0038-075X/04/16911-819–831
Soil Science

December 2004
Vol. 169, No. 12
Printed in U.S.A.

TECHNICAL ARTICLES

SOIL CARBON RELATIONSHIPS WITH TERRAIN ATTRIBUTES, ELECTRICAL CONDUCTIVITY, AND A SOIL SURVEY IN A COASTAL PLAIN LANDSCAPE

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Soil organic carbon (SOC) estimation at the landscape level is critical for assessing impacts of management practices on C sequestration and soil quality. We determined relationships between SOC, terrain attributes, field scale soil electrical conductivity (EC), soil texture and soil survey map units in a 9 ha coastal plain field (Aquic and Typic Paleudults) historically managed by conventional means. The site was composite sampled for SOC (0–30 cm) within 18.3 × 8.5–m grids (n = 496), and two data sets were created from the original data. Ordinary kriging, co-kriging, regression kriging and multiple regression were used to develop SOC surfaces that were validated with an independent data set (n = 24) using the mean square error (MSE). The SOC was relatively low (26.13 Mg ha^{-1}) and only moderately variable (CV = 21%), and showed high spatial dependence. Interpolation techniques produced similar SOC maps but the best predictor was ordinary kriging (MSE = 9.11 Mg^2 ha^{-2}) while regression was the worst (MSE = 20.65 Mg^2 ha^{-2}). Factor analysis indicated that the first three factors explained 57% of field variability; compound topographic index (CTI), slope, EC and soil textural fractions dominated these components. Elevation, slope, CTI, silt content and EC explained up to 50% of the SOC variability ($P \leq 0.01$) suggesting that topography and historical erosion played a significant role in SOC distribution. Field subdivision into soil map units or k-mean clusters similarly decreased SOC variance (about 30%). The study suggests that terrain attributes and EC surveys can be used to differentiate zones of variable SOC content, which may be used as bench marks to evaluate field-level impact of management practices on C sequestration. (Soil Science 2004;169:819–831)

Key words: Soil organic carbon, terrain attributes, Ultisols.

SOIL organic C is considered the most important soil quality indicator (Seybold et al., 1997) and is a sink or source of atmospheric CO_2 depending on land management (Smith et al., 1999). Soils are recognized as a major and active pool of organic C and play a key role in the global C cycle through their potential to influence global climate change. The importance of SOC as an indicator of soil quality and agronomic sustainability due to its impact on other soil properties is well documented (Reeves, 1997; Six, 2002).

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[a]Reference to trade or company name is for specific information only and does not imply approval or recommendation of the company by the USDA or Auburn University to the exclusion of others that may be suitable.

Received May 3, 2004; accepted Sept. 30, 2004.
DOI: 10.1097/01.ss.0000149368.71009.6f

The complex arrangement and combinations of soils, landscapes, biological processes and management practices within row crop settings result in high spatial variability of SOC. Thus, quantitative assessment of soil quality and its relation to C sequestration is needed on a site-specific basis (Bergstrom et al., 2001). Spatial variation of SOC and its response to soil management is affected by the combined influence of soil properties and terrain attributes on biological processes. For example, no tillage and perennial grasses increased microbial biomass and C mineralization in a study in Colorado, but only in productive landscape positions with high SOC (Burke et al., 1995). Bergstrom et al. (2001) found that a no-tillage Canadian field had more SOC than a conventional tillage field only at well-drained upper slope positions. VandenBygaart et al. (2002) found that landscape position and erosion deposition history were key factors in the ability of no-till soils to sequester C.

The semivariogram is commonly used to quantify and model the spatial dependence of a soil property, including the distance of the spatial correlation (range), the amount of variance due to error (nugget), the maximum variance between sampling points (sill) and the overall strength of the spatial correlation (Isaaks and Srivastava, 1989; Goovaerts, 1998). Some studies have indicated that SOC has moderate to high variability (CV 21–41%), has strong spatial correlation (nugget/sill ≈0.05) and long spatial dependence (range ≈ 250-m) (McBratney and Pringle, 1999).

Soil sampling schemes range from grid based approaches to area-based approaches such as zone sampling. Several techniques exist to assess spatial distributions of soil properties across landscapes including geostatistical techniques such as kriging (ordinary, universal, co-kriging, etc.), simpler methods like regression, or even hybrids such as regression-kriging (Bishop and McBratney, 2001). Interpolation methods allow prediction of SOC values at unsampled locations when spatial correlation between observations exists. Prediction methods may use only observations of SOC (kriging) or incorporate secondary information provided by correlated properties with SOC (co-kriging, regression-kriging) (Goovaerts, 1998).

Regression analysis is a relatively simple soil property mapping technique. Multiple regression between SOC and terrain attributes out-performed ordinary kriging at low intensity grid sampling schemes, explaining between 66 to 86% of the SOC variability of a Michigan field (Mueller and Pierce, 2003). However, Florinsky et al. (2002) using regression with nine terrain attributes, explained only 37% of SOC variability of a Canadian prairies landscape.

Rapid spatial measurement of soil EC has been proposed to assess spatial heterogeneity of soil properties (Anderson-Cook, 2002). Soil EC is related to multiple soil physical, chemical and biological properties. Moisture content, texture, SOC, and the mineralogy of the soil matrix are the main factors affecting EC in many Southeastern USA soils (Shaw and Mask, 2003). However, due to covariance, it is problematic to determine the unique property resulting in corresponding conductivity changes.

Zone sampling is a method where soil samples are composited from areas that are expected to have similar characteristics and less variability than the entire field. Multivariate statistics, including principal component analysis, factor analysis and cluster analysis, have been effective tools for identification of zones of soil variability within fields using terrain attributes and soil properties (Fraisse at al., 2001; Taylor et al., 2003).

Future research evaluating SOC dynamics in agricultural soils and the effects of management practices should consider landscape variability. Estimation and mapping of SOC at the landscape level and improved understanding of SOC relationships with other soil properties and terrain attributes is a prerequisite for assessing the impact of soil management practices on C sequestration at the field scale.

The objective of this study was to establish relationships between SOC and terrain attributes and soil properties in an Alabama coastal plain field under conventional tillage management for more than 30 years. In unison with this, we evaluated various techniques for assessing SOC spatial variability across the landscape.

MATERIALS AND METHODS

Study Site

The research was conducted at the Alabama Agricultural Experiment Station's E.V. Smith Research Center in central Alabama (85°53′50" W, 32°25′22" N). The site consists of a 9 ha field with a long history of row cropping, mostly cotton (*Gossypium hirsutum* L.), under conventional tillage (moldboard or chisel plowing and disking) for the last 30 years.

Soil and Terrain Attributes Creation

A detailed soil survey, digital elevation, and EC surveys were developed for delineating soil and landscape variability within the field.

A detailed soil survey (scale ≈1:5000) was developed according to National Cooperative Soil Survey standards. Soils at the site are mostly fine and fine-loamy, kaolinitic, thermic Typic and Aquic Paleudults. Drainage classes were assigned for each map unit and depth to the seasonal water table (WTD) was estimated using the Soil Interpretation Records (SIR). Map units were rasterized (5 × 5-m grid) using ArcInfo® 8.0 ([1]ESRI, Redland, California).

The field was surveyed by a direct contact Veris® Technology 3100 Soil EC Mapping System ([1]Veris Technology, Salina, KS) equipped with a GPS. The field was at fallow during the survey (winter) and soil moisture conditions were near field capacity. Measurements were taken in transects spaced approximately 9-m apart at a speed of ≈ 4 km h^{-1}. Geo-referenced EC data (mS m^{-1}) were recorded at 1-s intervals at 0–30 cm (EC_s) and 0–90 cm (EC_d) depths.

A Trimble® 4600 L.S. Surveyor Total Station was used to determine elevations across the field. Elevation measurements were taken each second with a vehicle traveling ~ 5 km h^{-1} in concentric circles ~5-m apart. Digital elevation models and terrain attributes were developed using the appropriate algorithms and commands in ArcInfo®. Terrain attributes included elevation (ELEV), slope, aspect (ASP), profile curvature (PROFC), plan curvature (PLANC), flow accumulation (FA), catchment area (CA), specific catchment area (SCA) and compound topographic index (CTI). Slope identifies the maximum downhill rate of change in value from each cell to its neighbors. Aspect (measured in degrees clockwise from N) identifies the down-slope direction of the maximum rate of change in value from each cell to its neighbors. Profile curvature is a measure of the convexity or concavity of the surface in the direction of slope, while PLANC relates the curvature of the surface perpendicular to the slope direction. Flow accumulation was calculated for each pixel based on the accumulated weight for all cells that flow into each downslope cell. Catchment area was calculated for each pixel as the product of FA times cell area (25 m^2). Specific catchment area is the area orthogonal to the flow direction and was calculated as the CA divided by the grid size (5-m). The CTI represents the landscape areas where water accumulates and was computed for each pixel according to Moore et al. (1993):

$$\mathrm{CTI} = \ln\left(\mathrm{SCA} / \tan\beta\right) \qquad (1)$$

Where β is the slope angle (degrees).

Soil Sampling

Soil samples were collected during Jan-Feb 2001 from 496 regular grid points (8.5 × 18.3 m; 64 grids ha^{-1}). Forty-eight of the grid lines transected the field (E-W) across the maximum variability. An additional set of 24 independent samples was collected as a validation set. Ten 2.5-cm dia. sampling cores to a depth of 30-cm were taken and composited within a 2.5-m radius from the center of each grid. Two additional data sets were created from the original 496 sampling grids ($G_{64/ha}$) using a procedure similar to Mueller and Pierce (2003). The first set was created by removing 1/2 of the transects creating a 17 × 18.3-m regular grid with ≈32 points ha^{-1} ($G_{32/ha}$). The second set was created by removing 3/4 of the transects and doubling the separation distance of points within transects, creating a 34 × 36.6-m grid with ≈8 points ha^{-1} ($G_{8/ha}$).

Soil samples were dried at 55 °C for 48 h and ground to a 2-mm sieve. Two ground subsamples from each of the 496 grid points and three subsamples from each of the validation points were analyzed for SOC by dry combustion using a LECO® CN-2000 analyzer ([1]Leco Corporation, St. Joseph, Michigan). Particle size distribution was determined for 82 of the samples (25.5 × 36.6-m grid) using the pipette method following organic matter removal (Kilmer and Alexander, 1949). A soil core sampler (5.3-cm dia.) was used to determine soil bulk density (0–30-cm) in 5-cm increments. Bulk density was determined in 62 of the 496 SOC sampling sites with three subsamples per site. These values were averaged and used to compute the SOC on a volume basis (Mg SOC ha^{-1} in the top 30 cm).

Data Manipulation and Statistical Analysis

Transformation of soil and terrain attributes was considered only when high departure from normality existed. Soil organic C data for which log-transformation resulted in skewness closer to 0 compared with nontransformed data were log-transformed prior to analysis. Data were back-transformed to the original data domain for final reporting using a weighted back transformation.

Geostatistical analyses were conducted on geo-referenced SOC, texture, EC and elevation data using GS+® ([1]Gamma Design Software, Plainwell, Michigan). Spatial structure of the SOC and soil data were analyzed using semivariograms. Only isotropic models were used for terrain and soil data (except SOC) due to the lack of significant anisotropy. For SOC data, spherical and exponential models were fit to both isotropic and anisotropic variograms. Directional (anisotropic) semivariograms were calculated for SOC using angular tolerances of ± 30°. Anisotropic semivariance surfaces were used to find the principal axis for defining the anisotropic variogram model (Isaaks and Srivastava, 1989). The nugget:semivariance ratio was used to define spatial dependence of the variables. Residual sums of squares (RSS) was used as a criterion for model selection.

Ordinary kriging was used to interpolate values of EC, sand, silt and clay content for both 5 × 5-m grids and for each SOC sampling point. Cross-validation with replacement was used to evaluate interpolated surface quality (Goovaerts, 1998). Interpolated surfaces of EC, sand, silt and clay content were stacked with terrain attributes and depth of seasonal high water table resulting in a total of fourteen layers (ELEVA, SLOPE, ASP, PROFC, PLANC, CA, SCA, CTI, EC_{30}, EC_{90}, clay, silt, sand and WTD).

Factor analysis was used to reduce the dimensionality of the original data and express original variables in terms of a few common factors (Khattree and Naik, 2000). The FACTOR procedure of SAS® (Principal component method and Varimax orthogonal rotation) was used with soil and terrain attributes to create groups of correlated variables (latent variables). Factors with eigenvalues > 1 were used as criteria for selection. Scores for the retained factors were obtained for each of the 496 sampling points using factor loadings and original values.

Pearson correlation coefficients ($P < 0.01$) were obtained between SOC and terrain and soil attributes for the 496 SOC sampling points. Regression models between SOC and soil and terrain attributes were obtained using the Maximum R^2 Improvement procedure (MAXR) of SAS® (SAS Institute, Cary, NC) with $P \leq 0.01$ and Mallow's C(p) statistics as criterions for variable selection (Freund and Littell, 2000). Variance inflation factors (VIF) exceeding 10 were used for detection of multicolinear variables.

Values of SOC were interpolated at the same 5 × 5-m grid using four methods: ordinary kriging, co-kriging, regression and regression-kriging. Ordinary kriging and co-kriging operations were performed with GS+®. Regression-kriging was performed using ordinary kriging of the residuals of the multiple regression models showing some degree of spatial structure and subsequently adding the kriged residual values to the regression model estimations (Bishop and McBratney, 2001).

Cross validation of estimated vs actual values was performed to assess accuracy of kriged or regressed values using 24 independent sampling points. Mean square error (MSE) and prediction efficiency (PE) were used as indicators of map accuracy (Gotway et al., 1996; Mueller and Pierce, 2003):

$$MSE = 1/n \sum (z(x_i) - z^*(x_i))^2 \quad (2)$$

Where $z(x_i)$ = actual SOC content and $z^*(x_i)$ = predicted SOC content.

$$PE = [1 - (MSE_p / MSE_a)] \times 100 \quad (3)$$

Where MSE_p is the mean square error obtained from interpolation and MSE_a is the mean square error using the sample average.

The field was subdivided into zones using a clustering procedure similar to Fraisse et al. (2001) and Fridgen et al. (2004). The cluster analysis was performed with the data that explained most of the field variability and was highly correlated with SOC as evidenced by the factor and correlation analysis, respectively. Data layers were normalized (0 – 100) prior to clustering. Zones were created by unsupervised classification using the Management Zone Analyst® software (Fridgen et al., 2004). This software uses a fuzzy k-means unsupervised clustering algorithm to assign multivariate data into clusters. Two performance indices (fuzziness performance index and normalized classification entropy) were used to determine the optimal number of clusters. Optimum numbers of zones were selected based on evaluation of the two performance indices and in the reduction of within-zone SOC variance. The SOC differences between clusters or soil map units were analyzed with the SAS® MIXED procedure where clusters were considered as fixed effects and sample points within each zone as repeated observations.

RESULTS AND DISCUSSION

Soil and Terrain Attribute Variability

Soils ranged from well-drained upland Paleudults to somewhat poorly drained soils in concave and relatively lower landscape positions. The nine soil map units identified within the study area and their description, drainage class and area are summarized in Table 1. Soils mainly vary due to differences in both drainage class and surface horizon textures (mostly due to historical erosion). Soil map units explained 34% of the SOC variation ($P \leq 0.05$). Classification of soil into drainage classes and estimated seasonal high water table accounted for only 16% of the SOC variability ($P \leq 0.05$). Map units classified as somewhat poorly to poorly drained had 36% more SOC than well drained units (33.59 vs 24.68 Mg ha^{-1} respectively). Soils classified as moderately well to somewhat poorly drained possessed intermediate values (27.77 and 25.08 Mg ha^{-1}, respectively).

TABLE 1

Map Unit Description for the study site

Taxonomic classification	Symbol	Drainage class	WTD† (cm)	SOC‡ (Mg ha^{-1})	Area (ha)
Bama; Typic Paleudults; fine loamy, siliceous, subactive, thermic; 0–2% slope	BaA	Well drained	150	26.13	2.69
Bama; Typic Paleudults; moderately eroded; 2–4% slopes	BaB	Well drained	150	20.62	0.78
Bama; Typic Paleudults; severely eroded; 4–6% slope	BaC	Well drained	150	23.20	0.57
Goldsboro; Aquic Paleudults; fine-loamy, siliceous, subactive, thermic; 0–2% slope	GoA	Moderately well to somewhat poorly drained	60	26.55	1.03
Goldsboro; Aquic Paleudults; moderately eroded; 2–4% slopes	GoB	Moderately well to somewhat poorly drained	60	22.74	0.60
Goldsboro/Lynchburg; Aquic Paleudults and Paleaquults; 0–2% slopes	Go-LyA	Somewhat poorly to poorly drained	35	33.59	0.51
Oxyaquic Paleudults; fine-loamy, siliceous, subactive, thermic; 0–2% slopes	OpA	Moderately well drained	75	28.34	0.98
Oxyaquic Paleudults; fine-loamy, siliceous, subactive, therinic; 2–4% slopes	OpB	Moderately well drained	75	32.51	0.68
Oxyaquic and Aquic Paleudults; 0–2% slope	Op-GoA	Moderately well drained	75	24.60	1.19

†WTD = Estimated Seasonal High Water Table.
‡SOC = Soil Organic Carbon.

Soil properties and terrain attributes indicated substantial landscape variability for a 9 ha field in this region (Fig. 1). Elevation range was almost 3-m, and slope gradients ranged between 0 to 8%. All soil properties showed spatial dependence. Both EC_s and EC_d exhibited high spatial dependence as estimated by the nugget/sill semivariance ratio and by the low RSS and high R^2 of the fitted semivariogram models (Table 2). The R^2 and MSE between measured vs predicted EC_s and EC_d indicated both variables were accurately interpolated. Although soil textural fractions displayed low nugget/sill ratio, the R^2 and RSS of the models suggest that they had only moderate spatial dependence, likely due to the less intensive sampling scheme used. As a result, interpolated values of sand, silt and clay contents had relatively more error as indicated by the R^2 and MSE obtained in the cross validation procedure.

Pearson linear correlation coefficients between topography and soil attributes are presented in Table 3. The EC_s was highly correlated with slope ($r = 0.60$) and moderately correlated with clay content ($r = 0.39$), as expected from results reported in other landscape studies (Mueller et al., 2003; Shaw and Mask, 2003). The EC variability across the site is somewhat related to historical erosion, with higher EC found in areas of exposed subsoils with higher clay content. Our EC values are relatively low compared with other studies because of the sandy nature of these soil surfaces, low organic carbon and soil water content, and low ionic strength of the soil solution. Because EC variability is related to soil-terrain characteristics that largely control soil properties (Mueller et al., 2003), similar patterns are observed between soil survey, certain terrain attributes, and EC (Fig. 1).

Factor analysis was performed using twelve variables: ELEVA, SLOPE, ASP, PROFC, PLANC, CA, CTI, EC_s, EC_d, silt, sand and WTD. The first three factors explained 57% of the variance; the first five factors had eigenvalues >1 and explained 79% of the data variability (Table 4). The CA, CTI and PLANC had the highest load-

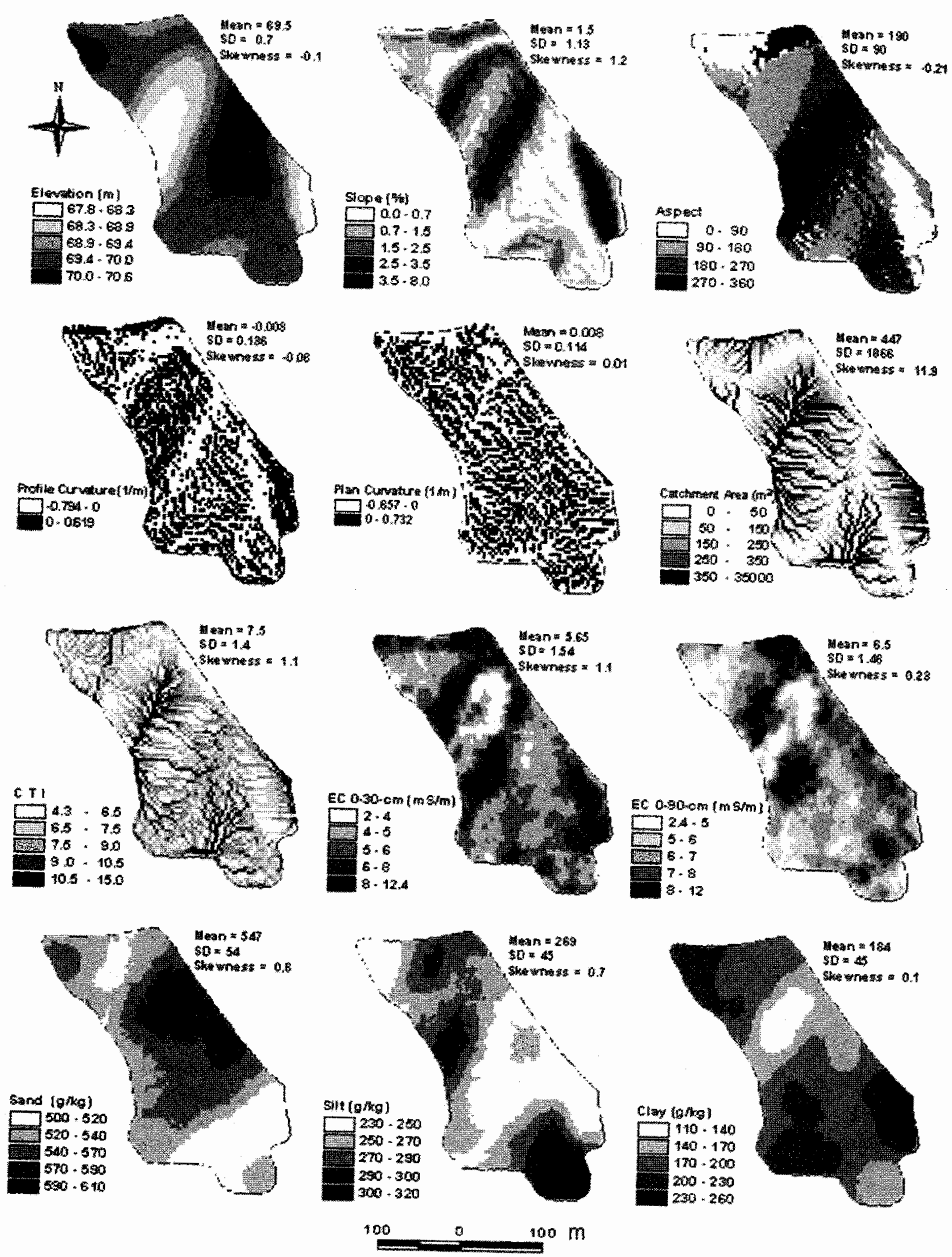

Fig. 1. Surfaces of soil properties (0–30-cm) and terrain attributes within the field.

TABLE 2

Isotropic semivariogram model parameters for electrical conductivity (EC), sand, silt and clay content

Variable	N	Model†	Range	Nugget	Sill	R^2	RSS‡	Kriging Cross Validation (R^2)	MSE§
			m	------(units)^2-------					
EC 0–30-cm (mS m^{-1})	4611	Sph	78	0.29	2.70	0.99	0.03	0.87	0.317
EC 0–90-cm (mS m^{-1})	4611	Sph	79	0.33	2.32	0.99	0.007	0.87	0.275
Sand 0–30-cm (g kg^{-1})	82	Sph	60	1.00	2916	0.81	402084	0.39	1851
Silt 0–30-cm (g kg^{-1})	82	Sph	73	1.00	2079	0.85	243460	0.52	949
Clay 0–30-cm (g kg^{-1})	82	Sph	82	1.00	2014	0.95	67014	0.49	1110

†Sph = Spherical.
‡RSS = Residual Sums of Squares.
§MSE = Mean Square Error.

TABLE 3

Pearson correlation coefficients between soil properties (0–30–cm) and terrain attributes at the SOC sampling points (n = 496 $P \leq 0.01$)

Variables†	ELEVA	SLOPE	ASP	PROF	PLAN	In CA	CTI	EC_s	EC_d	Sand	Silt	Clay	WTD
ELEVA	1	–	–	–	–	–	–	–	–	–	–	–	–
SLOPE	0.41	1	–	–	–	–	–	–	–	–	–	–	–
ASP	NS	NS	1	–	–	–	–	–	–	–	–	–	–
PROF	−0.46	NS	NS	1	–	–	–	–	–	–	–	–	–
PLAN	0.28	0.16	NS	0.38	1	–	–	–	–	–	–	–	–
In CA	−0.58	0.19	NS	0.41	0.51	1	–	–	–	–	–	–	–
CTI	0.25	0.39	NS	0.41	0.45	0.74	1	–	–	–	–	–	–
EC_s	−0.14	0.66	NS	NS	NS	NS	−0.38	1	–	–	–	–	–
EC_d	NS	0.45	NS	−0.12	NS	NS	−0.36	0.78	1	–	–	–	–
Sand	−0.12	NS	0.33	0.17	NS	0.14	NS	−0.32	NS	1	–	–	–
Silt	−0.27	−0.23	0.15	NS	NS	0.12	0.19	−0.15	NS	−0.36	1	–	–
Clay	0.34	0.17	−0.43	−0.16	NS	−0.23	−0.25	0.43	NS	−0.63	−0.50	1	–
WTD	0.55	0.12	0.20	−0.21	0.14	−0.26	−0.23	NS	NS	0.22	−0.64	0.33	1
SOC	−0.17	−0.41	NS	−0.13	0.16	0.29	0.48	−0.31	−0.42	−0.25	0.39	NS	−0.29

†ELEVA = Elevation; ASP = Aspect; PROF = Profile Curvature; PLAN = Plan Curvature; In CA = Natural Log of Catchinent Area; CTI = Compound Topographic Index; ECs = Electrical conductivity 030 cm; ECd = Electrical conductivity 0-90 cm; WTD = Water Table Depth; SOC = Soil Organic Carbon.
‡NS = not significant at $P \leq$ 001 level.

TABLE 4

Eigenvalues, cumulative contribution of explained variance, and loading factors for the first five factors

Soil and terrain attributes	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
Elevation	−0.26	−0.13	0.20	0.87	0.06
Slope	−0.02	0.70	−0.33	−0.48	−0.07
Aspect	0.02	0.05	0.02	0.03	0.94
Profile curvature	0.66	0.01	0.01	−0.16	−0.06
Plan curvature	−0.79	−0.09	0.02	0.05	0.04
In catchment area	0.87	0.03	−0.01	−0.25	0.09
Compound Topographic Index	0.86	−0.27	0.12	0.04	0.09
Electrical Conductivity 0–30 cm	0.02	0.93	0.03	−0.06	−0.15
Electrical Conductivity 0–90 cm	−0.06	0.85	0.06	0.06	0.20
Sand (0–30–cm)	−0.02	−0.29	−0.65	−0.27	0.46
Silt (0–30–cm)	0.01	−0.06	0.89	−0.13	0.21
Water table depth	−0.06	0.14	−0.70	0.53	0.17
Eigenvalue	2.63	2.28	1.90	1.47	1.26
Cumulative Explained Variance (%)	0.22	0.41	0.57	0.69	0.79

ing for the first factor, the second factor was dominated by slope and EC, and the third factor was dominated by silt, WTD and sand. The terrain attributes that dominated the first two latent variables are highly related to hydrology and soil erosion, which likely affect SOC distribution within the field. The first three factors were the most significantly ($P \leq 0.01$) correlated with SOC (r = 0.30, -0.38 and 0.43 for the first, second and third factors, respectively). Regression analysis between SOC and the first five factors explained up to 40% of the SOC field variability ($P \leq 0.01$).

Soil Organic Carbon and Landscape Variability

Correlation of SOC with terrain attributes and soil properties for the 496 sampling points ($G_{64/ha}$) are also shown in Table 3 ($P \leq 0.01$). Soil organic C was negatively correlated with EC, slope, elevation, water table depth and sand content, and positively correlated with CTI, catchment area, and silt content. The CTI, EC_d, slope and silt content had the highest correlation with SOC, suggesting that historical erosion and field-scale water dynamics play a major role in SOC spatial distribution. Results for correlation between SOC and EC are contradictory in the literature; some studies have found negative correlation (Johnson et al., 2001), while others have found positive correlation (Kitchen et al., 2003). Zones with higher CTI values are likely to have higher biomass production, lower SOC mineralization, and higher sediment deposition compared with zones of low CTI. Positive correlation between SOC and CTI, and negative correlation between SOC and slope and elevation, are in agreement with other studies (Moore et al., 1993; Gessler et al., 2000; Florinsky et al., 2002).

Depending on the SOC grid scheme used, regression models explained between 52 to 58% of the SOC variability (Table 5). Multicollinearity was not a problem as indicated by variance inflation factors of the selected model variables. The CTI, EC_d, silt and sand content explained up to 40% of field variation in SOC. Slope, ELEVA, EC_s and WTD were also related with SOC, but their contributions to the regression models were less. Coefficients of determination (R^2) relating SOC with terrain attributes in our study were higher than the R^2 (0.37) reported by Florinsky et al. (2002). Moore et al. (1993) explained 48% of the SOC variability in Colorado Argiustolls using terrain attributes. Gessler et al. (2000) found that best models for SOC prediction for a California site were developed using CTI (R^2 = 0.78) or a combination of slope and FA (R^2 = 0.80). Similar to our results, these studies also found that CTI is an important terrain attribute for explaining SOC and associated soil property variability. Mueller and Pierce (2003), in a study conducted at Michigan, found that terrain attributes (particularly elevation) and x-y coordinates explained 66%, 77% and 89% of the SOC variability using grids of 30.5, 61 and 100-m, respectively. These studies did not consider soil drainage class or soil EC information in their models. In our study, the R^2 did not increase when a less intensive grid sampling was used, and x-y coordinates were not significantly correlated with SOC.

TABLE 5

Regression parameter coefficients, R^2, and Mallow's C(p) at different SOC grid sampling schemes ($P \leq 0.01$)

	GRID SCHEME		
	SOC† ($G_{64/ha}$) 8.5 × 18.3–m	SOC ($G_{32/ha}$) 17 × 18.3–m	SOC ($G_{8/ha}$) 34 × 36.6–m
Intercept	246.59	369.03	45.95
Elevation (m)	−3.176	−3.741	NS‡
Slope (%)	−2.294	−2.349	NS
Aspect (degrees from N)	NS	NS	NS
Profile curvature (m^{-1})	NS	NS	NS
Plan curvature (m^{-1})	NS	NS	26.460
Catchment area In (m2)	NS	NS	2.241
Compound Topographic Index	1.142	1.011	NS
Electrical Conductivity, 0–30 cm (mS m^{-1})	1.388	1.549	NS
Electrical Conductivity, 0–90 cm (mS m^{-1})	−2.023	−2.402	−1.465
Clay 0–30–cm (g kg^{-1})	NS	−0.074	NS
Sand 0–30–cm (g kg^{-1})	−0.039	−0.128	−0.077
Silt 0–30–cm (g kg^{-1})	0.070	NS	0.077
Water table depth (cm)	0.031	0.037	NS
Mallow's C(p)	16.3	18.7	14.2
R^2	0.52	0.58	0.52

†SOC = Soil Organic Carbon.
‡NS = not significant at $P \leq 0.01$.

Spatial Variability of Soil Organic Carbon

The SOC semivariograms parameters indicated that SOC was highly spatially structured for all grid schemes (Table 6). The ranges for isotropic models were about 70-m, and nugget/sill ratios were low in all cases. Thus, the SOC data were well suited for kriging because it had well developed spatial structure, a low nugget/sill ratio, and the range was much larger than sample spacing. Anisotropy was not significant in these data.

TABLE 6

Semivariogram and Cross-Semivariograms model parameters for soil organic carbon (0–30-cm) sampled with different grid schemes

Variables†	Data Set	N	Model‡	Direction	Range	Nugget	Sill	R2	RSS§
					m	-------(Units)^2------			
In SOC	Grid 8.5 × 18.3-m	496	Sph	Omnidirectional	73.0	0.0043	0.0407	0.997	$1.55*10^{-6}$
In SOC	Grid 17 × 18.3-m	248	Sph	Omnidirectional	69.2	0.0001	0.0428	0.981	$1.32*10^{-5}$
In SOC	Grid 34 × 36.6-m	68	Exp	Omnidirectional	63.4	0.0093	0.0534	0.966	$1.21*10^{-5}$
				Cross–Semi Variograms for co-kriging					
SOC × CTI	Grid 8.5 × 18.3-m	496	Sph	Omnidirectional	74.8	0.38	4.05	0.991	0.081
SOC × EC_d	Grid 8.5 × 18.3-m	496	Sph	Omnidirectional	81.5	−0.01	−3.162	0.934	0.812
SOC × CTI	Grid 17 × 18.3-m	248	Sph	Omnidirectional	35.0	0.09	4.81	0.718	0.572
SOC × EC_d	Grid 17 × 18.3-m	248	Sph	Omnidirectional	79.1	−0.01	−3.420	0.935	0.763
SOC × EC_d	Grid 34 × 36.6-m	68	Sph	Omnidirectional	84.6	−0.01	−2.91	0.748	0.526

†In SOC = Natural log of Soil Organic C, SOC = Soil Organic C, CTI = Compound Topographic Index, EC_d = Soil Electrical Conductivity 0–90 cm.
‡Sph = Spherical, Exp = Exponential.
§RSS = Residual Sums of Squares.

Soil EC_d and CTI were the variables selected for co-kriging because they were the most highly correlated with SOC (r = -0.42 and r = 0.48 respectively), were intensively sampled, and had high spatial structure (Table 2 and Table 3). However, correlation coefficients for both variables were lower than the value suggested as the lower limit (r = 0.70) for co-kriging (Mueller and Pierce, 2003). Regression kriging was performed with residuals obtained from multiple regression of $G_{64/ha}$ and $G_{32/ha}$ data sets because these were the only regression residuals showing some degree of spatial structure. Regression residuals for both grid schemes were fit to well-structured semivariogram spherical models (nugget/sill < 0.15) with ranges of ≈ 37-m (Data not shown).

Similar to results obtained by Crawford and Hergert (1997) and Mueller and Pierce (2003), SOC maps developed by the different techniques generally showed similar SOC patterns, but differences at finer scales existed between techniques and grid sampling schemes (Fig. 2). Similar SOC means, standard deviations and spatial distribution were observed between the surfaces generated with the different techniques. However, the proportion of the area occupied for the five ranges selected to represent SOC distribution across the field fluctuated as much as 60% between interpolation methods, even with the same grid scheme. In general, maps obtained by regression presented the highest level of dissimilarity when compared with the ones obtained by other methods.

Map quality between different interpolation and zone selection methods was assessed at the validation set using MSE and PE approaches (Gotway et al., 1996; Bishop and McBratney, 2001; Mueller and Pierce, 2003). The best prediction method for SOC was ordinary kriging and the worst was regression for all grid sampling schemes (Table 7). Ordinary kriging reduced MSE by 74% compared with the field average approach. Multiple regression was clearly inferior to all kriging alternatives when spatial correlation was detected. Prediction of SOC by regression was improved when model residuals were incorporated using regression-kriging, but regression-kriging did not outperform ordinary kriging. In general, prediction accuracy increased when $G_{32/ha}$ was used instead of $G_{8/ha}$; however, no significant advantage was obtained using a more intensive grid sampling ($G_{64/ha}$). These results are in agreement with the general finding that more intensive grid schemes increase map quality but such dense sampling is hardly affordable in agricultural fields. The fact that ordinary kriging out-performed hybrid methods like co-kriging and regression kriging contradicts some previous studies (Bishop and McBratney, 2001; Mueller and Pierce, 2003).

Clusters and Soil Organic Carbon

Variable selection for cluster analysis was based both on factor analysis loading factors (Fraisse et al., 2001) and correlation with SOC. For example, CTI was selected for clustering because of its high loading in the first factor and its high correlation with SOC. The CTI, silt con-

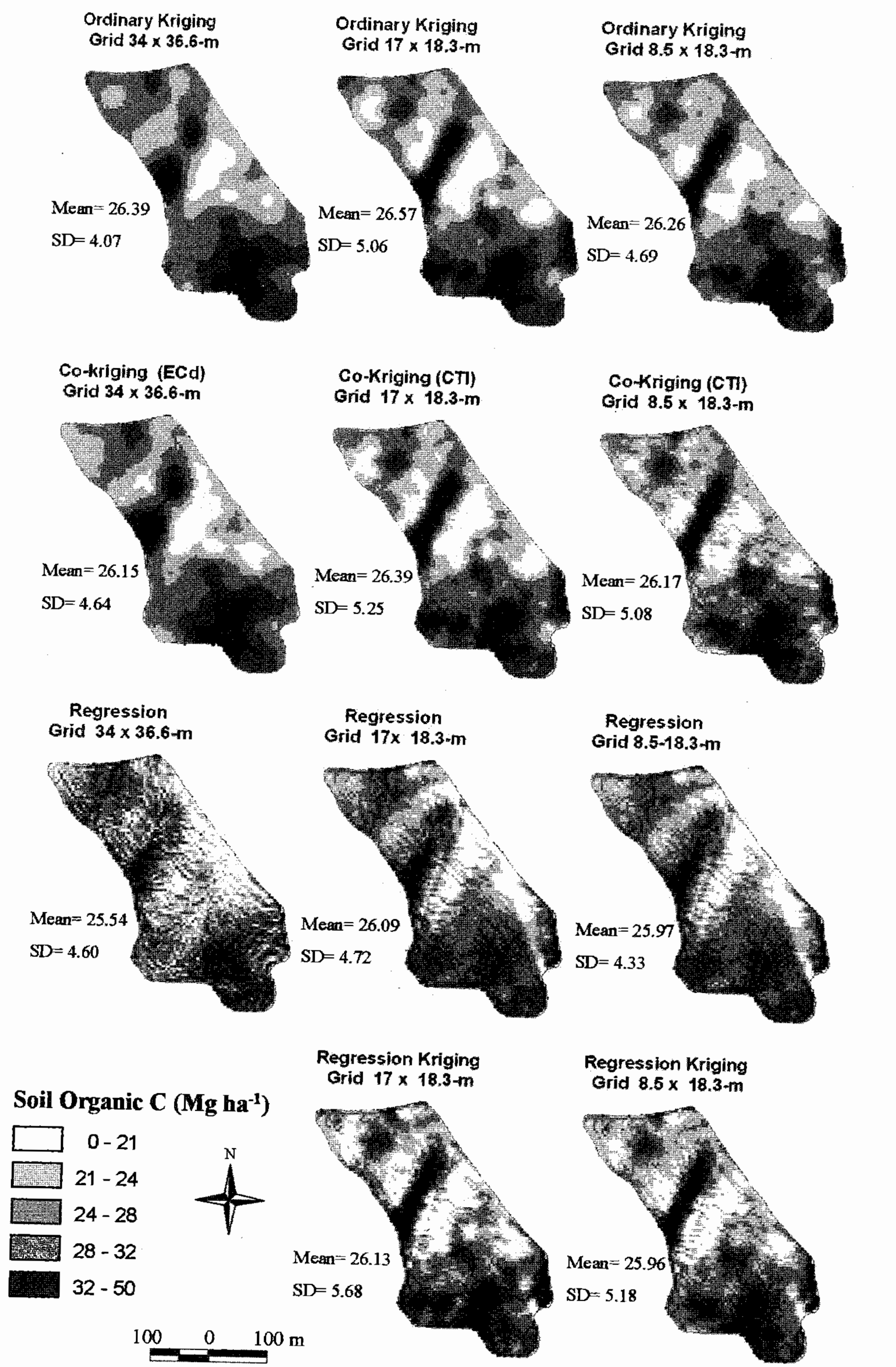

Fig. 2. Maps of soil organic carbon (0–30-cm) generated with different interpolation techniques and grid sampling intensities

TABLE 7

Comparison of mean square errors and prediction efficiencies obtained with different SOC interpolation methods using a jackknifing validation procedure (n = 24)

	Ordinary kriging (isotropic)	Co-kriging (ECd†)	Co-kriging (CTI‡)	Multiple regression	Regression kriging
			Grid 34 × 36.6-m		
R^2	0.70	0.63		0.38	
MSE§ (Mg ha^{-1})^2	13.027	14.737		20.735	
PE¶ (%)	63	58		41	
			Grid 17 × 18.3-m		
R^2	0.78	0.75	0.76	0.43	0.72
MSE (Mg ha^{-1})^2	9.099	10.081	9.758	22.552	12.792
PE (%)	74	71	72	36	64
			Grid 8.5 × 18.3-m		
R^2	0.79	0.74	0.75	0.45	0.78
MSE (Mg ha^{-1})^2	9.110	11.426	11.424	20.649	9.872
PE (%)	74	67	67	41	72

†EC_d = Electrical Conductivity 0–90-cm.
‡CTI = Compound Topographic Index.
§MSE = Mean Square Error.
¶PE = Prediction Efficiency.

tent, EC_d and EC_s, slope, ELEVA, CA and WTD were the variables selected for cluster analysis and zone delineation (Fig. 3). Because the fuzziness performance index and normalized classification entropy index differed in the optimal number of clusters for our field (Fridgen et al., 2004), the SOC variance reduction as a function of number of clusters (Fraisse et al., 2001) was used as an alternative approach for obtaining the optimal number of classes (Data not shown).

Descriptive statistics for SOC and some of the terrain attributes for each of the six clusters created are presented in Table 8. Independent of the grid scheme used, the highest SOC content was found in clusters 4 and 5, while clusters 2 and 3 had the lowest values. Analysis of variance using the intensive grid scheme data set (n = 496) indicated that most SOC differences between clusters were significant ($P \leq 0.05$). Cluster 5 corresponds to a concave drainage way position occupying the lowest elevation in the field. This is a depositional landscape and contains more poorly drained soils with accumulation of eroded sediments from upslope areas. Cluster 4 is an area of relatively flat topography located at both ends of the field. Clusters 4 and 5 had higher CTI and silt content, and lower EC values compared with the other clusters. Clusters 2 and 3, with relatively low SOC, corresponded to areas situated on sloping eroded soils, with high EC and clay content, and low CTI. Similar to other studies (Florinsky et al., 2002; VandenBygart et al., 2002), topography and historical erosion strongly influenced the spatial distribution of SOC at this site. For example, clusters 2 and 3 possessed soil and terrain attributes more likely related to low SOC through their effects on the field-scale water regime, biomass production, C mineralization and erosion. Cluster 5 is an area of C accumulation through sedimentation, relatively high biomass production, and decreased C decomposition associated with wetter (anaerobic) conditions.

Subdivision of the field into clusters explained between 28 to 35% of SOC variability depending on the grid scheme. These results were similar to the soil survey approach (34% of the SOC variability). Soil map units had significant statistical differences in SOC, suggesting both detailed (Order 1) soil surveys and cluster analysis may be used to guide sampling for estimating SOC at the field-scale.

CONCLUSIONS

Spatial variability of SOC of this field was highly structured. Ordinary kriging outper-

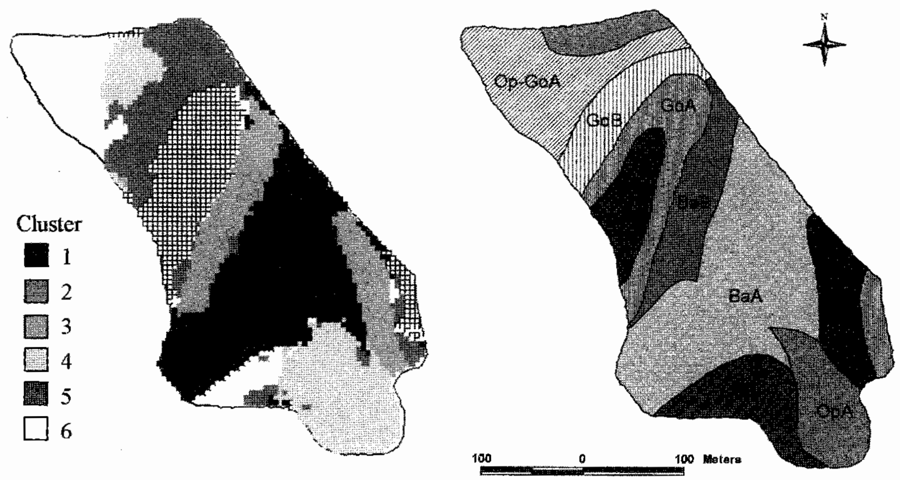

Fig. 3. Order 1 soil survey and field classification by fuzzy k-means cluster analysis into six zones using soil and terrain attributes: elevation, slope, catchment area, compound topographic index, electrical conductivity (0–30-cm and 0–90-cm), silt content (0–30-cm) and seasonal high water table depth. Map Units symbols are those described in Table 1.

formed all prediction methods used; even those that incorporated secondary information like co-kriging or regression kriging. Compared with the field average approach, ordinary kriging reduced the MSE by 74%. The fact that no further significant improvement on SOC quality surfaces were obtained with $G_{64/ha}$ compared with $G_{32/ha}$ suggest that a grid of ~20 × 20-m seems to be the optimal for our field. Nevertheless, such sampling intensity appears to be hardly affordable for larger areas and justifies the exploration of alternative methods for SOC mapping and monitoring.

Our results suggest field-scale EC variability was mostly related to soil properties related to historical erosion, while terrain attributes affected SOC variability through their influence on the field-scale soil water regime. Soil water regime impacts soil C inputs and outputs through its effects on biomass production, SOC mineralization, erosion and deposition. Our study indicates that landscape SOC redistribution as a result of these processes should be accounted for in studies of C sequestration potential at the field level. Slope, elevation and CTI in combination with soil EC, texture and depth to seasonal high water table explained up to 50% of SOC variability in this coastal plain field. Subdivision of the field into clusters or soil map units provided an alternative method for assessing soil and terrain attributes that influence SOC. Analyzing within soil map units or clusters developed using terrain and soil attributes will improve evaluation of the impacts of soil management practices on SOC at field scales.

TABLE 8

Averages for soil properties (0–30 cm) and terrain attributes for the clusters developed by k-means clustering procedure

Variables†	Elevation	Slope	CTI	EC 0–30 cm	EC 0–90 cm	WTD	Silt	Clay	SOC
Cluster	(m)	(%)		(mS m^{-1})	(mS m^{-1})	(cm)	(g kg^{-1})	(g kg^{-1})	(Mg ha^{-1})
1	70.1	0.8	7.5	5.0	6.3	149	254	191	25.97 c‡
2	69.3	2.1	7.0	7.0	8.0	66	275	190	23.55 d
3	69.4	3.5	6.8	7.0	7.4	147	251	196	21.76 e
4	69.8	0.9	7.6	5.2	6.4	78	303	180	30.65 a
5	68.4	1.6	8.3	4.5	5.9	58	284	146	29.05 b
6	69.8	1.1	7.4	5.0	5.4	77	257	206	24.99 cd

†CTI = Compound Topographic Index; EC = soil Electrical Conductivity; WTD = Water Table Depth; SOC = Soil Organic C.
‡Means followed by the same letter within the column are not significantly different at $P \leq 0.05$ level.

ACKNOWLEDGMENT

The authors wish to thank M.Sc. D. Ashford, Mr. J. Owen, Ms. P. Mitchell, Dr. J. Rodriguez, M.Sc. E. Schwab, and Mr. J. Walker, for their assistance in data collection and laboratory analysis.

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