral features at a close range distances. The study relates the lab-and field based spectral signature to soil organic matter (here after SOM) in Pathanna Nikom area, Thailand. The paper introduced a new approach to develop prediction models from SOM-sensitive spectral signatures. Spectral measurements were conducted by portable field photometer (Nikon, model 2703) and in a laboratory based, StellarNet Spectroradiometer. Computed variability in spectral reflectance and absorption attributes were found SOM-dependent. Careful examination of sensitive bands allowed not only for the characterization and mapping of SOM, but also indicated the possibility for further application of knowledge-based integrated SOM classification maps. The combination of *in-situ* and spectrophotometer based laboratory techniques are promising methodologies to yield a fast, cheaper, and timely monitoring of SOM. This result could also form the basis for opting fine-tuned spectral bands for future satellite missions.

1. INTRODUCTION

The need to monitor the near real time status of dynamic soil properties necessitate an efficient system evading long procedures involved in traditional methods. The potential of remote sensing to retrieve soil attributes have long been attempted with several platforms of sensors and techniques.

By definition, the reflectance and emittance behavior of an object, such as soil is highly dependent on its biochemical and physical fabric. As photons enter the soil mineral, some are reflected, some passes through it, and some are absorbed. The absorption processes are variable and wavelength dependent. The reflected and emitted light allows us to derive information about the chemistry of soil. Field and lab based spectroscopes assists several application, such as aircraft and satellite calibration, data mining from remote sensing data, soil mapping. Detailed explanation on spectrometry is given on *http://www.asdi.com /asd/apps/remote__sensing.html*.

Satellites have a non-contagiously spaced broad bandwidth channels (e.g., TM, MODIS). They fail to resolve narrow absorption features. Explanation on the detailed effect of bandwidths on the shape of absprtion curves is illustrated by Clark (1999). Simulating spectral bands across varying width allows not only for obtaining scale-based spectral information, but also assist in sensor-to-sensor data conversion

SOM is a storehouse of plant nutrients serving as a "nutrient bank account" (Glendinning, 2000) and its loss is associated to declining soil productivity. SOM improves the soil physical conditions, increases water infiltration, improving tilth, decreases erosion losses, supplies plant nutrients, etc. Both the content and decomposition rates of SOM are highly variable. Hontoria *et al*., (1999) reported site characteristics explains almost 50% of the of SOM variability. High temperature and rainfall facilitates the rapid decomposition of SOM. Furthermore, SOM could be influenced by the farmer's management practices. Such a user-sensitive soil parameter calls for an efficient monitoring system accompanied with acceptable level of accuracy.

The fact that darker soils contain more SOM than lighter ones shows the relationship between visible reflectance and SOM. Humic acid has a very low reflectance (<2%), and obliterating both the reflectance as well as color of soils (Galvao and Vitorello, 1998). Various approaches have been employed in the translation of spectral information to SOM. Palacios-Orueta *et al.* (1998) used hierarchical foreground and background analysis to monitor the spectral characteristics of SOM from AVIRIS data yielding absorption features related to OM and iron contents. The absorption features representing SOM (Karneili, *et al.*, 1998) were at 1720 nm, 2180 nm, and 2309 nm. Galvao and Vitorello (1998) established a quantitative relation between the reflectance and soils, stratified at 100 nm intervals, in the 400-2500 nm interval, where a higher reflectance was observed in the 600-900 nm range. Karneili, *et al.* (1998) have attempted to quantify the wet biogenic soils with NDVI and obtained a value up to 0.30 due to their photosynthetic activity.

With the advancement of computer and detector technology, several spectroradiometers (Galvao and Vitorello, 1998; Henderson, *et al.*, 1992) have been used for research. Unlike vegetation, the shape of spectral signature of soils tends to be invariant especially in spectral regions below 1400 nm. This poses a bottleneck where the range of wavelength in the sensing instrument is less than this limit. These calls for other robust approaches to give render meaning to those data. In general, approaches so far were constrained by inadequacies in cross assessment between 1) field- and lab-based spectral data, 2) Statistical and polynomial prediction models, and 3) different interval width of simulated bands. In this paper, an attempt is made to fill those gaps with a new approach, which is translating the laboratory and field -based spectral reflectance and absorption information to a quantified SOM concentration.

2. MATERIAL AND METHODS

2.1 Study Site

The study area is located at the Phatthana Nikom district in Lop Buri Province, situated in the central plain (between $14^0\ 45' - 15^0\ 00'$ N and $100^0\ 50' - 101^0\ 10'$ E) of Thailand. The soil in the area is developed over two parent materials: Sand stone and limestone. Major crops of the area include rice, maize, sorghum, and cassava. Climatically, the region belongs to Tropical Savannah type “Aw”.

2.2 Sampling Design

Soil samples were collected from bare plough layer (about 5 cm) during the land preparation stage of subsequent cropping season. Forty-three soil samples (replicated in three) were collected over a 3 days of field survey (in April 2001). Sample points were positioned on a several transects running over two major parent materials. In-situ spectral measurements were conducted with portable photometer (Nikon, model 2703). A panel coated with $BaSO_4$ paint was used as reference for the reflectance calibration. However, the laboratory based spectral assessment (both reflectance and absorption) was undertaken on all the 3 replicates of 43 samples.

Sample data were randomly partitioned between 31 (73%) samples for model development and the remaining 27% for the cross validation. To validate model performance, R^2 was computed between the predicted and observed values of the cross validating data.

2.3 Soil Analysis

2.3.1 Chemical Analysis. OM concentration was analyzed from the soil samples in a laboratory at the Asian Institute of Technology, following Dry Ash Method (Boyd, 1995). Air-dried soil samples were placed in an oven at 105^0C for 24h. After cooling the sample in a desecrator and weigh, they were placed in a muffle furnace at 305^0C for 8 hrs and reweighed after. Finally, it was computed as:

$$SOM = 100 - \frac{W_F - W_T}{W_{TS} - W_T} \qquad \text{(Equation 1)}$$

Where, SOM= soil organic matter (%) W_T = weight of crucible (g); W_{TS} = weight of crucible and oven dry soil (g); W_F = weight of crucible and soil after ashing (g)

2.3.2 Spectral Reflectance and Absorption. Data for spectral characterization were acquired under field (*in-situ*) and laboratory conditions. The field spectral examined the spectral reflectance from 400nm to 1050nm. Measurements were made from a 1.5 m high directed at a 45^0-viewing angle facing from the illuminating sun both on the soil and white board. The spectral interval of field spectrometer is 25 nm (400 to 675), 50 nm (700 to 750) and 100 nm (750 to 1050). However, the spectral reflectance and absorption measured at the laboratory was undertaken at 10 nm intervals all over from 400 to 1190nm. However, the laboratory data were re-organized to a 10, 20, 50, and 100 nm bandwidths.

In the lab-based condition, a new measurement device, StellarNet Spectroradiometers (Figure 1) was used. It is composed of a fiber optic reflectance probe employed for solid samples, which measures sample absorbance, transmittance, and reflectance. These instruments are calibrated to measure over the wavelength range from 400-1100nm, at a 10nm interval. The instrument uses a white Reflectance Standard with a >97% reflectance. Specular reflectance from the soil was minimized using an angle of 45^0 between light beam and the normal axis, to the soil sample surface. Interference light multiple reflections were reduced by setting the measuring probe at 2-mm distance from the soil sample. Crucible with a 30-mm depth was filled with samples. Particular attention was given to the size of micro-aggregates, where a 2-mm sieve was used to make them homogeneous in dimension.

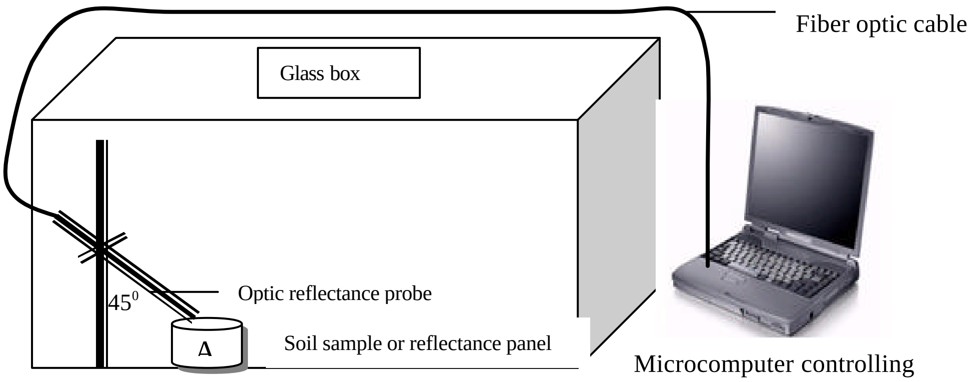

Figure 1. Schematic representation of lab-based spectroscopy.

2.4. Statistical Modeling

To determine the most responsive wavelength, both the reflectance and absorption spectra data were organized across different wavelength ranges. A stepwise statistical analysis technique has been used as a selection method to filter out the entry or removal of independent spectral variables from a regression model.

2.5 Polynomial Modeling

When the statistical analysis generates 3 SOM-sensitive spectral bands, a polynomial equation (Equation 2) was employed to yield a better model of SOM.

$$Y = a_0 + a_1x + a_2w + a_3z + a_4x^2 + a_5w^2 + a_6z^2 + a_7xw + a_8wz + a_9xz + a_{10}x^3 + a_{11}w^3 + a_{12}z^3 + a_{13}x^2w + a_{14}x^2z + a_{15}w^2x + a_{16}w^2z + a_{17}z^2x + a_{18}z^2w + a_{19}xwz \quad \text{(Equation 2)}$$

Twenty equations are required to find out coefficients ($a_0, a_1, \ldots, a_{19}$). A 20 x 20 matrix is used to obtain major and minor determinants, where those coefficients could easily be obtained. To reduce the long equation within a higher accuracy, some of the constant values were eliminated. The performance of reduced equation was computed against the original equation using R^2. The procedure continued as long as the R^2 retain above 0.95. The cut off point obtained with this strategy was an equation using 7 coefficients (Equation 3).

$$Y = a_0 + a_1x + a_2y + a_3z + a_4x^2 + a_5y^2 + a_6z^2 \quad \text{(Equation 3)}$$

Using 7 x 7 matrix, determinants were computed for a_0 to a_6. The equation predicts the dependent variable expressed with “Efficiency Index” (EI), ranging from 0 to1. Besides, the model would select the seven best (optimum) locations with minimum magnitude of prediction error.

3. RESULTS AND DISCUSSION

3.1 Soil OM Variability

The distribution of SOM concentration in the furrow slice of mineral soils in the study area, obtained from the traditional laboratory measurement, ranges from 6.72 to 19.31%. The mean and standard deviation are in order of 12.53 and 3.33 %. The concentration of SOM in the study area par exceeds the 4-6% reported from agricultural soils (Boyd, 1995). The discernible SOM variation within the study area calls for differential fertilizer application. High SOM concentration might be due to the higher temperature and rainfall distribution of the study area, which is favorable to higher decomposition rate of organic materials, high concentration of OM on top most layers of soils, or the farmer's good management.

3.2 Soil Spectral Variability

Out of the eighty (10 nm interval) spectral bands of reflectance and absorption variables, considered in a stepwise regression coefficient analysis, only bands 960, and 1110 were found to be SOM sensitive. Table 1 shows results of similar statistical analysis for 40, 16 and 8 input variables for 20, 50, and 100nm intervals respectively.

Table 1. Spectral based SOM statistical prediction models

Spectral Interval	A. Spectral reflectance	R^2	
		Model	Validation
10 nm	22.78 - 2.387 (B-960)+ 2.55 (B-1110)	0.6107	0.737
20 nm	22.55-2.2(B-960-970)+ 3.2(B-1120-1130) -1.09(B-520-530)	0.6369	0.8339
50 nm	23.619 - 2.06 (B-950-990) + 2.24 (B-1100-1140)	0.5873	0.6940
100 nm	24.0506- 1.4699 (B-1100-1190) + 1.580 (B-900-990)	0.5051	0.7502

Spectral Interval	B. Spectral absorption	R^2	
		Model	Validation
10 nm	8.82+ 164.86(B-960) -167.45(B-1120)+26.42(B-520)	0.6214	0.7941
20 nm	8.56+ 179 (B-970) -180.5 (B-1110) + 23.36 (B-530)	0.5844	0.7589
50 nm	8.32+ 165.48 (B-950-990) - 171.36 (B-1100-1140) + 30.47 (B-500-540)	0.6196	0.8015
100 nm	13.36+ 117.029 (B-900-990) -91.979 (B-1100-1190)	0.4901	0.7127

Almost identical bands were found SOM sensitive both at the reflectance and absorption at all interval levels. On overall, the spectral reflectance model outperforms the spectral absorption's prediction power (adjusted R^2) and cross validation (validation R^2). With respect to the specific band category, the 20 and 100 nm intervals are the best and least spectral reflectance predictors, respectively. On the other hand, the 10 and 100 nm intervals were found to be the best and worst predictors of spectral absorptions. In could be generalized that, the 100 nm interval is little potential of SOM prediction due mainly to the masking effect of several bands in one category.

When the spectral information was modeled with polynomial equation with the input variable of SOM-sensitive bands obtained from the statistical analysis. The performance, expressed in efficiency index, ranged from 0.58 (at 20 nm interval) to 66.17 (both at the 10 and 100-nm intervals) in spectral reflectance (Table 2). On overall, the spectral reflectance model outperforms the spectral absorption's prediction power (Efficiency Index) and cross validation (validation R^2). The same holds true for the comparison made on the cross validation between the two.

In terms of specific spectral resolution, the 50 nm interval category (Figure 2) of the polynomial model showed a better performance both in reflectance as well as absorptions. This holds true both in the model performance as well as the cross validation of the model. The efficiency index in the absorption curve exhibited a marked variability. The categories 10- and 20-nm bandwidths yielded inferior results as opposed to 50-and 100-nm intervals. However, the efficiency index of the reflectance curve showed little variability on the overall distribution. Hence, the combined interpretation of both the reflectance and absorption performance leads to the choice of the 50nm bandwidth as a best SOM sensitive spectral category.

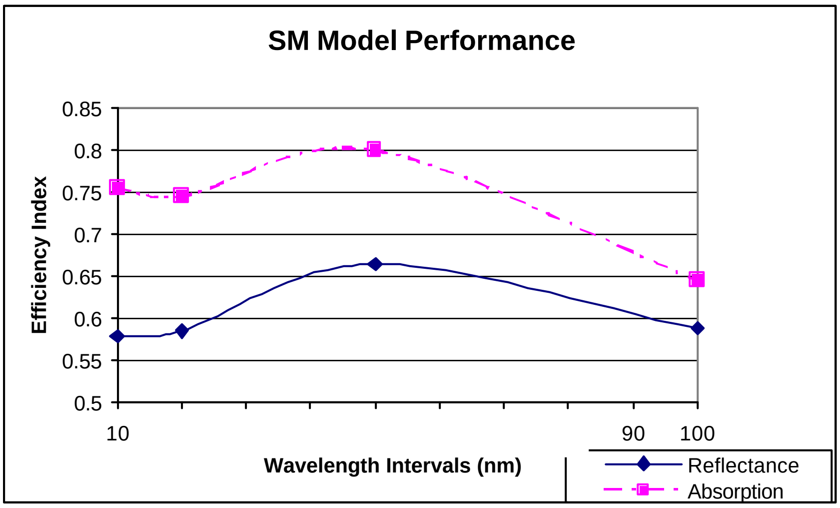

Figure 2. Evaluation of model performance in different wavelength intervals

Table 2. Spectral-based SOM polynomial prediction models

Spectral interval	A. Spectral reflectance	EI	Validation (R^2)
10 nm	22.61-2.95(B-960)+3.459(B-1110) +0.067(B-530) -0.01 (B-960)^2 0.015(B-1110)^2-0.022(B-530)^2	0.6617	0.79
20 nm	20.28+3.169(B-960-970)-2.17(B-1120-1130)-0.9286(B-520-530) -0.014 (B-960-970)^2 +0.0034(B-1120-1130)^2 + 0.013(B-520-530)^2	0.6534	0.80
50 nm	28.23-4.145(B-950-990)+5.189(B-1100-1140)-0.041(B-500-540)+0.0264 (B-950-990)^2-0.0417(B-1100-1140)^2 - 0.009(B-500-540)^2	0.5884	0.59
100 nm	23.5+ 3.23(B-900-990) -3.459(B-1100-1190) + 1.89(B-500-590) -0.028 (B-900-990)^2 + 0.0323(B- 1100-1190)^2 -0.092 (B-500-590)^2	0.6617	0.79

Spectral interval	B. Spectral absorption	EI	Validation (R^2)
10 nm	-66.019 + 1127.08 (B-960) -1161.88 (B-1110) +171.8 (B-530) - 1011.92(B-960)^2 + 1100.8 (B-1110)^2-100.36 (B-530)^2	0.5062	0.69
20 nm	-56.48 + 1822.58 (B-960-970) -1818.37 (B-1120-1130) +125.32 (B-520-530)-1566.62 (B-960-970)^2+ 1631.49 (B-1120-1130)^2 -78.677 (B-520-530)^2	0.5073	0.70
50 nm	-26.52 + 317.6 (B-950-990) - 442.55 (B-1100-1140) +213.76(B-500-540) + -159.3056 (B-950-990)^2 +235.2 (B-1100-1140)^2 -109.029 (B-500-540)^2	0.6756	0.80
100 nm	-36.859+2.291(B-900-990)-25 (B-1100-1190) +123.1191 (B-500-590) +106.5289 (B-900-990)^2-74.98 (B-1100-1190)^2 - 49.62 (B-500-590)^2	0.587	0.70

4. CONCLUSIONS

A new approach is developed to translate spectral information to the SOM. The model could be further useful for other the fertility parameter research in remote sensing field. Evidence from the experiment presented in this paper indicates that the radiometric model is capable to predict the concentration of SOM. In both the reflectance and absorption experiments, bands centering around 960, 1120, and 520 are fund best ones. This spectral-chemical composition allows the delineation of boundaries between different soils. With respect to the statistical modeling analysis, results obtained from field spectrophotometer showed very poor performance compared to the corresponding bands from the laboratory based spectrophotometer. The strong correlations that exist among several independent variables are the main bottlenecks. Other factors include, variation of distance between the sensors and the object of investigation; the variation in spectral resolution between the instruments; etc. The problem of correlation among the input variables calls for the utilization of neural network techniques, where correlation among the independent variables is of no impact.

The simulation of spectral bands with variable size of intervals allowed exploiting a better prediction model from the numerous narrow spectral bands. Such manipulation of wavelength intervals would allow for the precise prediction of the SOM-sensitive bands, which could further be used in future satellite mission.

It is highly recommended future research should be directed at employing the satellite spectral data. It should be recalled that the results of this study are only valid for the soil types represented in the study area. Variables like soil moisture and slope are not taken in to account. Further studies are required to examine the applicability of the radiometric indices on other soils. Since real set of data recorded from satellite do markedly differ from lab and field-based data, it is important to consider the atmospheric luminance values. Involvement of satellite data for prediction of SOM enables to consider wider area coverage with limited piece of work on the field.

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