Relationship between Soil Organic Carbon and Landsat TM Data in Eastern Washington

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Abstract

Analysis of digital data from Landsat Thematic Mapper (TM) images has been proposed as a complementary method for estimating surface organic carbon levels of soils. Our objective was to establish the relationship between soil organic carbon (SOC) and a selected transformation of TM band ratios corresponding to the soil component values in the Palouse region of eastern Washington State. TM data and surface SOC measurements were obtained and evaluated using linear regression methods at four field-sites. Results showed that regression models, each pooled with two field-sites (Plaza and Pullman, Thera and St. John) were appropriate for the data. Significant ($P \leq 0.01$) regressions between surface SOC and TM data were detected for both functions, and r^2 values (0.88 and 0.71) also indicated a strong linear association. Plots of TM data and surface SOC showed a general trend toward higher SOC with higher TM values, suggesting a useful relationship.

Introduction

Agricultural researchers are currently evaluating better methods for adjusting herbicide, fertilizer, and pesticide applications to soils in an attempt to address current environmental concerns. Such experiments have investigated the effects of variable rates of fertilizer applications, as well as the employment of smaller, more spatially homogeneous fields to achieve efficient fertilizer management (Carr *et al.*, 1991; Larson and Robert, 1991; Mulla *et al.*, 1992). Chemical fertilizer applications are known to be a major method for modifying soil organic carbon (SOC). Other principle means of changing SOC in agricultural systems are by crop selection, addition of organic matter, and tillage practices (Paustian *et al.*, 1992).

SOC is an important component of agricultural soils which is strongly associated with soil fertility, affecting plant nutrient supply, microbial activity, and soil physical properties (Tisdale *et al.*, 1985). Nitrogen fertilizer application rates and the subsequent wheat grain yields in eastern Washington are both responsive to SOC content. For example, using cokriging techniques, a significant association between SOC and winter wheat grain yield has been found in an on-farm field experiment (Bhatti *et al.*, 1991). A variogram model for SOC showed substantial spatial dependence in a breeder trial experiment (Ball *et al.*, 1992a; 1992b). Although the slope was larger for the SOC than for the grain yield variogram, the spatial patterns of the two properties were consistent.

To agronomists, the determination of SOC in many field experiments is essential, yet the sampling process for SOC is expensive in labor and time, especially if intensive soil sampling is needed to characterize the soil spatial variability. A few studies have suggested that the estimated soil surface reflectance, measured by Landsat Thematic Mapper (TM), is a potentially accurate and efficient method for estimating surface SOC content (Baumgardner *et al.*, 1985; Henderson *et al.*, 1989; Frazier, 1989). For example, remote sensing techniques have been used to determine the extent of regional patterns in soil erosion from measurements of SOC (Frazier and Cheng, 1989). A variation of this technique was developed using a principal component analysis approach which reduced soil reflectance variation due to roughness of the soil surface, e.g., crop residue, tillage patterns, and soil texture (Frazier and Jarvis, 1992).

While a few studies have used satellite imagery for evaluating the association between measured soil properties and observed TM reflectance data (Bhatti *et al.*, 1991; Frazier and Jarvis, 1992) of eastern Washington soils, little has been done to determine if the TM reflectance values are useful as a means to estimate surface SOC content. The objective of the research reported here was to estimate the relationship between measured SOC and observed Landsat TM reflectance data sets for four field-sites in the Palouse region of eastern Washington.

Methods

Study Area

The Palouse region covers much of southeastern Washington, as well as parts of western Idaho and northern Oregon, and is one of the most productive dry land farming regions in the United States (Kaiser, 1967) (Figure 1). This region is characterized by steep, rolling, loessial hills with complex patterns in crop productivity and soil fertility. The hills of this cropland range in steepness from about 2 to 50 percent (Mulla *et al.*, 1992). Vegetation includes agricultural crops (winter wheat, winter barley, peas, lentils, canola), bunchgrass, and sage, as well as fir and pine forests. The Palouse receives from about 40 to 50 cm of average annual precipitation and has average annual temperatures of about 10° C. Most of this moisture is supplied by rain and snow during the winter and spring. There are generally 45 or more days after the summer

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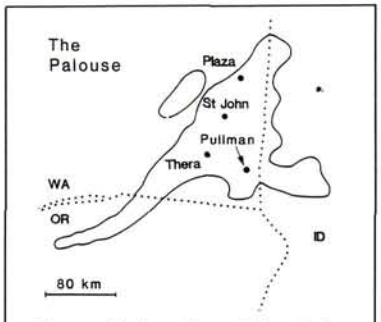

Figure 1. Location of the Palouse region (loess deposit) which covers most of southeastern Washington, as well as parts of eastern Idaho and northern Oregon.

solstice when the soil becomes dry due to the warm dry summers.

Soil parent material is predominately loessial silt and clay that originated in central Washington, although soil formation varies with longitude (from west to east). In addition, there are soil gradients which occur across the Palouse region, resulting in variation of crop dry matter production, crop residue decomposition, and the amount of organic matter in the soils. The soils are found in associations and each series is characteristic of a specific landscape position.

The field sites near St. John and Thera are separated by a distance of about 30 km. The Thera soils include (1) Athena silt loam (fine-silty, mixed, mesic Pachic Haploxerolls), (2) Lance silt loam (fine-silty, mixed (calcareous), mesic Durorthidic Xerorthents), and (3) Mondovi silt loam (coarse-silty, mixed, mesic Cumulic Haploxerolls). The St. John soils include (1) Latah silt loam (fine-silty, mixed mesic Xeric Argialbolls), (2) Palouse-Thatuna (fine-silty mixed, mesic Pachic Ultic Haploxerolls and Xeric Argialbolls), (3) Snow silt loam (fine-silty, mixed, mesic, Cumulic Haploxerolls), and (4) Thatuna silt loam (fine-silty, mixed, mesic Xeric Argialbolls) (Donaldson, 1980).

The other two field sites are near Plaza and Pullman, which are separated by a distance of about 65 km. The Plaza soils include (1) Naff silt loam (fine-silty, mixed, mesic Ultic Argixerolls), and (2) Caldwell silt loam (fine-silty, mixed, mesic Cumulic Haploxerolls). The Pullman soils include Naff silt loam, Palouse silt loam (fine-silty mixed, mesic Pachic Ultic Haploxerolls), and Palouse-Thatuna silt loam. Thus, the soils evaluated for associations between SOC content and Landsat TM reflectance values are spatially uniform and have similar physical properties (Frazier and Cheng, 1989). However, we expect SOC to vary for the field sites which vary in longitude.

Data Acquisition

The Landsat Thematic Mapper (TM) scenes (50135 18054 and 50503 18070) acquired on 14 July 1984 and 17 July 1985 from the Landsat World Reference System (coordinates 43-27) were selected for this study. Landsat TM data for two visible bands (Bands 1 and 3, centered on 0.485 and 0.660 μm) and two near infrared bands (Bands 4 and 5, centered on 0.830 and 1.650 μm) were obtained at each sample point for each field site (1 km^2 in area). Summer scenes were selected because summer fallow is used in dry-land crop rotation, assuring that imagery taken during the summer will include fields of bare soils. In addition, periodic cultivation is used to control weeds resulting in a relatively smooth soil surface.

The spatial structure within each field-site (Plaza, Pullman, Thera, and St. John) varies, and the patterns are considered useful for discriminating between soils differing in amounts of SOC. Three of the field sites—Pullman, Thera, and St. John—were sampled by transecting across the spatial patterns so that samples would be obtained from each pattern. At the fourth site, each pattern was sampled on a more random basis, not aligned in linear transects. Each method was considered representative of the field site in terms of soil distribution and management.

Soil reference data were sampled almost simultaneously with the date of satellite overpass from the Pullman and Thera field sites and several years later from the St. John and Plaza sites. Composite soil samples from the surface (0.08 to 0.10 m deep) were collected at each sample point (50-m intervals along the transects). The sample points were matched as closely as possible to pixel locations by plotting transects on image data and measuring from field boundaries to pixel locations on compass lines. The number of referenced data collected and analyzed varied due to labor and time constraints and our ability to match sample points with pixels. Nineteen samples were used from the Pullman field site, 39 at Thera, 145 at St. John, and 21 at Plaza.

The composite surface soil samples were analyzed to determine the range in SOC content at each field site. Organic carbon was analyzed according to standard procedures, i.e., it was determined to represent the darkening of soil color by organic matter (Nelson and Sommers, 1975). Organic matter is considered the dominant factor in soil reflectance values when its quantities exceed 2 percent of the oven dry weight of soil.

TM Data Transformation

The TM data were received as fully processed tapes (CCT-PT) and were also corrected to the UTM coordinate system. In an effort to reduce sample location error, a 2- by 2-pixel window (pixel = 28.5 m) was averaged and used for each sample and each band. The TM data were analyzed using the VICAR/IBIS system at the Digital Image Analysis Laboratory (DIAL) at Washington State University (Hart and Wherry, 1984). A dark-object substraction technique (first-order) was employed to correct for atmospheric scattering (Chavez, 1988). The resulting TM data were then converted to planetary reflectance using a sensor calibration information procedure (Markham and Barker, 1986).

Various transformation models have been applied to the scattering of optical radiation from soil surfaces (Becker *et al.*, 1985; Narayanan *et al.*, 1992). We selected reflectance ratios of Landsat TM data which have been shown to be relatively insensitive to incidence angle variation (i.e., account for shadowing effects) in the data. A number of researchers have used ratioing to reduce illumination and topographic effects on a scene (Holben and Justice, 1981; Jensen, 1986; Kauth *et al.*, 1979; Kriegler *et al.*, 1969). In addition, these ratios are strongly associated with measured soil reflectance values. Image processing of the corrected TM data included conversion into four reflectance ratios (TM bands 1/4, 3/4, 5/4, and 5/3) scaled from 0 to 255, considered useful to discriminate between SOC levels, eroded soils, and bare soil (Frazier and Cheng, 1989).

Principal component transformations (PCT) are com-

TABLE 1. ANALYSIS OF VARIANCE AND REGRESSION COEFFICIENTS FROM THE POOLED (A) PLAZA AND PULLMAN, AS WELL AS THE POOLED (B) THERA AND ST. JOHN FIELD SITES IN EASTERN WASHINGTON

Source of variation	df	*Analysis of variance* Mean square	$F(Ha:\beta \neq 0)$	*Regression coefficients* Regression coefficient	Parameter estimate	Standard error
(a) Plaza and Pullman						
Regression	2	584.77	129.01**	β_0	−23.89	2.46
X_1	1	1179.48	258.00**	β_1	0.50	0.03
$X_2 \mid X_1$	1	0.06	0.01	β_2	−0.08	0.68
Error	37	4.53		$r^2 = 0.88$		
(b) Thera and St. John						
Regression	2	1187.04	224.14**	β_0	−21.47	1.63
X_1	1	2373.81	448.22**	β_1	0.38	0.02
$X_2 \mid X_1$	1	0.26	0.50	β_2	0.09	0.44
Error	181	5.30		$r^2 = 0.71$		

** Denote significance at the 0.01 level of probability.

monly used to reduce the data redundancy and improve interpretation by producing a few linear combinations (new bands) of the original bands or ratios (Johnson and Wichern, 1988). It is generally accepted that with Landsat images of land surfaces the first three principal components contain over 98 percent of the total sample variance; hence, these components can replace the original bands without much loss of information (Rees, 1990; Gong and Howarth, 1992). The corrected and ratioed TM data were transformed using PCT operations, resulting in three principal components with improved interpretations (Frazier and Jarvis, 1992). Specifically, the first principal component contained variation due to crop greenness, the second principal component represented variation due to soils, and the third principal component contained variation due to wetness. This meaningful interpretation was visualized from a rotation of the coordinate axes, resulting in alignment of the soil component along the second principal component axis (Johnson and Wichern, 1988; Roman, 1984). The soil component data were selected from each field site for further analysis because the values are related to organic matter of soils in eastern Washington.

Data Analysis Techniques

Regression analysis (least-squares criterion) was used to examine the relationship between SOC content and Landsat TM ratio values. The four data sets were originally analyzed in a multiple regression model with three indicator variables and their interactions (Neter *et al.*, 1990). General linear tests were used for the analysis of the initial model, and these tests ($P \leq 0.05$) indicated that two separate regressions using the same model were appropriate for the data. The model is

$$Y_i = \beta_o + \beta_1 X_{i1} + \beta_2 X_{i2} + \epsilon_i$$

where Y_i is the response variable (SOC), X_{i1} is the transformed satellite ratio value, X_{i2} is the indicator variable, β_o is the intercept, β_1 is the slope, β_2 measures the differential effect of the locations, and the error term is ϵ_i.

If the regression function given above was the same (H_o:$\beta_2 = 0$) for both locations, implying the same location effect, we adopted a regression model without an indicator variable. This simple regression model is

$$Y_i = \beta_o + \beta_1 X_{i1} + \epsilon_i$$

where Y_i, β_o, β_1, X_{i1}, and ϵ_i were previously defined. The GLM, MEANS, and REG procedures of SAS/PC (SAS, 1988) were used to perform the analyses of organic carbon and the TM transformed ratio values.

Results and Discussion

Location differences in SOC content were evaluated using linear regression techniques derived from least-squares equations for each of the four (Plaza, Pullman, St. John, and Thera) field sites (Figure 1, Table 1). An analysis of variance from a combined multiple regression model (data not shown) indicated that the four field sites should be analyzed as two data sets, each comprised of two different field sites. The surface SOC reference and the selected Landsat TM data (the soil component) sets for the pooled field-sites (Plaza and Pullman, Thera and St. John) showed a substantial difference in response.

The F-tests in Table 1 showed that the differential effects of field sites were nonsignificant for each regression, indicating that the regression functions are the same for the two field sites. Therefore, the regression lines were computed from a simple regression function (the indicator variable was deleted from the model). Plots of TM soil component values versus surface SOC content indicated a general trend toward higher SOC content with higher transformed TM values (Figures 2 and 3). However, the intercepts and the rates of increase differed for the regression models.

Highly significant ($P \leq 0.01$) relationships between measured SOC and the transformed TM ratio values were detected for each regression of the pooled field-sites (Figures 2 and 3, Table 1). The coefficients of determination (r^2) for Plaza and Pullman ($r^2 = 0.88$), and Thera and St. John ($r^2 = 0.71$) also indicated a strong linear association between surface SOC and observed TM data. In comparison with Plaza and Pullman, the fit for the Thera and St. John regression function was not as good (i.e., the regression showed a larger scatter of data). In addition, normality of error terms was satisfied and the field sites within the pooled regression functions had error variances (data not shown). Thus, our TM data approach indicated that two separate regression models are needed to characterize the four field sites.

Results from the regression analyses (given above) correspond with the topographical differences measured in soils of the Palouse region of eastern Washington State. For in-

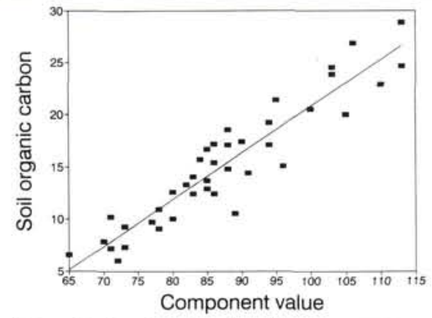

Figure 2. Regression function comparing the association between measured SOC content and observed Landsat TM values for the pooled Plaza and Pullman, Washington field sites. Regression line (see Table 1) was derived from a least-squares equation [$Y = -23.89 + 0.50X_1$, $r^2 = 0.88$, and $F(Ha{:}\beta_1 \neq 0) = 265^{**}$].

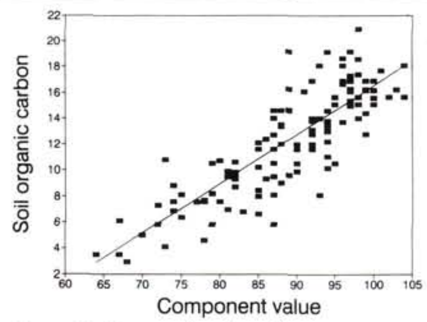

Figure 3. Regression function comparing the association between measured SOC content and observed Landsat TM values for the pooled Thera and St. John, Washington field sites. Regression line (see Table 1) was derived from a least-squares equation [$Y = -21.47 + 0.38X_1$, $r^2 = 0.71$, and $F(Ha{:}\beta_1 \neq 0) = 451^{**}$].

stance, patterns in measured SOC of surface soils corresponded to differences in soil association, mainly due to longitude (from west to east). The Plaza and Pullman soils contain more clays (less carbonates) on the hilltops, thicker A horizons, and are less eroded when compared to the Thera and St. John soils (Frazier and Cheng, 1989). Therefore, Plaza and Pullman soils are higher in surface SOC content and transformed TM values. We concluded that the response pattern of SOC was directly related to the TM values, implying that TM data may be used to estimate surface SOC and discriminate between SOC levels in soil types in eastern Washington.

These results also suggest that future research should develop more accurate methods of soil reference data collection, combined with carefully corrected satellite data to reduce variability, hence improving the SOC - TM association. For example, soil reference factors which may be potential sources of variability include spatial soil heterogeneity, SOC composition and analysis, and differences in crop residue cover, as well as location of pixels in fields.

The band ratios used in this study are sensitive to additive factors, i.e., the atmospheric correction process, and therefore may be biased (Frazier and Cheng, 1989; Lathrop, 1992). Subtraction of the additive atmospheric haze component can cause the data to shift vertically, depending on the dark-object reflectance and atmospheric type selected. These corrections were made for both dates. However, the process requires that all pixels receive the same correction, while it is common for haze to increase from east to west in eastern Washington. As a result, an uncorrected gradient may remain across the scene, though it would be diminished.

Conclusions

Results of linear regression techniques suggest a useful if not yet close relationship between measured surface SOC and Landsat TM values (for the ratioed and transformed soil component). Consequently, the selected TM data have potential as a complementary method for estimating surface SOC of Palouse soils in eastern Washington State. Thus, after a model is established for the soil zone in question, TM images could be used to predict the surface SOC values at nonsampled locations (throughout the area where the model was developed) at a fraction of the cost for surface reference data. In addition, a natural extension of this technique would be to interpolate TM values using spatial statistical methods to relate the effects of spatial heterogeneity in surface SOC to crop yields. These results also suggest that research to measure relationships between SOC and TM values continue for other soil zones in the Palouse toward efforts to increase the precision of the SOC estimates, and relationships to crop yield potential.

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