Published online June 2, 2005

Soil Carbon Storage Estimation in a Forested Watershed using Quantitative Soil-Landscape Modeling

James A. Thompson* and Randall K. Kolka

ABSTRACT

Carbon storage in soils is important to forest ecosystems. Moreover, forest soils may serve as important C sinks for ameliorating excess atmospheric CO_2. Spatial estimates of soil organic C (SOC) storage have traditionally relied upon soil survey maps and laboratory characterization data. This approach does not account for inherent variability within map units, and often relies on incomplete, unrepresentative, or biased data. Our objective was to develop soil-landscape models that quantify relationships between SOC and topographic variables derived from digital elevation models. Within a 1500-ha watershed in eastern Kentucky, the amount of SOC stored in the soil to a depth of 0.3 m was estimated using triplicate cores at each node of a 380-m grid. We stratified the data into four aspect classes and used robust linear regression to generate empirical models. Despite low coefficients of correlation between measured SOC and individual terrain attributes, we developed and validated models that explain up to 71% of SOC variability using three to five terrain attributes. Mean SOC content in the upper 30 cm, as predicted from our models, is 5.3 kg m^{-2}, compared with an estimate of 2.9 kg m^{-2} from soil survey data. Total SOC storage in the upper 30 cm within the entire watershed is 82.0 Gg, compared with an estimate of 44.8 Gg from soil survey data. A soil-landscape modeling approach may prove useful for future SOC spatial modeling because it incorporates the continuous variability of SOC across landscapes and may be transportable to similar landscapes.

An IMPORTANT component in understanding the role of soils in the global C cycle is developing reliable estimates of the amounts of C stored in the soil and other terrestrial C pools. Estimates of SOC storage have been made at global (Post et al., 1990; Akin, 1991; Eswaran et al., 1995), continental (Bajtes, 2000), national (Kern, 1994), state (Bliss et al., 1995; Kern et al., 1998; Amichev and Galbraith, 2004; Tan et al., 2004), regional (Homann et al., 1998; Galbraith et al., 2003), and landscape (Bell et al., 2000; Arrouays et al., 1995, 1998; Chaplot et al., 2001; Terra et al., 2004) scales. These studies have used a range of techniques by which point measurements of SOC are extrapolated to larger scale predictions of C storage.

These various techniques can be divided into two general methods of spatial extrapolation. The most prominent method of producing coarse predictions of SOC storage at regional to global scales is often referred to as "measure and multiply" (Schimel and Potter, 1995). Proxy information is used to stratify larger areas, and then measurements within each of these strata are aggregated and multiplied by the area of each stratum (Schimel and Potter, 1995). Soil survey maps and laboratory characterization data are the primary resources for estimating the amount of SOC stored in soils using this approach (e.g., Homann et al., 1998; Kern et al., 1998; Galbraith et al., 2003; Tan et al., 2004). There are numerous benefits to this approach (Arnold, 1995), but there also are several limitations. There may be significant variability of SOC content within map units due to natural soil variability and unmapped inclusions of higher or lower C soils (Eswaran et al., 1995). Galbraith et al. (2003) attributed the greatest source of uncertainty in their SOC maps to the high variation among SOC data from replicate samples from the same soil series. Also, the soil characterization data that are commonly used to establish SOC levels within a soil map unit were not originally collected for examining SOC content, and therefore may not include all of the necessary data for calculating SOC storage (Amichev and Galbraith, 2004). These data sets also may be biased toward different soil types or landscape settings, and may not adequately represent true range in variability of SOC (Tan et al., 2004).

An alternative to the measure and multiply approach is referred to as "paint by numbers" (Schimel and Potter, 1995). This approach incorporates information on multiple environmental factors within geographic areas that are used as input variables to models, which then are used to make predictions that can be multiplied by the areal extent of given combinations of each of these factors. This approach is akin to soil-landscape modeling (McSweeney et al., 1994), in which the variability of soils is analyzed with respect to changes in environmental variables known to influence soil property variability, such as topography, hydrology, or geology.

Soil-landscape modeling has been successfully applied to predict soil variability at the site or hillslope scale, focusing almost exclusively on small-scale landscapes of <100 ha, with some as small as 2 ha (Moore et al., 1993; Thompson et al., 1997, 2001; Chaplot et al., 2000; Gessler et al., 2000; Park et al., 2001; Florinsky et al., 2002). These studies have demonstrated that combinations of one to five terrain attributes derived from a digital elevation model (DEM) can explain 20 to 88% of the variability of selected soil properties. The empirical relationships between soil properties and terrain attributes are unique to each soil property and each soil-forming environment. Modeling examples at the watershed scale (and coarser) are more limited and require

J.A. Thompson, Division of Plant and Soil Sciences, West Virginia Univ., Morgantown, WV 26506-6108; R.K. Kolka, USDA Forest Service-North Central Research Station, Grand Rapids, MN 55744-3399. Received 30 Sept. 2004. *Corresponding author (james.thompson@mail.wvu.edu).

Published in Soil Sci. Soc. Am. J. 69:1086–1093 (2005).
Pedology
doi:10.2136/sssaj2004.0322

Abbreviations: CFI, continuous forest inventory; DEM, digital elevation model; SOC, soil organic carbon.

more complex modeling techniques (Gessler et al., 1995; McKenzie and Ryan, 1999; Ryan et al., 2000). Arrouays et al. (1995, 1998) and Chaplot et al. (2001) have recently applied environmental correlation techniques to generate SOC predictions, demonstrating the applicability of terrain attributes and other spatial data for developing empirical soil-landscape models of the spatial variability of SOC storage. This approach can also reduce the need for extensive field sampling and costly laboratory analysis by minimizing the number of samples needed to generate spatial predictions (Chaplot et al., 2001).

Our objective was to develop quantitative soil-landscape models that quantify relationships between SOC and topographic variables derived from a DEM. Our hypothesis was that the spatial patterns of SOC in a mountainous forested watershed could be predicted from spatial patterns of terrain attributes that have been shown to influence soil-forming processes. Quantification of the systematic soil-landscape relationships into quantitative soil-landscape models will overcome some of the limitations of the measure and multiply approach by ensuring a representative and complete dataset necessary for calculating SOC storage and resolving variability of SOC within map units. This approach provides a means to quantify the spatial distribution of soil properties by relying on the variability of correlated proxy variables that are easier to collect at a higher resolution than sampling and measuring soil properties directly. Such models may be transferable to similar landscapes, facilitating even broader scale prediction of SOC storage.

MATERIALS AND METHODS

The research was conducted at the University of Kentucky's Robinson Forest, a 6000-ha research and educational property located on the Cumberland Plateau in southeastern Kentucky (Fig. 1). Watersheds at Robinson Forest are dominated by mature, mixed, mesophytic forest. The bedrock is level-bedded with two distinct geologic formations (McDowell, 1985). Both the upper and lower formations are dominated by irregularly interbedded sandstones, siltstones, and shales (McDowell, 1985). A 1500-ha watershed within Robinson Forest, known as the Clemons Fork watershed, was selected for detailed study (Fig. 1). Clemons Fork flows from the northeast to the southwest, so slope aspects are predominantly southeasterly and northwesterly. The range in elevation in the Clemons Fork watershed is from 260 to 490 m. Slopes are steep, interrupted only by narrow ridges and narrow stream bottoms, with a mean slope gradient of 31%.

Our examination of SOC storage at Robinson Forest in-

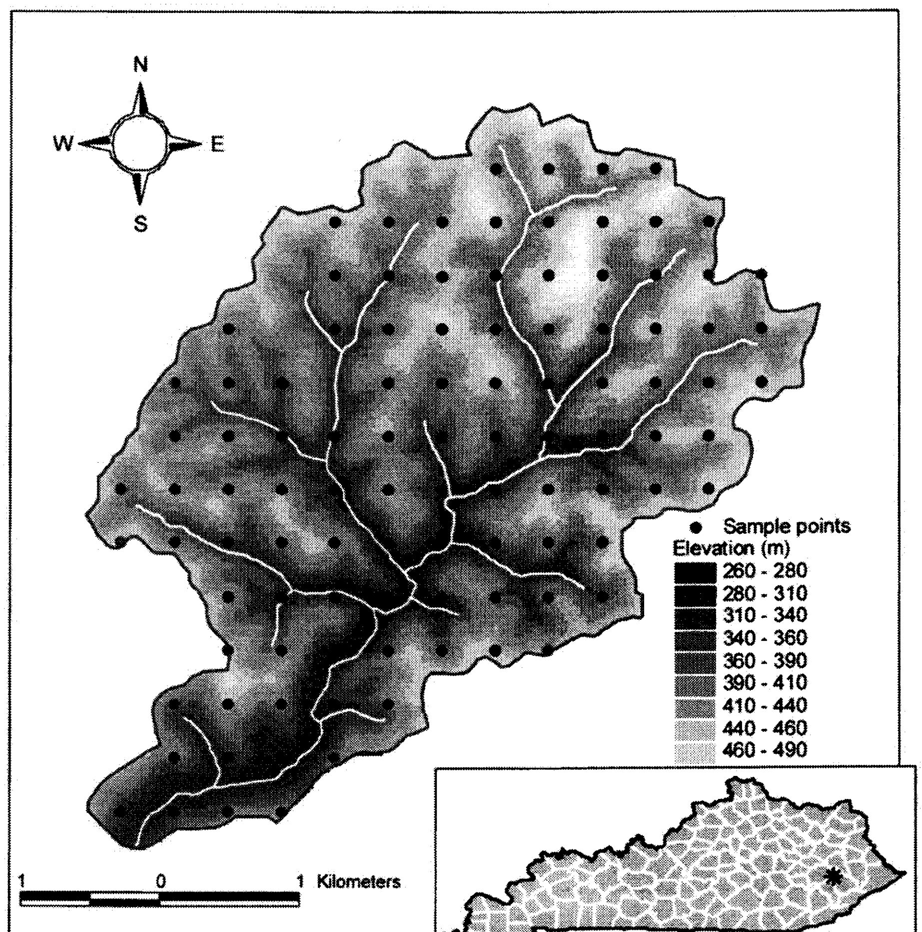

Fig. 1. Digital elevation model for the Clemons Fork watershed and the location of sample points. Streams (white) are shown for reference. Inset: The location of Robinson Forest in southeastern Kentucky.

cludes (i) a geographic information system-based inventory of SOC storage based on estimates from published soil survey data, and (ii) a soil-landscape modeling inventory based on soil samples collected from a regular grid of sample points. We generated SOC estimates using both the measure and multiply approach and the soil-landscape modeling approach to more clearly contrast these two methods and their results.

Analysis of Soil Survey Data

We acquired USDA NRCS Soil Survey Geographic (SSURGO) data for Breathitt County, Kentucky, and followed the methods of Bliss et al. (1995) to compute SOC storage within the upper 30 cm of soil on an areal basis (kg m^{-2}). The SSURGO database reports both a high and a low estimate of soil organic matter for each soil horizon. These values are converted to SOC values by dividing by 1.724 (Soil Survey Laboratory Staff, 1996). The SOC content of each horizon (to a depth of 30 cm) was calculated using SOC content, bulk density, thickness, and rock fragment content data of each horizon. The SOC content of each horizon was summed over the 30-cm depth to determine the SOC content of each soil in the survey area. The SOC content of each map unit was calculated as the weighted average of all the soils represented in each map unit. We calculated three SOC storage values: (i) a low value using the reported low estimate, (ii) a high value using the reported high estimate, and (iii) an average value from the midpoint of the high and low estimates.

Soil-Landscape Modeling

Sampling and Analysis

A systematic grid (384 m by 384 m) of continuous forest inventory (CFI) plots had been previously established as part of the long-term forest management at Robinson Forest. Our sampling was linked to the CFI to allow for the possibility of in the future combining results from this study to sampling of aboveground C storage at these plots. We collected triplicate soil samples from all 101 CFI plots located within the Clemons Fork watershed of Robinson Forest (Fig. 1). The three replicate samples were collected 3 m from the established center of the CFI plot, with the locations selected based on topography: one sample taken upslope of plot center, one taken downslope of plot center, and one taken to the right of plot center. We sampled soil below the forest floor to a depth of 30 cm (or to refusal) using 6.25-cm diam. core, which was driven into the soil with a slide hammer, then extracted with a shovel. Each sample was divided into three subsamples: the A horizon (based on color), the subsoil from the bottom of the A horizon to 20 cm, and the subsoil from 20 to 30 cm. These samples were not composited. Samples were air dried and sieved to remove rock fragments. A 20-g subsample was then removed for C analysis by dry combustion (Nelson and Sommers, 1996). The remainder was oven dried and we calculated a rock free bulk density (Blake and Hartge, 1986), correcting for the ovendry weight of the previous subsample. SOC content of each layer was calculated as:

$$\mathrm{SOC} = \mathrm{OC} \times D_b \times D \times \mathrm{UCF}$$

where SOC is soil organic C content (g m^{-2}), OC is the organic C concentration (%), D_b is bulk density of the rock-free soil (g cm^{-3}), D is the horizon thickness (cm), and UCF is a unit conversion factor (= 100 cm^2 m^{-2}). For each core, the total SOC was calculated as the sum of SOC from all layers. The mean total SOC for each CFI plot was calculated from the three replicate cores.

Terrain Analysis

Terrain data were derived from United States Geologic Survey (USGS) DEM with 30-m horizontal resolution and 1-m vertical precision. Terrain attributes were calculated using Arc/Info (Version 8.0.2, Environmental Systems Research Institute, Inc., Redlands, CA). Terrain attributes included elevation (Z), slope gradient (S), slope aspect (Ψ), profile (down slope) curvature (K_p), contour (cross-slope) curvature (K_c), total curvature (K), tangential curvature (K_t), upslope length (L), specific catchment area (A_c), specific dispersal area (A_d), topographic wetness index (TWI), stream power index (SPI), proximity to nearest stream (P_{stream}), elevation above nearest stream (E_{stream}), and slope to nearest stream (S_{stream}). Tangential curvature, a measure of local flow convergence or divergence, is a secondary terrain attribute calculated as the product of contour curvature and slope gradient ($K_t = K_c \times S$). The topographic wetness index, a predictor of zones of soil saturation, is the ratio of specific catchment area to slope gradient [TWI = $\ln(A_c/S)$] (Wilson and Gallant, 2000). The SPI, a measure of runoff erosivity, is the product of specific catchment area and slope gradient [SPI = $\ln(A_c \times S)$] (Wilson and Gallant, 2000). The values for these terrain attributes were extracted for all sample locations by assigning the terrain attribute values from the nearest cell of the DEM.

Statistical Analysis and Modeling

Simple exploratory data analysis functions were used to elucidate the primary topographic factors that appear to control SOC in the landscapes of Robinson Forest. We calculated the correlation coefficients between SOC and the various terrain attributes calculated from the DEM, and we examined scatter plots of SOC for these terrain attributes.

We developed empirical models of the distribution of SOC using a split-sample method, with 75% of data randomly selected and used for model training and the remaining 25% used for model validation. Stepwise linear regression (Neter et al., 1989) and regression trees were used to identify variables related to SOC, then robust linear regression (Rousseeuw and Leroy, 1987) was used to develop models using 75% of the data. Models were tested against the assumptions of linear regression analysis (Neter et al., 1989): lack of multicollinearity, equal error variance (no heteroscedasticity), and normal and random residuals. We validated the models using simple regression analysis on the remaining 25% of the data, comparing the observed SOC values with those predicted from individual linear models and the terrain attributes in the validation data set.

RESULTS AND DISCUSSION

Analysis of Soil Survey Data

The mean SOC content in the upper 30 cm as calculated from the SSURGO data from Clemons Fork watershed is 2.9 kg m^{-2}. The total SOC storage in the upper 30 cm within the entire watershed is 44.8 Gg. Soil organic C storage could be as high as 73.7 Gg, or as low as 14.6 Gg considering the high and low estimates reported in the SSURGO database. Patterns of soils and landforms are recognized in Robinson Forest and expressed in soil map unit delineations associated with four landscape positions: NE-facing slopes, SW-facing slopes, ridgetops, and floodplains. These differences translate to differences in average SOC levels in map units in the Clemons Fork watershed (Fig. 2), with high-

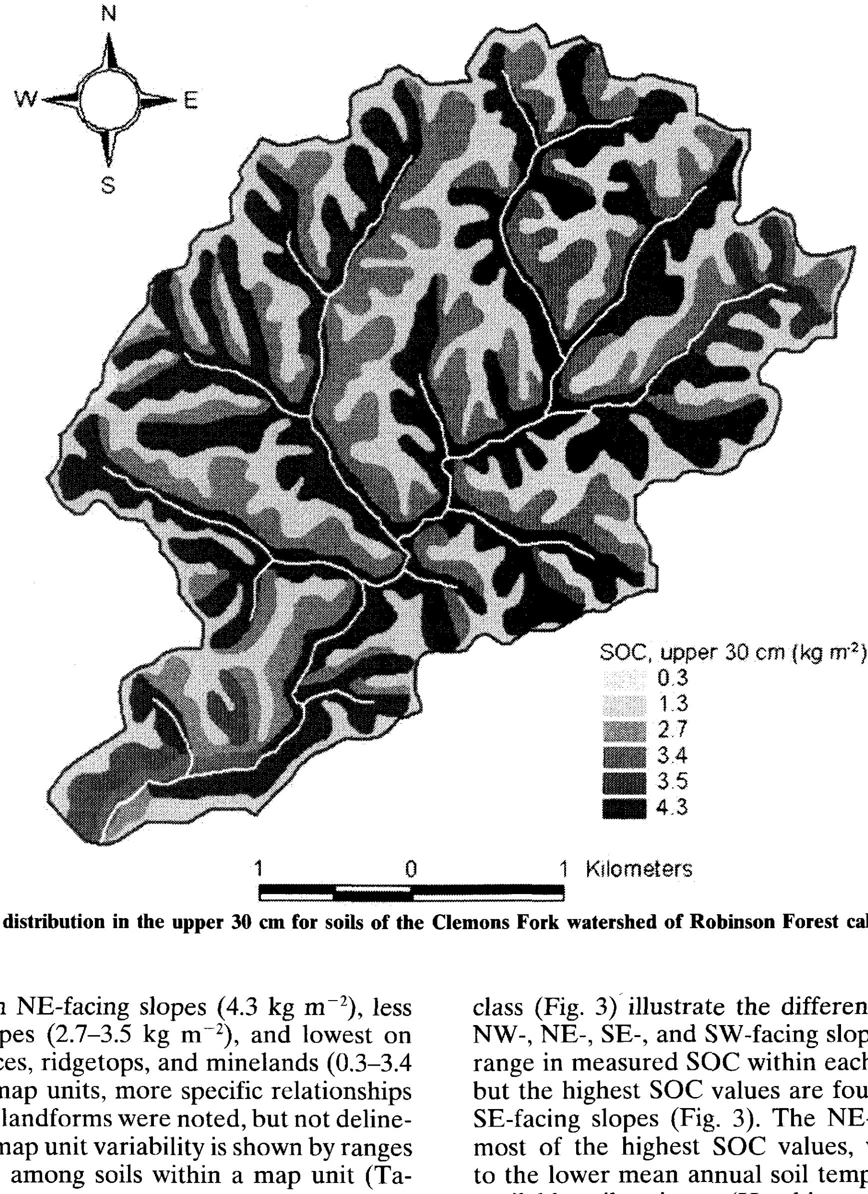

Fig. 2. Soil organic C distribution in the upper 30 cm for soils of the Clemons Fork watershed of Robinson Forest calculated from SSURGO soil map unit data.

est SOC levels on NE-facing slopes (4.3 kg m^{-2}), less on SW-facing slopes (2.7–3.5 kg m^{-2}), and lowest on floodplains, terraces, ridgetops, and minelands (0.3–3.4 kg m^{-2}). Within map units, more specific relationships between soils and landforms were noted, but not delineated. This within map unit variability is shown by ranges in SOC estimates among soils within a map unit (Table 1).

These differences, if elucidated, could be used to create more accurate spatial estimates of SOC content. Mapping of SOC in Robinson Forest using the SSURGO data is not ideal because: (i) all of Robinson Forest and the surrounding watersheds is mapped in soil complexes and undifferentiated soil groups, which have a higher degree of variability of SOC within map units; (ii) SOC ranges are unchanged among different phases of the same soil type; and (iii) SOC ranges are identical for soils when found in different complexes.

Soil-Landscape Modeling Approach

The mean amount of organic C in the upper 30 cm of soil (SOC) in the Clemons Fork watershed (based on the soil core samples) is 3.6 kg m^{-2}. The SOC, however, is not distributed equally throughout these landscapes. Box plots of SOC conditioned by slope aspect class (Fig. 3) illustrate the differences in SOC among NW-, NE-, SE-, and SW-facing slopes. There is a large range in measured SOC within each slope aspect class, but the highest SOC values are found on the NE- and SE-facing slopes (Fig. 3). The NE-facing slopes have most of the highest SOC values, which we attribute to the lower mean annual soil temperature and higher available soil moisture (Hutchins et al., 1976; Hunckler and Schaetzl, 1997). The observed differences in the distribution of SOC are statistically significant ($P < 0.05$) between the SW- and SE-facing and the SW- and

Table 1. Soil organic C (SOC) content estimates in the upper 30 cm determined from soil survey data, by soil series and landscape position.

Soil series	Landscape position	SOC content
		kg m^{-2}
	NE facing slopes	
Cutshin	benches, footslopes	6.2–14.6
Kimper	coves, benches	2.5–17.9
Shelocta	sideslopes, footslopes	0.9–6.6
Cloverlick	upper sideslopes	0.7–6.2
	SW facing slopes	
Kimper	coves, benches	2.5–17.9
Shelocta	sideslopes, footslopes	0.9–6.6
Hazelton	sideslopes, benches	0.7–6.2
Gilpin	sideslopes, ridges	0.3–2.7

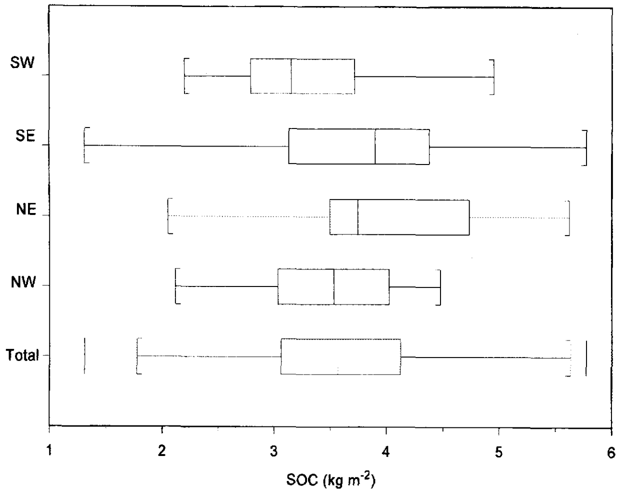

Fig. 3. Boxplots of SOC in the Clemons Fork watershed.

NE-facing slopes based on two-sample Kolmogorov-Smirnov goodness of fit test results. These data support the presence of landscape-scale differences in SOC in Robinson Forest.

Correlation coefficients between SOC and individual terrain attributes are low, with few statistically significant values (Table 2). Because of the effect of slope aspect on soil formation in these landscapes, when we stratified the data into four aspect classes, correlation coefficients within at least one the individual aspect classes are higher than for the whole data set (Table 2). Elevation had the highest correlation values with SOC in all cases except for on the SE-facing slopes, and always had a positive correlation, with higher SOC values associated with higher elevations in these landscapes. At regional scales in the southern Appalachians, Garten et al. (1999) and Bolstad and Vose (2001) found that SOC content increased with elevation over ranges of ≥1000 m. Bolstad and Vose (2001) attributed this to cooler soil temperatures at higher elevations, but their results were confounded by a change in parent material from mixed sandstone at lower elevations to gneiss at higher elevations (Bolstad and Vose, 2001). Within our study site the change in the geologic formation occurs at approximately 400 m. However, both the upper and lower formations are dominated by irregularly interbedded sandstones, siltstones, and shales, such that there is no clear lithologic distinction between the two formations (McDowell, 1985). Additionally, most soils have formed in colluvium (Hayes, 1998) from a mixture of rock types, and samples from within a single stratigraphic unit show increasing SOC with increasing elevation. Subtle differences in these two stratigraphic units, which are not represented in the available geologic map data, may have an influence on C dynamics in this landscape.

Table 3. Model parameters from soil-landscape models for the prediction of soil organic C content (kg m^{-2}) for each of four slope aspect classes at Robinson Forest.

	Model coefficient			
Model parameter	**SW**	**NE**	**SE**	**NW**
Intercept	**3436**	**−5022**	**1765**	**−835**
Elevation	**2.0**	**27.7**	**13.9**	**10.7**
Profile curvature	–	**1148**	–	–
Contour curvature	**369**	–	**2158**	**548**
Total curvature	–	**2879**	–	–
Specific catchment area	–	–	**−545**	–
Specific dispersal area	**70.4**	**−2.7**	**−30.5**	–
Stream power index	–	–	–	**89.4**
Slope to nearest stream	**−44.1**	**−62.8**	**−42.2**	–
Model R^2	**0.707**	**0.679**	**0.567**	**0.676**
Validation r^2	**0.020**	**0.324**	**0.182**	**0.802**

We stratified the data by slope aspect when generating the empirical models used to relate variation in SOC to variability in selected terrain attributes. The models explain up to 71% of the variability in SOC using selected terrain attributes (Table 3). Among all models, elevation was always a significant model variable, with higher SOC values found at higher elevations.

All models included a slope curvature attribute, with contour curvature being included in three of the four models. The NE model did not include contour curvature, but did include both profile and total curvature. In all cases, slope curvature had a positive correlation

Table 2. Coefficients of correlation between measured soil organic C (SOC) and various terrain attributes calculated from a digital elevation model (DEM).

	Slope aspect class				
Terrain attribute	**All**	**NE**	**SE**	**SW**	**NW**
Elevation, m	**0.354*** **	**0.576** **	**0.209**	**0.418***	**0.468***
Slope gradient, %	**−0.069**	**0.184**	**−0.183**	**−0.305**	**−0.006**
Slope aspect, °	**−0.236**	**0.070**	**−0.325**	**0.079**	**0.235**
Specific catchment area, m^2 m^{-1}	**−0.025**	**−0.180**	**−0.238**	**−0.214**	**−0.004**
Specific dispersal area, m^2 m^{-1}	**−0.009**	**0.229**	**−0.425**	**0.244**	**0.221**
Total curvature, m m^{-2}	**0.118**	**−0.050**	**−0.050**	**0.255**	**0.165**
Profile curvature, m m^{-2}	**−0.040**	**0.088**	**0.033**	**−0.123**	**−0.011**
Contour curvature, m m^{-2}	**0.153**	**0.002**	**−0.048**	**0.304**	**0.246**
Tangential curvature, cm m^{-2}	**0.109**	**−0.149**	**0.007**	**0.224**	**0.187**
Upslope length, m	**−0.057**	**−0.121**	**−0.048**	**−0.324**	**−0.038**
Topographic wetness index	**−0.104**	**−0.047**	**−0.018**	**−0.195**	**−0.146**
Stream power index	**−0.045**	**−0.166**	**−0.238**	**−0.240**	**−0.013**
Proximity to nearest stream, m	**0.226***	**0.478***	**0.145**	**0.153**	**0.085**
Elevation above nearest stream, m	**0.137**	**0.247**	**0.062**	**0.118**	**0.079**
Slope to nearest stream, %	**−0.044**	**−0.192**	**−0.078**	**−0.048**	**−0.031**

*** Significant at the 0.05 probability level.**
**** Significant at the 0.01 probability level.**
***** Significant at the 0.001 probability level.**

with SOC, indicating that convex sites had higher SOC than did concave sites. In low-relief landscapes, soils in concave positions have been shown to have greater SOC contents than those in convex positions (Gessler et al., 2000). On the steeper slope gradients in these landscapes the convex sideslopes may be somewhat more stable than the concave sideslopes, where there appears to be some convergence of flow and greater rates of soil erosion, which in turn produces relatively shallow and rocky soils, low in SOC.

Slope gradient to the nearest stream was the third terrain attribute that occurred in multiple models and exhibited a consistent relationship with SOC. In all cases, slope gradient to the nearest stream had a negative correlation with SOC, indicating that SOC decreased as the gradient to the nearest stream increased. This is likely attributable to drier soil conditions on steeper slopes, due to more rapid removal of water.

Independent validation data did not consistently reflect high correlations between measured SOC and SOC predicted from the various models (Table 3). The best relationship was seen on the NW slopes ($r^2 = 0.802$), however the quality of prediction on the other slopes may not be as poor as suggested by the coefficients of correlation. Scatterplots of measured vs. predicted SOC indicate that these low r^2 values are due to two or three outliers, while the bulk of the data are clustered around the 1:1 line (Fig. 4). The majority of the outliers are from the SE-facing slopes, which had the lowest model R^2 (Table 3).

Models (Table 3) were used to predict SOC content of the upper 30 cm throughout the Clemons Fork watershed (Fig. 5). The resulting map depicts the coarse variability in SOC within the watershed, with SOC levels that are higher on the NE-facing slopes and lower on the SW-facing slopes. The mean SOC content in the upper 30 cm as predicted from our models within Clemons Fork watershed is 5.3 kg m^{-2}, with a range from 0 to 11.8 kg m^{-2}. The total SOC storage in the upper 30 cm within the entire watershed is 82.0 Gg, similar to the high SOC value calculated from the SSURGO data (73.7 Gg), but almost twice the average SOC value (44.8 Gg).

While the models tend to predict greater SOC storage throughout the Clemons Fork watershed relative to the SSURGO data, these differences are not uniform across the study site. The greatest positive differences in SOC (model−SSURGO) are found on the summits and NE slopes where SOC levels are greater, while the least differences are found in lower slope positions, particularly on the SW slopes, and the floodplain soils near the watershed outlet where SOC levels are lower (Fig. 6).

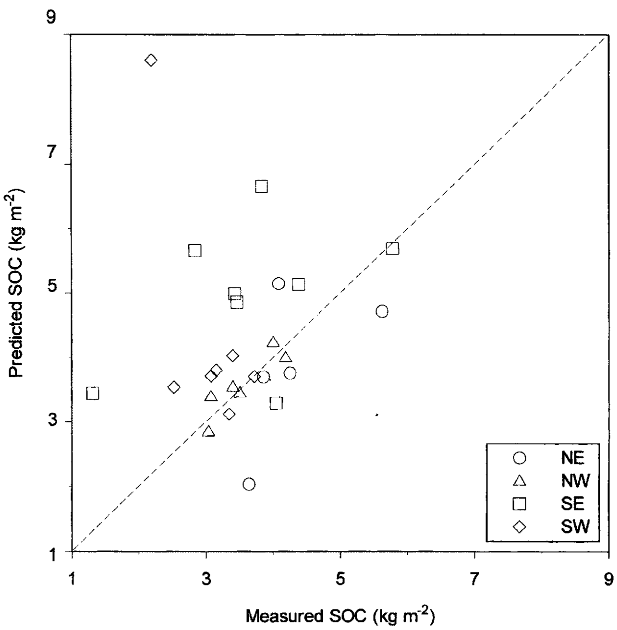

Fig. 4. Predicted vs. measured SOC at 26 independent validation points within the Clemons Fork watershed of Robinson Forest. Different symbols indicate samples from different slope aspect classes (○ = NE, △ = NW, □ = SE, ◇ = SW).

CONCLUSIONS

Systematic soil-landscape relationships exist in Robinson Forest and these relationships can be quantified using a soil-landscape modeling approach, which provides for an ability to (i) resolve variability of soils and SOC within combined mapping units common on steep slopes, (ii) represent continuous variability of soil properties across landscapes, and (iii) quantitatively relate environmental factors (e.g., topography) to soil properties, including organic C storage. Up to 71% of the variability in SOC was explained using three to five terrain attributes calculated directly from a 30-m DEM. Results suggest that in SOC content in soils of these steep mountainous landscapes increases as elevation increases and as slope gradient to the nearest stream decreases. However, these and other soil-landscape relationships were significantly influenced by slope aspect, with more SOC in soils on east-facing slopes. Stratification of the data by slope aspect improved modeling results, suggesting that modeling efforts at the watershed scale and above will require stratifying data into similar landscape units where soil-landscape processes have a similar effect on soil development. It is unlikely that a single model can be developed to be applicable to all soil-landscapes in an area (e.g., Bell et al., 2000).

The methods used in this study and the results obtained may be applicable to areas outside of Robinson Forest. The use of these or similar models to estimate the spatial distribution of SOC requires additional evaluation because of the discrepancy between the SOC storage estimates based on soil-landscape models (82.0 Gg) and those derived from a measure and multiply approach using SSURGO data (44.8 Gg). Different methods of estimation normally produced varying inventories of SOC storage (Homann et al., 1998; Galbraith et al., 2003). Systematic differences between the two estimates generated here indicate that traditional soil survey maps, especially those in steep mountainous areas, do not depict enough of the landscape-scale soil variability within map units. Reported SOC content values may not be adequate for these purposes because typical values cannot represent the full range in varia-

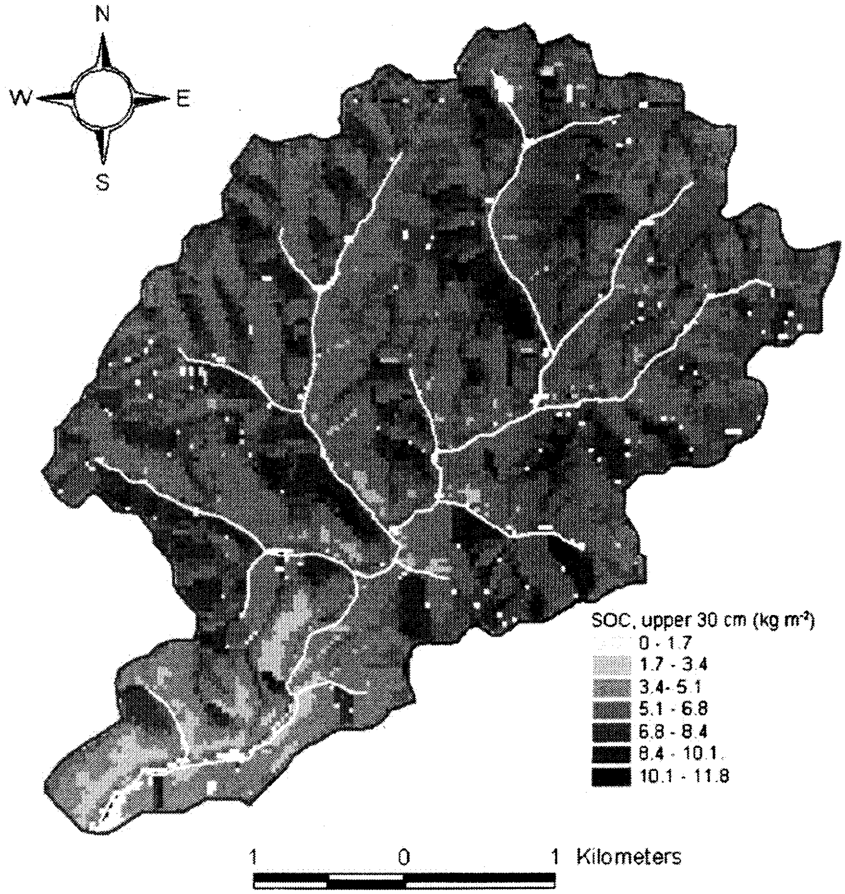

Fig. 5. Soil organic C distribution in the upper 30 cm for soils of the Clemons Fork watershed of Robinson Forest calculated using developed soil-landscape models.

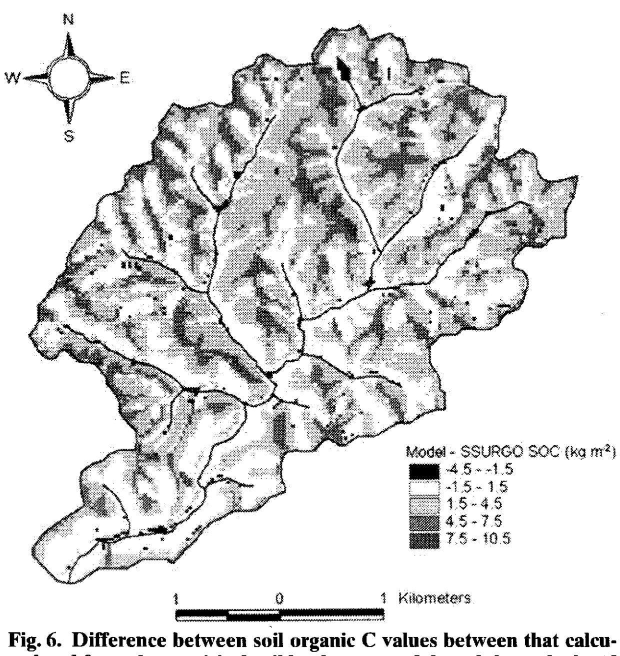

Fig. 6. Difference between soil organic C values between that calculated from the empirical soil landscape models and that calculated from SSURGO soil map unit data.

tion across a survey area. Such discrepancies among SOC storage estimates will be more important as greater attention is given to the role of SOC in ameliorating excess atmospheric CO_2, particularly how proper soil management can deliberately increase SOC storage.

ACKNOWLEDGMENTS

We acknowledge the contributions of Laura Harris, Peter Hadjiev, and Amanda Abnee (University of Kentucky) for assistance in data collection and analysis, and Will Marshall and his staff at Robinson Forest, who provided much logistical support for this research. Portions of this research were supported by the Kentucky Agricultural Research Service. We also thank Dr. David Lindbo, Dr. Wendell Gilliam, and Dr. Michael Wagger for offering many thoughtful comments that improved this manuscript.

REFERENCES

Akin, W.E. 1991. Global patterns: Climate, vegetation, and soils. University of Oklahoma Press, Norman, OK.

Amichev, B.Y., and J.M. Galbraith. 2004. A revised methodology for estimation of forest soil carbon from spatial soils and forest inventory data sets. Environ. Manage. 33 (Suppl. 1):S74–S86.

Arnold, R.W. 1995. Role of soil survey in obtaining a global carbon budget. p. 257–263. *In* R. Lal et al. (ed.) Soils and global change. Adv. Soil Sci. CRC Press, Boca Raton, FL.

Arrouays, D., I. Vion, and J.L. Kicin. 1995. Spatial analysis and modeling of topsoil carbon storage in temperate forest humic loamy soils of France. Soil Sci. 159:191–198.

Arrouays, D., J. Daroussin, L. Kicin, and P. Hassika. 1998. Improving topsoil carbon storage prediction using a digital elevation model in temperate forest soils of France. Soil Sci. 163:103–108.

Bajtes, N.H. 2000. Effects of mapped variation in soil conditions on estimates of soil carbon and nitrogen stocks for South America. Geoderma 97:135–144.

Bell, J.C., D.F. Grigal, and P.C. Bates. 2000. A soil–terrain model for estimating spatial patterns of soil organic carbon. p. 295– 310. *In* J.P. Wilson et al. (ed.) Terrain analysis—Principles and applications. John Wiley & Sons, New York.

Blake, G.R., and K.H. Hartge. 1986. Bulk density. p. 363–375. *In* A. Klute (ed.) Methods of soil analysis. Part 1. 2nd ed. Agron. Monogr. No. 9. SSSA, Madison, WI.

Bliss, N.B., S.W. Waltman, and G.W. Petersen. 1995. Preparing a soil carbon inventory for the United States using geographic information systems. p. 275–295. *In* R. Lal et al. (ed.) Soils and global change. Adv. Soil Sci. CRC Press, Boca Raton, FL.

Bolstad, P.V., and J.M. Vose. 2001. The effects of terrain position and elevation on soil C in the southern Appalachians. p. 45–51. *In* R. Lal et al. (ed.) Assessment methods for soil carbon. Lewis Publishers, Boca Raton, FL.

Chaplot, V., C. Walter, and P. Curmi. 2000. Improving soil hydromorphy prediction according to DEM resolution and available pedological data. Geoderma 97:405–422.

Chaplot, V., M. Bernoux, C. Walter, P. Curmi, and U. Herpin. 2001. Soil carbon storage prediction in temperate hydromorphic soils using a morphologic index and digital elevation model. Soil Sci. 166:48–60.

Eswaran, H., E. van den Berg, P. Reich, and J. Kimble. 1995. Global soil carbon resources. p. 27–43. *In* R. Lal et al. (ed.) Soils and global change. Adv. Soil Sci. CRC Press, Boca Raton, FL.

Florinsky, I.V., R.G. Eilers, G.R. Manning, and L.G. Fuller. 2002. Prediction of soil properties by digital terrain modelling. Environ. Modell. Software 17:295–311.

Galbraith, J.M., P.J.A. Kleinman, and R.B. Bryant. 2003. Sources of uncertainty affecting soil organic carbon estimates in northern New York. Soil Sci. Soc. Am. J. 67:1206–1212.

Garten, C.T., Jr., W.M. Post, III, P.J. Hanson, and L.W. Cooper. 1999. Forest soil carbon inventories and dynamics along an elevation gradient in the southern Appalachian Mountains. Biogeochemistry 45:115–145.

Gessler, P.E., O.A. Chadwick, F. Chamran, L.D. Althouse, and K.W. Holmes. 2000. Modeling soil-landscape and ecosystem properties using terrain attributes. Soil Sci. Soc. Am. J. 64:2046–2056.

Gessler, P.E., I.D. Moore, N.J. McKenzie, and P.J. Ryan. 1995. Soil–landscape modelling and spatial prediction of soil attributes. Int. J.Geograph. Info. Syst. 9:421–432.

Hayes, R.A. 1998. Soil Survey of Breathitt County, Kentucky. USDA-NRCS. U.S. Gov. Print. Office, Washington, DC.

Homann, P.S., P. Sollins, M. Fiorella, T. Thorson, and J.S. Kern. 1998. Regional soil organic carbon storage estimates for western Oregon by multiple approaches. Soil Sci. Soc. Am. J. 62:789–796.

Hunckler, R.V., and R.J. Schaetzl. 1997. Spodosol development as affected by geomorphic aspect, Baraga County, Michigan. Soil Sci. Soc. Am. J. 61:1105–1115.

Hutchins, R.B., R.L. Blevins, J.D. Hill, and E.H. White. 1976. The influence of soils and microclimate on vegetation of forested slopes in eastern Kentucky. Soil Sci. 121:234–241.

Kern, J.S. 1994. Spatial patterns of soil organic carbon in the contiguous United States. Soil Sci. Soc. Am. J. 58:439–455.

Kern, J.S., D.P. Turner, and R.F. Dodson. 1998. Spatial patterns of soil organic carbon pool size in the northwestern United States. p. 29–43. *In* R. Lal et al. (ed.) Soil processes and the carbon cycle. Adv. Soil Sci. CRC Press, Boca Raton, FL.

McDowell, R.C. 1985. The geology of Kentucky—A text to accompany the geologic map of Kentucky. U.S. Geol. Surv. Professional Pap. 1151-H. U.S. Gov. Print. Office, Washington, DC.

McSweeney, K., P.E. Gessler, B. Slater, R.D. Hammer, J.C. Bell, and G.W. Petersen. 1994. Towards a new framework for modeling the soil-landscape continuum. p. 127–145. *In* R.G. Amundson et al. (ed.) Factors of soil formation: A fiftieth anniversary retrospective. SSSA Spec. Publ. 33. SSSA, Madison, WI.

McKenzie, N.J., and P.J. Ryan. 1999. Spatial prediction of soil properties using environmental correlation. Geoderma 89:67–94.

Moore, I.D., P.E. Gessler, G.A. Nielsen, and G.A. Peterson. 1993. soil-landscape continuum. p. 127–145. *In* R.G. Amundson et al. J. 57:443–452.

Nelson, D.W., and L.E. Sommers. 1996. Total carbon, organic carbon, and organic matter. p. 961–1010. *In* D.L. Sparks (ed.) Methods of soil analysis. Part 3. SSSA Book Ser. No. 5. SSSA, Madison, WI.

Neter, J., W. Wasserman, and M.H. Kutner. 1989. Applied linear regression models. 2/E. Richard D. Irwin, Homewood, IL.

Park, S.J., K. McSweeney, and B. Lowery. 2001. Identification of the spatial distribution of soils using a process-based terrain characterization. Geoderma 103:249–272.

Post, W.M., T.H. Peng, W.R. Emmanuel, A.W. King, V.H. Dale, and D.L. DeAngelis. 1990. The global carbon cycle. Am. Sci. 78:310–326.

Rousseeuw, P.J., and A.M. Leroy. 1987. Robust regression and outlier detection. John Wiley & Sons, New York.

Ryan, P.J., N.J. McKenzie, D. O'Connell, A.N. Loughhead, P.M. Leppert, D. Jacquier, and L. Ashton. 2000. Integrating forest soils information across scales: Spatial prediction of soil properties under Australian forests. For. Ecol. Manage. 138:139–157.

Schimel, D.S., and C.S. Potter. 1995. Process modelling and spatial extrapolation. p. 358–383. *In* P.A. Matson and R.C. Harriss (ed.) Biogenic trace gases: Measuring emissions from soil and water. Blackwell Science Ltd., Cambridge, MA.

Soil Survey Laboratory Staff. 1996. Soil survey laboratory methods manual. Soil Surv. Invest. Rep. 42. Version 3.0. Natl. Soil Surv. Center, Lincoln, NE.

Tan, Z., R. Lal, N.E. Smeck, F.G. Calhoun, B.K. Slater, B. Parkinson, and R.M. Gehring. 2004. Taxonomic and geographic distribution of soil organic carbon pools in Ohio. Soil Sci. Soc. Am. J. 68:1896–1904.

Terra, J.A., J.N. Shaw, D.W. Reeves, R.L. Raper, E. van Santen, and P.L. Mask. 2004. Soil carbon relationships with terrain attributes, electrical conductivity, and soil survey in a coastal plain landscape. Soil Sci. 169:819–831.

Thompson, J.A., J.C. Bell, and C.A. Butler. 1997. Quantitative soil–landscape modeling for estimating the areal extent of hydromorphic soils. Soil Sci. Soc. Am. J. 61:971–980.

Thompson, J.A., J.C. Bell, and C.A. Butler. 2001. Digital elevation model resolution: Effects on terrain attribute calculation and quantitative soil–landscape modeling. Geoderma 100:67–89.

Wilson, J.P., and J.C. Gallant. 2000. Digital terrain analysis. p. 1–27 *In* J.P. Wilson and J.C. Gallant (ed.) Terrain analysis. John Wiley & Sons, New York.