Soil Moisture, Organic Matter, and Iron Content Effect on the Spectral Characteristics of Selected Vertisols and Alfisols in Alabama

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ABSTRACT: A field-portable multiband radiometer (Modular-Multiband Radiometer Model 12-1000) was used to obtain spectral data on two Vertisols and two Alfisols of the Black Belt region of Alabama. The wavelength bands used were 0.45 to 0.52, 0.52 to 0.60, 0.63 to 0.69, 0.76 to 0.90, 1.15 to 1.30, 1.55 to 1.75, and 2.08 to 2.35 μm. Correlation, regression, and discriminant analyses were used in evaluating soil-moisture, organic matter, and iron oxide effects on the spectral characteristics of the soils. High correlations were found among reflectance and the variables studied. The soils were accurately differentiated based on their spectral properties or physical and chemical properties. A middle infrared band (2.08 to 2.35 μm) was most important in imparting variation due to soil moisture. The red band (0.63 to 0.69 μm) and a near infrared band (1.15 to 1.30 μm) were most important for explaining variability due to the presence of iron oxides. A near infrared band at 0.76 to 0.90 μm was the key band in explaining variability due to organic matter content. An increase in soil moisture and organic matter results in a decrease in reflectance spectra, while an increase in iron oxide produces an increase in reflectance spectra in all wavelength bands. A combination of bands from selected portions of the electromagnetic spectrum was used to develop prediction equations for the soil variables.

INTRODUCTION

SOIL MAPPING and determining various diagnostic properties of soils promise to be significant applications of satellite remote sensing data. Methods presently used for preparation of soil maps require a soil scientist to traverse the landscape, examining the soil at intervals and recording his/her observations on a suitable map base, usually an aerial photograph. Detailed soil and landscape evaluation of the same areas by several soil scientists may lead to different separations because of differences in their experience and individual biases. The use of multispectral imagery and computer-aided data processing techniques in soil studies has been reported by several authors (Baumgardner *et al.*, 1970; Cihlar and Protz, 1973; Kristof, 1971; Kristof and Zachary, 1971 and 1974; Mathews *et al.*, 1973; Michalyna and Eileus, 1973).

Landsat imagery has been used to identify soil associations and attendant range sites (Seevers *et al.*, 1974). In regions where polypedons are related to soil drainage, soil color, topography, and vegetation (Parks and Bodenheimerkr, 1973; Westin, 1973; Westin and Frazee, 1976; Lewis *et al.*, 1975), soil associations have been stratified by manual interpretations from Landsat color composite imagery. Cipra *et al.* (1980) found that, in situations where soil color is highly correlated with other soil series characteristics, identifying soil series differences by spectral characteristics is possible. Westin and Frazee (1976) described the characteristics of Landsat imagery that are applicable to its use in soil survey programs. Using tone, color, land-use patterns, and drainage patterns on a Landsat color composite transparency, they prepared a low-intensity soilscape map that needed only moderate refinement after field checking.

Weismiller *et al.* (1977) made an inventory of soils in Chariton County, Missouri, using Landsat and topographic data; however, they did not attempt to relate soil cover to soil type. In using digital analysis of Landsat data from Clinton County, Indiana, to delineate and analyze soil map unit composition, Kirschmer *et al.* (1978) defined 12 soil spectral classes and four vegetation spectral classes.

The objectives of this research were twofold: First, to evaluate the effect of soil moisture, organic matter, and iron oxide on the spectral characteristics of Vertisols and Alfisols from the Black Belt region of Alabama; and second, to determine if soil-moisture, organic matter, and iron oxide levels can be predicted using spectral properties.

MATERIALS AND METHODS

The spectral data were collected on 15 and 16 November 1983 under natural field conditions with a portable Barnes Modular-Multiband Radiometer Model 12-1000 (MMR). The data were collected in seven wavelength bands: 0.45 to 0.52 μm (blue), 0.52 to 0.60 μm (green), 0.63 to 0.69 μm (red), 0.76 to 0.90 μm and 1.15 to 1.30 μm (near infrared), and 1.55 to 1.75 μm and 2.08 to 2.35 μm (middle infrared).

Four soils were selected for study: Sucarnoochee (Aquentic Chromudert), Mayhew (Vertic Ochraqualf), Kipling (Vertic Hapludalf), and Okalona (Typic Chromudert). These soils were selected because they represent the major soils in the Black Belt region of west-central Alabama.

A total of 33 randomly chosen sites within a mapping unit of the four soil series were used in obtaining the spectral and soil parameter data. A barium sulfate panel was used as a calibration standard (Robinson and Biehl, 1979). Soil samples were taken to determine soil moisture; sand, silt, and clay percentage; iron oxide content; and organic matter content. Soil-moisture content by weight was determined gravimetrically with oven drying (Gardner, 1965). Particle size analyses were determined by the hydrometer method (Bouyoucos, 1951). Iron oxide was determined according to the method of Jackson (1958).

Bidirectional reflectance factors (BRF) were determined according to the procedure described by Nicodemus *et al.* (1977). BRF can be described as the ratio of the flux reflected by an object under specified conditions of negligible, small, solid angles of irradiation and viewing to the flux reflected by the ideal completely reflecting, perfectly diffusing surface, identically irradiated and viewed.

The spectral and soil parameter data were placed in a databank and analyzed statistically using correlation, regression, and discriminant analysis (Ray, 1982).

RESULTS AND DISCUSSION

The spectral curve forms suggests that there may be some confusion in distinguishing among these soils based on the shape and presence or absence of adsorption bands (Figure 1). Reflectance increased continuously from band 1 (0.45 to 0.52 μm) to band 6 (1.55 to 1.75 μm) where it reached a maximum before sharply declining in band 7 (2.08 to 2.36 μm). The Okalona soil, which is one of the Vertisols, is easily distinguishable from the two Alfisols, Mayhew and Kipling. However, the Sucarnoochee

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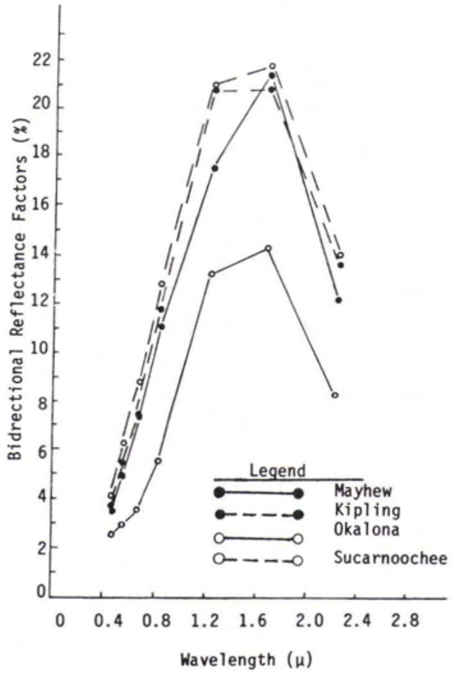

FIG. 1. Representative reflectance spectra of surface soil samples from Okalona, Sucarnoochee, Mayhew, and Kipling soils.

soil spectral properties lie between the two Alfisols and has substantially higher reflectance values than the Okalona soil in each spectral band.

These differences referenced above may be attributed to the physical and chemical nature of these soils (Table 1). An increase in soil moisture and organic matter results in a decrease in reflectance spectra in all wavelength bands, while an increase in iron oxide produces an increase in reflectance spectra (Table 2). These findings concur with results reported by Stoner and Baumgardner (1981), Condit (1970 and 1972), Cipra *et al*. (1971), and Montgomery (1976); however, these authors used reflectance data generated from uniformly moist samples in an indoor laboratory setting, whereas the data used here were generated under natural field conditions on undisturbed soils.

Discriminant functions were employed to compare the ability of spectral data versus soil parameters data in differentiating among the soils (Rao, 1973). The discriminant functions are determined by a measure of the generalized squared distance between groups. The classification criterion is based on either the individual within group covariance matrix or the pooled covariance matrix, taking into account the prior probabilities of the groups.

The soils used in this study were accurately differentiated (100 percent) using either reflectance spectra or soil parameters data (Figure 2). The generalized squared distance between the soils, as shown in Table 3, gives a numerical indication of how the discriminant function performed. The greater the distances between the soils, the less likely a misclassification. The distances shown in Table 3 between the soils using either the spectral or soil data were large enough to produce a classification accuracy of 100 percent (Figure 2).

A test of homogeneity of the data was performed using the within covariance matrices to test the null hypothesis: i.e.,

$$-\ 2\ \mathrm{RHO\ LN}\left[\frac{N^{PN/2}\ V}{N(I)^{PN(I)/2}}\right]$$

where

K = *number of groups,*

P = number of variables,

N = total number of observations,

$N(I)$ = number of observations in the Ith group,

$$V = \pi \left| \frac{\text{within SS matrix } (I)\ |^{N(I)/2}}{|\text{pooled SS matrix}|^{N/2}} \right.,$$

$$\mathrm{RHO} = 1.0\left[\mathrm{sum}\frac{1}{N(I)-1} - \frac{1}{N-K}\right]\frac{2p^2 + 3P - 1}{6(P+1)(K-1)},\ \text{and}$$

$$\mathrm{DF} = 0.5\ (K-1)P(P+\mathrm{s}1).$$

The test chi-square values produced were found to be significant at the 1 percent level of probability (Table 4) using both the reflectance spectra and soil parameters data. The multivariate statistics used in differentiating among the soils are given in Table 5. The spectral data generated using bands 1, 2, 3, 4, and 5 accounted for 84.5 percent of the variation in the data in differentiating among these soil orders. The soil parameters accounted for 70.1 percent of the variability among the soils. Wilks Lambda and the averaged squared canonical correlation measures the ability of the data source variables in differentiating among the soils. If Wilks Lambda is close to zero and the average squared canonical correlation is close to one, the soils can be accurately differenated using the variables selected.

PREDICTION OF SOIL VARIABLES USING SPECTRAL PROPERTIES

Estimation of soil variables from spectral data for use in soil mapping is an important potential application of multispectral remote sensing. Understanding the relation of soil properties to reflectance in various regions of the spectrum leads to the development of models for estimating soil variables from reflectance measurements in selected bands. Table 6 shows results from a stepwise regression procedure in the selections of the best one to seven wavelength bands for predicting the soil variables. In general, the ability to predict each soil variable increased as additional bands were added. By computing all possible regressions and considering the amount of variability explained and the biasness of the resulting regression equation, the best subset of spectral bands was selected.

The middle-infrared, red, and near-infrared bands were found to be most important in explaining the variation in soil variables. For soil moisture, the 2.08 to 2.35 μm wavelength band was most important, accounting for 81 percent of the variability; for iron oxide, the 0.63 to 0.69 μm and 1.15 to 1.30 μm wavelength bands were the key bands, accounting for 62 percent of the variability; and the 0.76 to 0.90 μm band was the most important wavelength band, accounting for 58 percent of the variation in predicting organic matter content.

TABLE 1. AVERAGE SOIL PHYSICAL AND CHEMICAL PROPERTIES FOR EACH SOIL.

Soil	Iron Oxide (ppm)	Organic Matter (%)	Soil Moisture (%)	Sand (%)	Silt (%)	Clay (%)
Mayhew	82.38	1.97	25.32	27.00	35.00	36.00
Kipling	90.90	2.00	18.22	17.00	43.11	39.89
Okalona	18.29	3.17	29.86	12.75	43.00	43.25
Sucarnoochee	9.03	2.32	18.41	17.33	37.44	45.23

TABLE 2. LINEAR CORRELATIONS (r) OF REFLECTANCE IN THE MMR MODEL 12-1000 WAVELENGTH BANDS AND SOIL PARAMETERS.

Variables[a]	0.45-0.52	0.52-0.60	0.63-0.69	0.76-0.90	1.15-1.30	1.55-1.75	2.08-2.35	Clay	Organic Matter	Moisture Content	Iron Content
0.45-0.52		0.979**	0.954**	0.938**	0.878**	0.778**	0.890**	−0.126	−0.637**	−0.750**	0.490**
0.52-0.60			0.987**	0.973**	0.927**	0.784**	0.919**	−0.119	−0.689**	−0.827**	0.523**
0.63-0.69				0.991**	0.923**	0.809**	0.923**	−0.182	−0.752**	−0.821**	0.589**
0.76-0.90					0.952**	0.826**	0.946**	−0.174	−0.766**	−0.845**	0.522**
1.15-1.30						0.811**	0.955**	−0.050	−0.698**	−0.901**	0.399
1.55-1.75							0.859**	−0.239	−0.632**	−0.672**	0.539**
2.08-2.35								−0.183	−0.701**	−0.902**	0.399*
Clay									0.265	0.068	−0.482**
Organic Matter										0.655**	−0.573**
Moisture Content											−0.236
Iron Content											

*,**Denotes significance at the 5 and 1 percent levels, respectively.
[a] n = 33

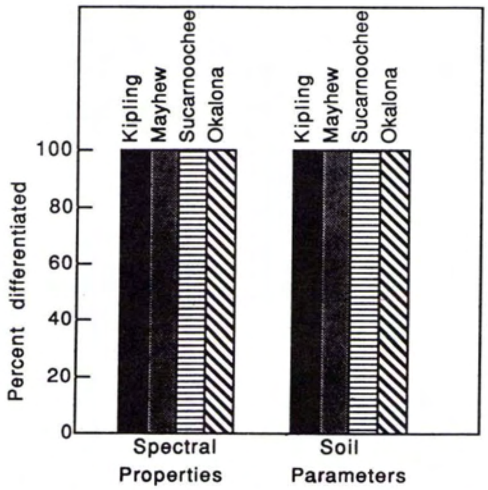

FIG. 2. Percentage of samples accurately differentiated using spectral and soil parameters data.

Of the three or four best bands for predicting a variable, each one was almost always from a different region of the spectrum, illustrating the importance of collecting spectral information in several different regions of the spectrum. Similar results were reported by Ahlrichs and Bauer (1983) and MacDonald *et al.* (1972), studying various canopy variables and southern corn leaf blight, respectively.

The difference between the number of bands entered where the resulting prediction equation is unbiased was also examined. An unbiased equation (based on the data entered) results when the Cp value is equal to or less than the number of terms in the resulting regression equation (Mallows, 1973). For soil-moisture, iron oxide, and organic matter content, the near maximum R^2 value was reached after the entry of four of the possible seven bands. However, the Cp values indicated that five bands would be needed to produce an unbiased prediction equation for soil-moisture, four bands for iron oxide, and six bands for organic matter.

Prediction of these variables using spectral data is possible as shown by the high R^2 values and low coefficients of variability that were produced from these data (Table 7). Three equations are shown for each variable–one showing the entry of a single band, the best band combination for that particular variable, and all seven spectral bands. The equations shown here may be geographically dependent and may or may not be applicable to other areas; however, equations can easily be developed for any locality or geographic region. Predicting the content of these variables in surface soils can have an enormous impact on soil survey and management practices. Hence, iron oxide content in the surface horizon is a good indicator of soil erosion problems. This may also give important information on fertilizer needs or possible areas where deficiencies may occur.

SUMMARY

The ability to differentiate among soils and soil properties based on spectral characteristics is dependent upon select portions of the electromagnetic spectrum. When differentiating among soil orders, spectral bands 1, 2, 3, 4, and 5 were determined to be the best combination.

Strong relationships among spectral reflectance and soil moisture, iron oxide, and organic matter content were found. Differentiating and predicting these soil properties using spectral data were successful. The middle infrared band 7 (2.08 to 2.35 μm) was the key band in predicting soil moisture. The red band 3 (0.63 to 0.69 μm) and near infrared band 5 (1.15 to 1.30 μm) are best for evaluating iron oxide content. The near infrared

TABLE 3. THE PAIRWISE SQUARED GENERALIZED DISTANCE BETWEEN SOILS.

From Soil	Generalized Squared distance to Soil: Kipling	Mayhew	Sucarnoochee	Okalona
Kipling		18.2453	28.9719	27.7238
Mayhew	68.8897		43.0713	17.5803
Sucarnoochee	39.1891	69.4136		21.4772
Okalona	46.2414	56.9808	24.8896	

TABLE 4. TEST OF HOMOGENEITY OF WITHIN COVARIANCE MATICES UTILIZING CHI-SQUARE.

Data Source	Chi-Square Value	DF	Probability Chi-Square
Spectral	217.9736	84	0.0001
Soil Parameters	145.1697	63	0.0001

TABLE 5. MULTIVARIATE STATISTICS USED IN DIFFERENTIATING AMONG SOILS.

Data Source	Partial R^2	*F* Statistics	Prob. *F*	Wilks[1] Lambda	Av. Squared[2] Canonical Correlation
Spectral	0.6590	16.104	0.0001	0.0029	0.8452
Soil Parameters	0.2728	3.250	0.0379	0.0177	0.7006

1. Wilks[1] Lambda is close to 0 if the groups are well separated
2. ASCC is close to 1 if all groups are well separated

band 4 (0.76 to 0.90 μm) is the key band for organic matter. Equations for predicting soil moisture, iron oxide, and organic matter were generated using the best band combinations determined for each variable.

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TABLE 6. DETERMINATION OF THE SPECTRAL BANDS NEEDED FOR PREDICTING SOIL VARIABLES.

Soil Variable	No. Bands	R^2	Cp[+]	Spectral Bands entered (μm)[++] 0.45-0.52	0.52-0.60	0.63-0.69	0.76 0.90	1.15-1.30	1.55-1.76	2.08-2.35
Soil	1	0.81	35							x
Moisture	2	0.85	24						x	x
	3	0.86	20					x	x	x
	4	0.91	7	x	x	x				x
	5	0.92	6	x	x	x	x			x
	6	0.92	7	x	x	x	x		x	x
	7	0.92	8	x	x	x	x	x	x	x
Iron	1	0.34	75			x				
Oxide	2	0.62	32			x		x		
	3	0.70	22			x		x	x	
	4	0.83	3		x	x	x		x	
	5	0.84	4		x	x	x		x	x
	6	0.84	6	x	x	x	x		x	x
	7	0.84	8	x	x	x	x	x	x	x
	1	0.58	5				x			
Organic	2	0.64	2		x		x			
Matter	3	0.65	1	x	x	x				
	4	0.68	2	x		x			x	x
	5	0.69	4	x	x	x			x	x
	6	0.69	0	x	x	x	x		x	x
	7	0.69	8	x	x	x	x	x	x	x

[+] The regression equation is unbiased when the 'Cp' value is equal to or less than the number of terms in the equation.
[++] The letter x denotes when a spectral bands has been entered into the equation.

TABLE 7. REGRESSION EQUATIONS FOR PREDICTING SOIL VARIABLES.

Variable	Regression Equation[+]	R^2	C.V.[++]
Organic	$Y = 3.90 - 0.15X_4$	0.587**	16.71
Matter	$Y = 3.59 + 0.24X_1 - 0.33X_4$	0.650**	15.90
	$Y = 4.04 - 0.60X_1 + 1.82X_2 - 1.32X_3 + 0.25X_4 - 0.14\ X_5 + 0.03X_6 - 0.003X_7$	0.697**	15.94
Soil	$Y = 45.35 - 1.87X_7$	0.813**	10.82
Moisture	$Y = 41.63 + 11.38X_1 - 12.17X_2 + 4.92X_3 - 1.04X_4 - 1.67X_7$	0.916**	7.76
	$Y = 37.68 + 13.47X_1 - 15.48X_2 + 7.79X_3 - 2.76X_4 + 0.80X_5 + 0.15X_6 - 2.16X_7$	0.928**	7.48
Iron	$Y = 29.61 + 11.46X_3$	0.347**	70.72
Oxide	$Y = 31.36 - 90.40X_2 + 154.59X_3 - 63.89X_4 + 3.60X_6$	0.836**	37.24
	$Y = 26.88 + 17.23X_1 - 104.99X_2 + 157.32X_3 - 62.49X_4 + 1.85X_5 + 3.83X_6 - 4.41X_7$	0.843**	38.58

**Denotes significance at the 1 percent level

[++]Coefficient of Variability

[+]$X_1, X_2, \ldots, X_7$ denote band 1, band 2,. . ., band 7, respectively

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