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Management Practice Effects on Surface Total Carbon: Differences in Spatial Variability Patterns

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ABSTRACT

Lack of information about the spatial variability of soil C in different management systems limits accurate extrapolation of C sequestration findings to large scales. The objectives of this study were to: (i) describe and quantify variability of total C in three management systems, chisel-plow (CT) and no-till (NT) with conventional chemical inputs and a chisel-plow organic management practice with cover crops (CT-cover) 15 yr after conversion from conventional management; (ii) assess the strengths of spatial correlation in the three studied systems; and (iii) evaluate contributions of topography and texture to the overall total C variability and its spatial components. The data were collected at 12 60 by 60 m plots at the Long Term Ecological Research site, Kellogg Biological Station, MI. The data consisted of elevation measurements taken on a 2 by 5 m grid and a total of 1160 measurements of total C, sand, silt, and clay contents taken from the 0- to 5-cm depth. Overall variability of total C in NT was more than four times greater than in CT, and in CT-cover the variability was more than two times greater than CT. Spatial correlation of total C was the strongest in NT, followed by CT-cover, and then by CT. Stronger spatial structures in NT and CT-cover were found to form in response to topographical and texture gradients. Effects of texture were largely associated with topographical effects; however, even when topography was controlled for, texture still substantially contributed to explaining total C variability.

There is a growing need for more accurate assessments of soil C, including more accurate estimations of sizes of existing soil C pools, their vulnerability to change, and the impact of the changes on atmospheric CO_2. The release of soil C due to intensive agriculture is an historically significant source of atmospheric CO_2 loading (Wilson, 1978) and the potential for agricultural soils to regain some of this lost C with conversion to conservation tillage practices, including no-till and management systems with cover crops, is likely to become a modest but potentially important part of the U.S. and global CO_2 stabilization portfolio (Caldeira et al., 2004, Council for Agricultural Science and Technology, 2004).

Despite a large body of recent research on comparisons between different types of agricultural management practices for soil C storage (e.g., Franzluebbers, 2004), accurate estimates of soil C gains and losses on large scales remain problematic. One of the components contributing to the low accuracy is a large spatial variability in soil C cycling processes that occur across diverse landscapes, and a lack of accurate means to quantify this variability (Lal et al., 1995). Even though the spatial variability of soil C within individual agricultural fields has been assessed in a number of studies (Robertson et al., 1993, 1997; Cambardella et al., 1994; Robertson et al., 1997; Bergstrom et al., 2001), there is only limited information on how conversion from a conventional to a no-till management system or conversion from a conventional chemical to an organic management system influences spatial variability of soil C. Gathering such information will greatly aid the efforts to accurately upscale C sequestration findings from experimental plots to field- or watershed-scale levels.

Conversion from conventional tillage to no-till results in changes in soil physical and hydraulic properties, including bulk density, saturated hydraulic conductivity, and soil water retention (Hill and Cruse, 1985; Hill, 1990; Zhai et al., 1990; Díaz-Zorita et al., 2004), thus affecting water flow and solute and material transport across the landscape. These changes are expected to result in changing patterns of organic C accumulation and decomposition in no-till compared with the land that remained in conventional tillage. One of the main driving forces behind the changes is removal of the soil mixing by tillage that has a homogenizing effect on all topsoil processes. Therefore, in areas with relatively flat topography and negligible erosion, topsoil distribution of total C can be expected to be more variable in long-term no-till management systems than in intensively tilled systems. For example, Perfect and Caron (2002) have observed lower variability of total C in conventional tillage than in no-till systems on an Alfisol with 1 to 3% terrain slope.

There is a lack of quantitative information, however, on the factors contributing to the increase in variability and on the site-specific soil and environmental characteristics contributing to differences in the factor effects. We hypothesize that not only the overall variability of total C will be greater in no-till but also the spatial correlation in the total C distribution will be stronger. That is, more pronounced patterns of high and low C values will be found in no-till than in conventional tillage systems. Since topography and texture are among the most important factors affecting soil C (Parton et al., 1987; Hook and Burke, 2000), we hypothesize that a stronger spatial correlation is largely related to topographical

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Abbreviations: CT, conventional tillage (chisel-plowed) corn–soybean–wheat rotation system with conventional chemical inputs; CT-cover, conventional tillage (chisel-plowed) corn–soybean–wheat rotation with zero chemical inputs and leguminous cover crops; G, goodness-of-fit criterion; LTER, Long Term Ecological Research site; NT, no-till corn–soybean–wheat rotation with conventional chemical inputs; POM, particulate organic matter.

features of the landscape and to the spatial distribution patterns of soil texture. Local differences in topography and soil texture can be expected to have a wide range of local influences on C accumulation (Wood et al., 1990).

Conversion from a conventional tillage management system with conventional chemical inputs to a conventional tillage organic management system with cover crops can produce a greater spatial diversity in the availability of plant nutrients across a landscape. Greater diversity of plant growing conditions results in a greater diversity of biomass production. For example, greater variability of crop yields and stronger spatial structure of yield variability was found in organic-based management systems with cover crops compared with conventional systems (Kravchenko et al., 2005). We hypothesize that the overall variability of total C and the spatial structure of the variability of the long-term organic-based management system with cover crops will be greater than those of the conventional chemical input system. The larger variability of plant growth conditions will probably be developed in response to local variations in topography and soil texture.

The first objective of this study was to describe and quantify variability of total C in a no-till system and organic conventional tillage system with cover crops, 15 yr after conversion from conventional management system, and to compare it with conventional tillage with conventional chemical inputs. The second objective was to assess the strengths of spatial correlation in the three studied systems and to quantify the spatial components of the total C variability. The third objective was to evaluate the contributions of topography and texture to the overall total C variability and to its spatial components. We concentrated efforts on the 0- to 5-cm portion of the soil profile, as this is the depth at which soil C is most sensitive to management-induced changes.

MATERIALS AND METHODS

Data Collection

The data for the study were collected at the LTER (Long Term Ecological Research) site, Kellogg Biological Station, in southwest Michigan (85°24′ W, 42°24′ N). Soils are well-drained Typic Hapludalfs of the Kalamazoo (fine-loamy, mixed, mesic) and Oshtemo (coarse-loamy, mixed, mesic) series, developed on glacial outwash.

The LTER experiment was a randomized complete block design with six replications established in 1988; for details on site description, experimental design and research protocols, see http://lter.kbs.msu.edu (verified 21 July 2006; Kellogg Biological Station, 2005). Before experiment establishment, the studied site had been cultivated for at least a century (Robertson et al., 1997). The three studied LTER treatments included (i) a conventional tillage (chisel-plowed) corn (*Zea mays* L.)–soybean [*Glycine max* (L.) Merr.]–wheat (*Triticum aestivum* L.) rotation with conventional chemical inputs (CT), (ii) a no-till corn–soybean–wheat rotation with conventional chemical inputs (NT), and (iii) a conventional tillage (chisel-plowed) corn–soybean–wheat rotation with zero chemical inputs and leguminous cover crops (CT-cover). The weed control in the CT-cover system was achieved by intensive cultivations early in the growing season; thus, CT-cover management had the greatest amount of tillage disturbance among the three studied systems. For each treatment, we randomly selected three plots from Replications 1 through 4 and included the plot from Replication 6 that was known to have a coarser textured soil than the other replications. Soil sampling of Replication 1 through 4 plots was conducted in May of 2003; soil sampling of Replication 6 plots was conducted in May of 2004.

The sampled area of each 1-ha plot was ~60 by 60 m in size (Fig. 1). To avoid plot boundary effects, all samples were located at least 15 m away from the boundaries. The northern ~20-m portions of the plots were also avoided in soil sampling for this study, since these portions are designated for potential applications of various manipulative treatments supplementary to those of the main LTER experiment (Kellogg Biological Station, 2005).

A total of 1164 samples were collected from the studied site with ~100 georeferenced soil samples per plot (Fig. 1). Within each plot, 20 samples were collected on a 15- by 18-m triangular grid and an additional 80 off-grid samples were collected at four distances, 1.0, 2.5, 5.0, and 7.5 m, from the grid points. The directions for identifying placements for off-grid samples from the grid points were selected randomly from eight direction possibilities, i.e., north, northeast, east, etc. All grid points had at least one off-grid sample located at 1-m distance from them. Seven grid points had one or two off-grid samples at other distances, in addition to the 1-m sample. Three grid points in the middle part of the sampled area had ~20 off-grid samples located next to them: four or five 1-m distance samples, four 2.5-m samples, four 5-m samples, and six 7.5-m samples. This sampling scheme provided a sufficient number of samples for spatial variability evaluation with minimized sampling effort and was found to be practical and efficient in its implementation in the field. At each sampling location, the sample was collected at 0- to 5-cm depth from between the plant rows and was composited from five 2.5-cm-diameter cores collected within a 0.2-m-radius circle.

The samples were air dried at room temperature and cleaned of visible plant residues and stones. Sample preparation for total C measurements consisted of removing smaller plant material by gentle air blowing and grinding the samples on a rolling grinder to pass a 100-mesh sieve. Total C was measured using a Carlo-Erba CN analyzer. In each plot, ~10% of the samples had three replicated total C measurements for quality control of laboratory procedure and for assessment of laboratory measurement error. Previous studies conducted at the LTER site have found inorganic C at the soil surface to be negligible, thus, the measured total C values are considered to be representative of the organic C. Soil texture, i.e., sand, silt, and clay content, measurements were conducted using the hydrometer method (Gee and Bauder, 1986).

The elevation data set included 597 elevation measurements collected from the LTER site using a land-based laser in 1988 (Robertson et al., 1997) and the elevation measurements collected in 2004 using a 12-channel Leica SR530 real-time kinematic DGPS (dual-frequency global positioning system) receiver, which was mounted on an all-terrain vehicle. In the studied plots, the data were collected every 2 m in rows 5 m apart. The elevation measurements were converted into a cell-based terrain map on a 4 by 4 m grid using inverse distance weighting with power of two and six nearest neighbors in ArcGIS 9.0 Spatial Analyst (ESRI, 2004). Then terrain slope, aspect, and terrain curvature were derived from the elevation data using surface hydrologic analysis functions of ArcGIS 9.0 Spatial Analyst. Preliminary analysis of aspect effects on total C at the studied site showed that the largest difference in total C existed between sites with southern aspects (south, southeast, and southwest) and the sites with all other aspects. Thus,

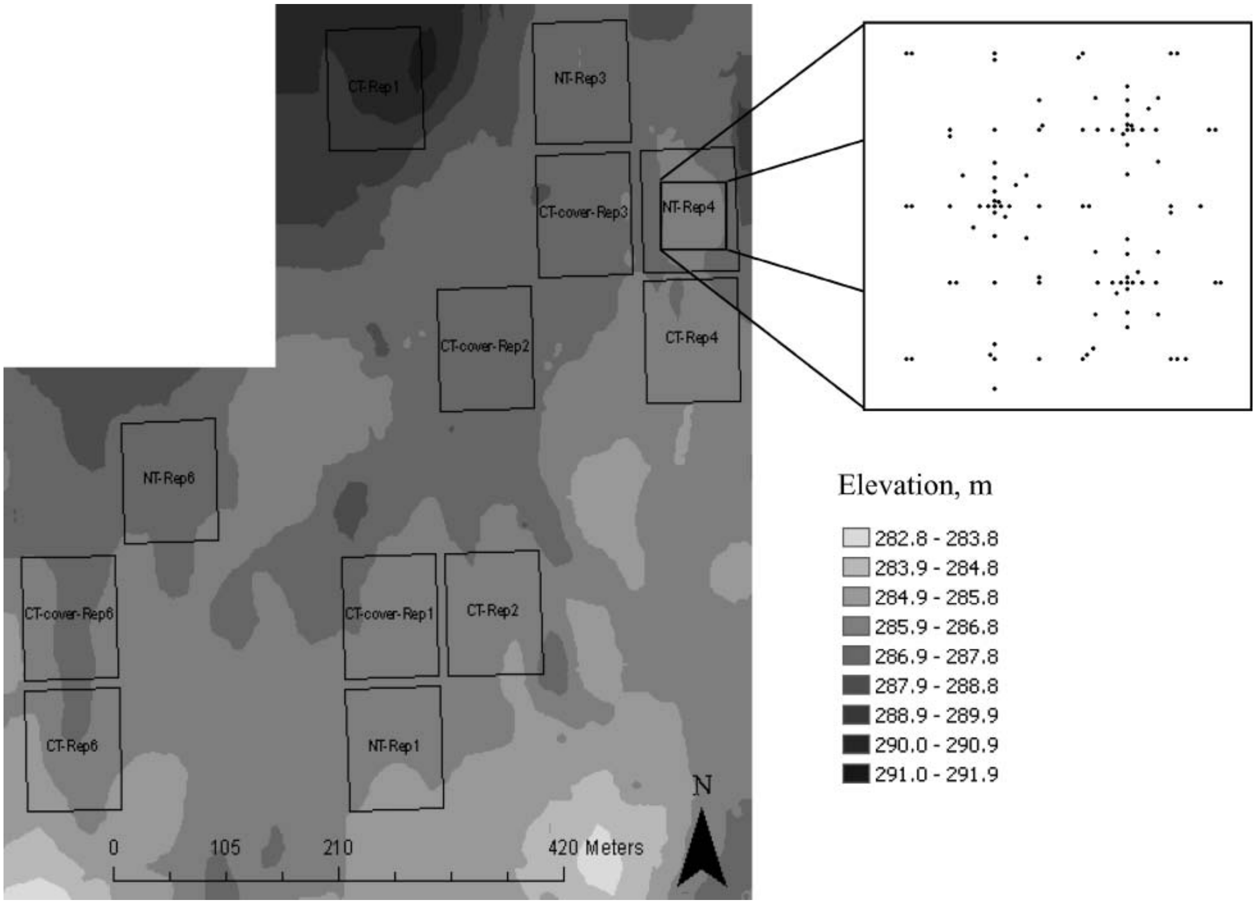

Fig. 1. Locations of the experimental plots along with an example of the soil sampling scheme used within each plot and the 4 by 4 m interpolated elevation map.

in this study we reclassified aspect as a categorical variable with only two values, namely, 0 for southern orientation and 1 for the other orientations.

Data Analysis

The data analysis consisted of three main components. First, comparisons between the total C variances were conducted using Levene's test (Milliken and Johnson, 1992). Estimation of variance components due to measurement error, plot, and block effects was conducted using the restricted maximum likelihood method in PROC MIXED (SAS Institute, 2001; Milliken and Johnson, 1992; Littell et al., 1996).

The second analysis consisted of assessment of continuous topographical and soil texture influences on the spatial distribution of total C using multiple regression methods in PROC REG (SAS Institute, 2001). Topographical influences on total C were described using multiple regression equations that included linear effects of elevation, terrain slope, curvature, and the reclassified aspect. These were the effects that were found to be statistically significant ($p < 0.05$) in three or more of the studied plots and for consistency purposes all these effects were included in multiple regression equations. The need for quadratic terms for elevation, terrain slope, and curvature was investigated separately in each plot and the quadratic terms were added to the regression equation whenever significant at the $p = 0.05$ level.

To assess the contribution of texture, we considered adding either one or two of the three studied texture variables (clay, silt, and sand contents) to the previously selected topographical regression model of each studied plot. Topography is regarded as the primary influence factor that simultaneously affects spatial distributions of both total C and texture. Thus we used partial regression coefficients to study the influence of texture when topographical variables were controlled for. Partial regression coefficients allowed for quantifying the component of total C variability that could be explained by texture independent of topographical effects. Detailed descriptions of partial regression coefficients are presented in texts on multiple regression (e.g., Pedhazur, 1997).

The third analysis consisted of using geostatistical methods to evaluate spatial variability in the original total C data and the spatial components of the variability that remained unexplained by the topographical and texture effects (Goovaerts, 1997; Webster and Oliver, 2000). For that, the variograms of the original total C data as well as the variograms of the residuals for total C from topographical regression models and from regression models with topography and texture were obtained for each management treatment based on combined data from all four plots. Spatial analyses were performed via GSLIB software (Deutsch and Journel, 1998) and PROC VARIOGRAM (SAS Institute, 2001). Variogram models were fitted using weighted least squares using PROC NLIN (Schabenberger and Pierce, 2002). A ratio between the number of data pairs available at each lag distance and the squared value of the variogram model prediction at that lag was used as a weighting factor (Cressie, 1985). We compared the weighted least square fitting results of spherical, Gaussian, and exponential models and selected the model that produced the smallest mean square error. To quantify the variogram behavior near the origin, we used the variogram value at the shortest lag distance of 1.5 m (Kravchenko et al., 2005).

Evaluation of Practical Implications of Differences in Variability among the Management Systems

Accurate estimation of soil property values across agricultural fields is one of the primary goals of soil sampling for agricultural management purposes (Ruffo et al., 2005) and is indispensable for large-scale assessments of soil C. Accuracy is commonly judged by the size of standard errors for means, which are calculated based on the variances of the studied variable within the whole studied field and the sample number. The larger the variance, the larger the number of samples needed to achieve the desired level of accuracy in estimating the mean. Accounting for spatial correlation in the distribution of the studied variable may lead to more accurate mean estimates, since their standard errors are based on the variances obtained not for the whole field but for small polygons drawn around every sampled location (McBratney and Webster, 1981; Webster and Oliver, 2000). As in the traditional approach, larger variances produce greater standard errors; however, the presence of strong spatial correlation will lower the standard errors and result in higher estimation accuracy.

Comparisons between the mean values from different management practices also depend on variability and can be negatively affected if variabilities of the studied practices are substantially different; however, lower standard errors can be achieved with a smaller number of samples if the management practice that leads to higher variability is sampled more intensively than the practice with lower variability. As an example, consider the use of a *t*-test for independent samples with unequal variances to compare the means of two studied management practices. Assume that it is known that the variance in the first practice, σ_1^2, is a times less than the variance in the second practice, σ_2^2:

$$\frac{\sigma_1^2}{\sigma_2^2} = a, 0 < a < 1 \quad [1]$$

A total of n samples will be collected and analyzed from both practices. It can be shown that the smallest standard error for the difference between the practice means can be achieved when the number of samples collected from the first practice is equal to bn and the number of samples collected from the second practice is respectively equal to $n - bn$, where the coefficient b is related to the ratio between the variances (Eq. [1]) as

$$b = \frac{\sqrt{a}}{1 + \sqrt{a}} \quad [2]$$

Thus, by taking into consideration potential differences in treatment variability, researchers can devise more effective and less time-consuming sampling strategies.

Besides mean estimations and comparisons, accurate mapping of total C is another important goal of many agricultural field studies and it also depends on the overall variability and on the strength of the spatial correlation. To evaluate how differences in spatial structure affect the accuracy of total C maps that could be obtained for the studied site via kriging methods, we used the jack-knifing approach. For that, the data from each management were separated into a test data set that consisted of 60 randomly selected samples and a model data set containing the remaining samples (>300). Then, regression analyses and variogram calculation and fitting were performed on the model data set following the same procedures as those used in the analyses of the complete data. Relevant variogram and regression parameters were then used in predicting the test data set values via ordinary kriging and regression kriging (Hengl et al., 2004). Kriging predictions for the test data sets were compared with the true values. Ten test data sets were used in each of the three management systems selected based on sampling with replacement. To compare the performance of kriging methods, we used the goodness-of-prediction criterion G (Agterberg, 1984; Gotway et al., 1996):

$$G = \frac{1 - \mathrm{MSE}}{\mathrm{MSE}_{\mathrm{average}}} 100\%$$

where MSE is the mean square error obtained from using kriging methods for test data predictions and $\mathrm{MSE}_{\mathrm{average}}$ is the mean square error obtained from using a mean value of the model data set as a sole predictor of total C values of the test data set. Positive G values indicate that the map obtained by using kriging methods is more accurate than a field average.

RESULTS AND DISCUSSION

General Site Description and Management Effects on Total Carbon Mean and Variance Values

The studied plots had relatively flat topography. Except for the CT-Rep6 plot, the range of elevation values in the studied plots did not exceed 1.5 m and average terrain slopes were <2.0° (Table 1). Sand content in the studied samples ranged from 5 to 73%, silt content ranged from 18 to 75%, and clay content ranged from 2 to 33%. Analysis of the baseline soil data collected in 1987 from the experimental site before establishing the experiment (Robertson et al., 1997) indicated that the treatment plots were relatively evenly distributed along textural and topographical gradients, with no significant differences in terms of soil texture or C existing initially among the treatments (Hao and Kravchenko, 2006).

The overall mean total C values for CT, NT, and CT-cover were 7.1, 11.9, and 10.9 g kg^{-1}, respectively. Mean total C values for individual plots are shown in Table 1. As expected, total C was found to be significantly higher in NT and CT-cover than in CT management ($p < 0.01$), while the NT total C was significantly higher than the total C from CT-cover management ($p < 0.01$). These results are consistent with a number of studies that reported higher total C values in the soil surface layer under no-till than conventional tillage (Wood et al., 1991; West and Post, 2002; Eve et al., 2002).

Overall total C variability was greater in NT and CT-cover managements than CT management ($p < 0.05$; Table 2). The higher variance observed in the no-till management compared with the two chisel plow managements supports our hypothesis that total C variability increased as a result of the elimination of soil mixing by tillage during the 15-yr period after conversion to no-till. This observation is consistent with the results reported by Perfect and Caron (2002).

Higher variability of total C was observed in the CT-cover treatment than in the CT treatment (Table 2). The CT-cover treatment had extra tillage via weed-suppressing cultivations, i.e., it was the management practice

Table 1. Summary of the soil and topographical properties of the studied plots. For total C, sand, silt, and clay averages, coefficients of variation (%) are shown in parentheses.

Plot†	No. of samples	Total C	Sand	Silt	Clay	Elevation range	Avg. terrain slope
		g kg^{-1} soil				m	°
CT							
Rep1	99	6.5(17)	430(13)	440(14)	130(21)	1.46	1.37
Rep2	94	8.0(18)	410(14)	450(12)	140(14)	0.85	0.67
Rep4	96	8.0(11)	400(9)	480(7)	120(17)	0.75	0.84
Rep6	98	6.0(20)	670(7)	250(15)	80(28)	1.70	1.51
NT							
Rep1	96	11.2(14)	390(16)	460(14)	150(16)	0.74	0.83
Rep3	100	13.7(18)	300(28)	300(31)	150(22)	0.71	0.67
Rep4	100	12.6(28)	330(34)	510(17)	160(24)	0.44	0.44
Rep6	94	9.9(19)	520(12)	370(13)	110(21)	0.72	0.72
CT-cover							
Rep1	98	11.1(27)	360(42)	440(30)	190(29)	1.05	1.29
Rep2	94	9.8(19)	440(25)	450(22)	110(25)	0.56	0.54
Rep3	97	10.7(17)	370(18)	500(12)	130(18)	1.03	1.17
Rep6	98	8.8(17)	590(9)	290(18)	110(20)	1.06	0.94

† CT, conventional chisel-plow; NT, no-till; CT-cover, organic chisel-plow with cover cropping.

with the greatest soil mixing among the three studied treatments. This indicates that soil mixing by tillage was not the only factor affecting total C variability and supports our hypothesis of potentially greater variability of biomass inputs contributing to an increase in variability of total C in CT-cover. The tendency for greater variability of corn, soybean, and wheat grain yields in the CT-cover in the years with stressful weather conditions compared with variability in CT and NT treatments was reported by Kravchenko et al. (2005) for the LTER experiment. Likewise, Rockström et al. (1999) observed higher variability in millet yields in unfertilized than in fertilized management systems under water-stressed conditions in the Sahel (Niger).

Variance components due to laboratory measurement error constituted 0.24, 0.16, and 0.18 for CT, NT, and CT-cover treatments, respectively. The measurement error variance components were not significantly different among the three studied management systems ($p < 0.05$).

Spatial Variability of Total Carbon in the Three Management Systems

Total C variability was strongly spatially structured in all three studied management systems as demonstrated by the variograms of the original total C data (Fig. 2a, Table 2). The presence of spatial correlation in total C spatial distributions reflected the presence of continuous sources of influence on total C acting across the studied landscape. Since nearby locations are affected by the same influences, the total C values in them are more similar to each other than those at samples located farther apart.

Stronger spatial structure was observed in NT and CT-cover treatments than in CT, however, indicating that patterns in spatial distribution of total C across the landscape were more pronounced in NT and CT-cover management systems (Fig. 2a). The spatial correlation ranges of the NT and CT-cover treatments were 30 and 38 m, respectively, while the range for CT variogram was only 20 m (Table 2). Larger correlation ranges of NT and CT-cover showed that the total C values were spatially correlated in these treatments across larger distances compared with those of CT. In the NT and CT-cover treatments, the sample variograms were best fitted with Gaussian models, while a spherical model was used in CT. Gaussian models reflected a more spatially continuous nature of total C distribution at short lag distances (<10 m) in NT and CT-cover treatments (Fig. 2a). The ratios between the variogram values at the smallest lag distance (1.5 m) and the sills were 20 and 19% in NT and CT-cover treatments, respectively, while in CT it was 31%. This indicated that in CT, a larger portion of the overall total C variability was occurring at very short distances (<1.5 m) while in NT and CT-cover, a larger portion of the overall variability was spatially structured. Note, that laboratory measurement error constituted 52% of the variability observed at the smallest lag dis-

Table 2. Variances and variogram model parameters for the variograms of the original total C data and of the residuals from the regression models with topography and the regression models with topography and texture (sand and silt content) for the three studied management practices.

		Original total C data				Residuals from regression models with topography				Residuals from regression models with topography and texture			
Management practice†	Variance	Variogram type‡	Variogram at 1.5 m	Sill	Range	Variogram type‡	Variogram at 1.5 m	Sill	Range	Variogram type‡	Variogram at 1.5 m	Sill	Range
					m				m				m
CT	2.1a§	sph	0.5	1.5	20	exp	0.5	0.9	10	sph	0.5	0.6	5
NT	8.5b	Gau	1.6	8.0	30	sph	1.6	2.8	18	sph	1.7	2.2	15
CT-cover	5.5b	Gau	1.2	6.5	28	exp	1.2	2.2	27	sph	1.3	1.5	5

† CT, conventional chisel-plow; NT, no-till; CT-cover, organic chisel-plow with cover cropping.
‡ Types of the variogram models: sph, spherical; Gau, Gaussian; exp, exponential.
§ Variances followed by the same letter are not significantly different ($p < 0.05$, Levene's test).

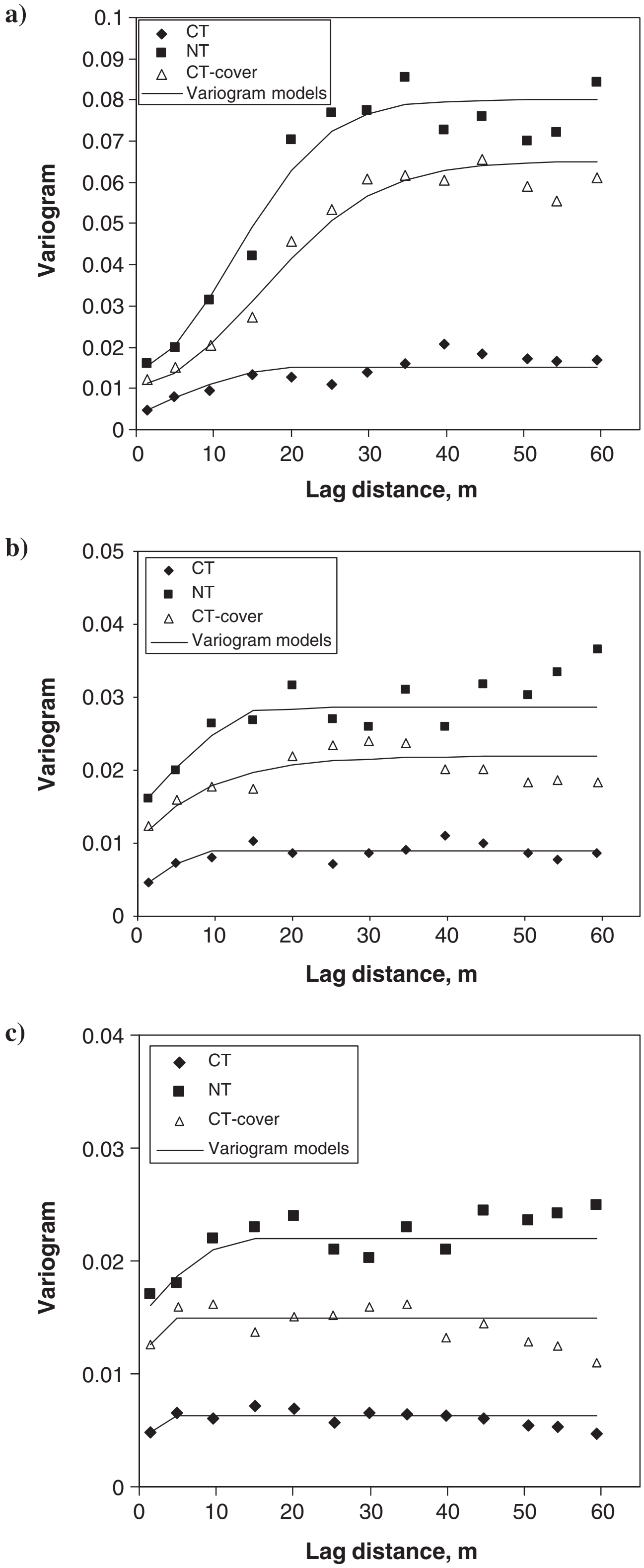

Fig. 2. Sample variograms and variogram models for: (a) original total C data; (b) residuals from topographical regression models; and (c) residuals from regression models with topographical variables and texture in conventional chisel-plow (CT), no-till (NT), and organic chisel-plow with cover cropping (CT-cover) management systems. Model parameters are shown in Table 2.

tance of 1.5 m in the CT management system, while it constituted only 10 and 14% of the 1.5-m variability of the NT and CT-cover systems, respectively (Table 2).

Topographical features explained a substantial portion of the total C variability in all three studied treatments, with R^2 values from topographical regression models ranging from 0.11 (CT-Rep4 and NT-Rep6) to 0.83 (CT-cover-Rep1) (Table 3). Topographical regression models were significant ($p < 0.05$) or highly significant ($p < 0.01$) in all studied plots. These results were expected, since on a scale of an agricultural field or a small watershed, which is the scale of this experiment, topography is known to operate as one of the main factors of soil formation that substantially influences spatial patterns of soil C distribution. Strong topographical effects on total C observed in this study were consistent with the results of many other field studies conducted on a comparable scale, among the most recent of which are studies by Moore et al. (1993), Gessler et al. (2000), Kravchenko and Bullock (2000), Mueller and Pierce (2003), and Terra et al. (2004).

To assess the spatial component of variability unexplained by the topographical influences, we calculated variograms of the residuals for total C from the respective multiple regression topographical models (Fig. 2b). The spatial correlation ranges of the residual variograms decreased and ratios between variogram values at the shortest lag distance (1.5 m) and sills increased greatly. The short-distance variability, as expressed by 1.5-m variogram value/sill ratios, constituted 56, 55, and 52% of the overall variability of the residuals for NT, CT-cover, and CT management systems, respectively. Note that the variogram values at the shortest lag distances (1.5 and 5 m) remained unaffected by removing the topographical influences. That result is expected since 1.5 m is less than the 4-m cell resolution of topographical maps of this study and 5 m is just above that resolution. The more substantial increase in the 1.5-m value/sill ratio of NT and CT-cover residual variograms than that for CT is a further reflection of the stronger spatially continuous influence of topography on total C of these treatments. Once the topographical influences were removed, the spatially structured portion of their spatial variability dropped greatly. The spatial correlation ranges of NT and CT-cover management systems were 18 and 27 m, respectively, while the range for CT was only 10 m. The spatial structure, still pronounced in the variograms of the residuals in all three treatments, indicated that not all the factors influencing the spatial correlation of total C were accounted for by the topographical regression models. The differences in spatial correlation range values of the three treatments indicated that the influences of these remaining spatial factors more strongly affected the spatial distribution patterns of total C in the NT and CT-cover management systems than in the CT system.

Texture was hypothesized to be one of the factors the effects of which on soil C spatial distribution across the landscape was, to a certain extent, explained by topography. Indeed, the regressions between sand and silt contents with topography were highly significant ($p < 0.01$) in all but one plot, with R^2 values ranging

Table 3. Results of multiple regressions for total C at the 0- to 5-cm depth with topographical variables and texture.

Plot†	R^2/RMSE (total C vs. topography‡)	R^2/RMSE (sand vs. topography)	R^2/RMSE (total C vs. topography, sand and silt)§	Partial R^2, sand¶	Partial R^2, silt#
CT					
Rep1	0.54/0.08**	0.72/0.03**	0.65/0.07**	0.17**	0.23**
Rep2	0.32/0.12**	0.32/0.05**	0.63/0.09**	0.42**	0.27**
Rep4	0.11/0.08*	0.21/0.03**	0.22/0.08**	0.11**	0.05*
Rep6	0.34/0.10**	0.32/0.04**	0.53/0.09**	0.27**	0.19**
NT					
Rep1	0.27/0.14**	0.63/0.04**	0.41/0.13**	0.19**	0.15**
Rep3	0.54/0.18**	0.63/0.06**	0.63/0.15**	0.20**	0.13**
Rep4	0.74/0.18**	0.77/0.05**	0.83/0.15**	0.34**	0.26**
Rep6	0.11/0.18*	0.02/0.06NS	0.19/0.18**	0.10**	0.10**
CT-cover					
Rep1	0.83/0.13**	0.85/0.06**	0.86/0.12**	0.20**	0.13**
Rep2	0.27/0.17**	0.33/0.09**	0.57/0.13**	0.40**	0.37**
Rep3	0.27/0.16**	0.43/0.05**	0.48/0.14**	0.29**	0.27**
Rep6	0.26/0.14**	0.27/0.05**	0.41/0.12**	0.23**	0.18**

* Significant at the 0.05 probability level.
** Significant at the 0.01 probability level.
† CT, conventional chisel-plow; NT, no-till; CT-cover, organic chisel-plow with cover cropping.
‡ Topographical regression models of all plots included linear effects of relative elevation, terrain slope, curvature and aspect. Quadratic terms were added to the models when found to be significant at 0.05 level.
§ Linear effects of both sand and silt were added to the topographical regression model.
¶ Partial regression coefficient for sand was calculated from a regression model that included linear and quadratic effects of topographical variables and sand content.
# Partial regression coefficient for silt was calculated from a regression model that included linear and quadratic effects of topographical variables and silt content.

from 0.02 to 0.83 for sand (Table 3) and from 0.19 to 0.67 for silt (data not shown). In this study, sand and silt contents were found to be the only texture components that were closely related to total C, and thus were added to the topographical regression models (Table 3). Partial regression coefficients for sand when sand was included in a topographical regression model for total C and for silt when silt was included in a topographical regression model for total C indicated that there was also an additional effect of texture itself on soil C, independent of the effect of topography (Table 3). Once topography was controlled for, the remaining influence of sand on total C in terms of partial regression coefficients ranged from 0.10 in the NT-Rep6 plot to 0.42 in the CT-Rep2 plot. These findings are consistent with other reports on texture as a major influence on soil C distribution within a landscape (Hook and Burke, 2000) due to greater physical protection of soil organic C in fine-textured soils (Tisdall and Oades, 1982; Hassink, 1994).

To study whether the portion of total C variability unexplained by the combined effects of topography and texture still exhibited spatial correlation, we examined the variograms of the residuals from regression models with topography and sand and silt variables (Fig. 2c). In the variograms of the CT-cover and CT management systems, the spatial correlation ranges were very small (5 m), while in NT the range was 14 m. The ratios between the variogram values at 1.5-m lag distance and sills were equal to 77, 85, and 75% in NT, CT-cover, and CT management systems, respectively.

These comparisons among variograms of raw total C data and residuals of the three management systems further support our hypothesis that, in NT, elimination of the uniform soil mixing caused greater spatial diversity of soil C accumulation conditions in response to spatially variable topographical and texture influences. One of the mechanisms of topographical and texture influences on total C spatial variability is their effects on water and heat redistribution across the landscape, which produces greater spatial diversity of soil moisture and temperature regimes (Johnson and Lowery, 1985). Greater diversity in soil texture, moisture, and temperature affects diversity in microbial activity (Skopp et al., 1990), soil C mineralization (Amador et al., 2005), decomposition, and accumulation (Parton et al., 1987), thus producing greater differences in the rates of C processes across a landscape. Stronger relationships between total C and soil moisture and bulk density (Perfect and Caron, 2002) in the absence of soil disturbance by plowing further support the notion of a stronger influence of site-specific soil characteristics on total C in a no-till management system.

Greater spatial diversity of total C observed in the organic CT-cover management system also appears to form in response to topographical and texture gradients. Higher sensitivity of plants to topographical and textural variations in CT-cover and the resulting higher diversity of produced biomass might be the most likely mechanism of this response. For example, Kravchenko et al. (2005) observed significant correlations between the variability of crop grain yields and terrain slope in the CT-cover management system of the LTER experiment in three of the six studied years, while the correlation was significant in only one of the six studied years in the NT and CT management systems.

The variogram values for the residuals from the topography and texture regression models of NT and CT-cover were much higher than those of CT at all lag distances (Fig. 2c). Thus, when both topographical and texture effects were accounted for, both NT and CT-cover still had overall greater variability of total C than the CT treatment, while NT was more variable than CT-cover. One possible explanation for the remaining variability being greater in the NT and CT-cover treatments might be the contribution to the variability from particulate organic matter (POM), which has been often found to be higher at the 0- to 5-cm depth in no-till and in management systems with cover crops than in soils under conventional tillage (Willson et al., 2001; Franzluebbers, 2004) and also has been found to respond rapidly to a switch from conventional to no-till management (Wander, 2004). Particulate organic matter also has been found to be much more variable than total soil C (Burke et al., 1999; Hook and Burke, 2000). For example, Hook and Burke (2000) observed that the microscale variability of POM was comparable in magnitude to its landscape-scale variability. Several studies also indicated that total POM, free POM, or its soil C content were often not related to soil texture (Franzluebbers and Arshad, 1997; Kölbl and Kögel-Knabner, 2004; Plante et al., 2006). Thus, we hypothesize that the distribution of POM on the scale of this study might not be well structured spatially or the presence of spatial structure in the POM distribution across the landscape might be masked by the overall high variability of POM. That is, greater amounts of POM in NT and CT-cover might be contributing only to the increase in overall variability but not to the changes in the components of spatial structure. It might seem that the proportion of POM in the total C is too small to cause substantial differences in the overall variability of total C of the studied management systems; however, the variograms of the residuals (Fig. 2c) also reflect a relatively small remaining portion of variability that was not explained by the topographical and textural differences. The sills of the variograms of these residuals constitute 30, 25, and 25% of the sills of the raw total C variograms for NT, CT-cover, and CT treatments, respectively. The magnitude of the differences between the management systems in this remaining variability is comparable with the size of the POM fraction in total C of these soils (Degryze et al., 2004). Further testing of this hypothesis based on actual POM measurements is needed.

The variograms of total C residuals from regression with topography and texture for the chisel-plowed management systems (CT and CT-cover) had no spatial correlation beyond 5-m distances (Fig. 2c). This indicates that topography and texture were the main spatial influences on total C variability in these plots and only random spatially unstructured variation remained after they were accounted for. For NT, however, the spatial correlation was still present at distances up to 15 m, even though the spatially structured component of it was very small. The remaining observed spatial structure might be indicating that there are other spatially continuous sources of influence on the total C distribution within the landscape besides those explained by the topographical regression and texture model. Initially, we hypothesized that some spatial structure would be observed in the residual variograms in all three studied managements. We believed that the remaining spatial structure would reflect the historical effects of individual longer lived perennial plants of preagricultural vegetation patterns noted to be possibly present in the studied area (Robertson et al., 1997). These influences would not necessarily be explained by texture and topography, and thus were expected to manifest themselves through the spatial structure of the residual variograms. Only the NT variogram, however, exhibited such residual spatial structure. It is not clear what influences caused this remaining spatial correlation.

Some Practical Implications

The accuracy of the total C estimations using confidence intervals, e.g., 95%, varies between the three studied management systems as a function of the total C variability. Consider as an illustration a soil sampling effort where collection of 16 samples is planned from the studied area. Using the variances for the three managements obtained in this study as estimates of the total C variability, the widths of the 95% confidence intervals can be anticipated to be around ± 0.8, ± 1.6, and ± 1.3 g kg^{-1} for the CT, NT, and CT-cover management systems, respectively. The variances observed in this study suggest that to achieve the same accuracy in total C estimation as could be obtained when sampling the areas in CT, the sampling intensity in areas in NT and CT-cover would have to be four and >2.5 times greater, respectively, that sampling in CT.

Using information on spatial correlation in total C variability allows substantial improvement in the accuracy of total C mean estimation. For example, if 16 samples are planned to be collected on a 4 by 4 regular grid in a 1-ha area, based on the variogram model parameters obtained in this study, the widths of the 95% confidence intervals can be anticipated to be around ± 0.4, ± 0.6, and ± 0.5 g kg^{-1} for CT, NT, and CT-cover, respectively. The differences in confidence interval widths between the treatments are substantially less than those obtained in the traditional approach based on 16 samples, due to the stronger spatial correlation of NT and CT-cover compensating for the greater overall variability of total C in these systems than in CT. Achieving the same width of confidence intervals will require the number of samples in NT and CT-cover to be only 1.7 and 1.2 times greater, respectively, than in CT.

Consider the use of the information on total C variability to plan an experiment for comparing two management practices, namely, NT and CT, via a *t*-test with unequal variances. The ratio between CT and NT variances observed in this study is equal to 0.247 (Eq. [1]). Based on this information, the most efficient will be the sampling where $b = 0.33$ (Eq. [2]); that is, where approximately a third of a total n planned samples is collected in CT and the remaining two-thirds are collected in NT.

The spatial variability information obtained in this study can also be used to plan a grid sampling effort to collect the data for mapping total C within a given field on soils similar to those of this study. Assuming similar variogram parameters and specifying a desired level of mapping accuracy, i.e., desired kriging variance, a grid spacing can be obtained such that will provide the desired accuracy (McBratney and Webster, 1981; Ruffo et al., 2005).

Stronger spatial structures and better regression models lead to better mapping accuracy by ordinary and regression kriging (Isaaks and Srivastava, 1989; Goovaerts, 1997). Jack-knifing results of this study illustrate the level of accuracy in predicting the total C values at unsampled locations of this site that can be achieved in the three studied management systems. In NT, the average G values obtained based on 10 test data sets were equal to 47 and 49% for ordinary kriging and regression kriging, respectively. In CT-cover and CT, the average G values of ordinary kriging and regression kriging were 43 and 44%, and 39 and 40%, respectively. This result indicates that in the studied soils, assessment of total C based on maps obtained from georeferenced individual samples produces substantially more accurate results than the predictions based on whole-field mean total C values in all three studied management systems. The advantages of mapping total C appear to be even greater, however, in the conservational management practices, such as CT-cover and especially NT, compared with the conventional chisel-plow management system.

CONCLUSIONS

Comparisons between the CT and NT management systems and the CT-cover organic management system 15 yr after conversion from conventional management demonstrated that at the 0- to 5-cm depth, the overall variability of total C was the highest in NT followed by CT-cover and then by CT. Spatial correlation of total C was the strongest in NT, followed by CT-cover, and then by CT. Stronger spatial structure in NT and CT-cover was found to form in response to topographical and texture gradients in the studied landscape. The effects of texture were largely associated with topographical effects; however, even when topography was controlled for, the texture contribution to the total C variability was still highly significant.

The overall higher variability of conservational management systems (NT and CT-cover) indicates that sampling efforts in designed field experiments can be made more efficient by performing more intensive subsampling of the conservational management systems and less intensive of the conventional system. In all three studied management practices, assessment of total C via creating maps based on spatial sampled data in the studied soils can be expected to be much more accurate than the assessments based on the overall field average total C values. The advantage of spatial predictions over whole-field average estimates has been found to be greater in NT and CT-cover than CT.

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