MANAGEMENT AND LANDSCAPE INFLUENCES ON SOIL ORGANIC CARBON

IN THE SOUTHERN PIEDMONT AND COASTAL PLAIN

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MANAGEMENT AND LANDSCAPE INFLUENCES ON SOIL ORGANIC CARBON

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Héctor Javier Causarano-Medina

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VITA

Héctor Javier Causarano-Medina, son of Víctor J. Causarano (Baby) and Francisca Medina de Causarano (Betty) was born September 12, 1963 in Asunción, Paraguay. He graduated from High School (Colegio Nacional de la Capital, Paraguay) in 1981. He attended college in San Lorenzo, Paraguay (Facultad de Ingeniería Agronómica, Universidad Nacional de Asunción), for five years (1982-1986), and graduated cum laude with a Bachelor of Science degree in Agricultural Engineering. After working for four years as an Agronomist at the Department of Agriculture (Ministerio de Agricultura) of Paraguay, he entered Graduate School, Reading University, England in October, 1990. He received the degree of Master of Agricultural Science (Soil Science) in July, 1992. From 1992 to 1995 he worked as a Soil Scientist at the Department of Agriculture of Paraguay, and from 1995 to 2002 as an Assistant Professor and Researcher at the Faculty of Agriculture (Facultad de Ciencias Agrarias), San Lorenzo, Paraguay. In August 2002, he received a Fulbright Grant and began working toward a Ph.D. in Agronomy and Soils at Auburn University. He married Clara Núñez, daughter of Inocencio Núñez and Arminda Patiño, on January 23, 1988. Clara and Hector have two children, Yamile and Rodrigo.

DISSERTATION ABSTRACT

MANAGEMENT AND LANDSCAPE INFLUENCES ON SOIL ORGANIC CARBON IN THE SOUTHERN PIEDMONT AND COASTAL PLAIN

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Southern Piedmont and Coastal Plain soils have undergone severe degradation, which is reflected in low soil organic carbon (SOC) contents. Restoration of SOC would improve soil quality and C sequestration, leading to a more sustainable agriculture and potentially mitigating the greenhouse effect. This dissertation examined the effects of soil management, climate, and landscape attributes on total SOC and related fractions within upland, well drained, Southeastern Ultisols. In Chapter 1, SOC fractions under croplands and pastures were determined on 87 fields distributed within the Piedmont and Coastal Plain. Total SOC (TOC) (0-20 cm) followed the order: pasture (38.9 Mg ha^{-1}) > conservation tillage (27.9 Mg ha^{-1}) > conventional tillage (22.2 Mg ha^{-1}). Management affected TOC primarily at the soil surface (0-5 cm). Variation in TOC was explained by management (41.6%), clay content (5.2%), mean annual temperature (1.0%), and mean

annual precipitation (0.1%). Higher soil clay content and precipitation, and slightly cooler temperatures contributed to higher TOC. All SOC fractions were strongly correlated across a diversity of soils and management systems (r = 0.85 to 0.96). In Chapter 2, TOC within two Piedmont pastures (Alabama and Georgia) was spatially evaluated and related to easily obtainable secondary data; i.e., terrain attributes, remote sensing data (aerial photographs), and field-scale electrical conductivity. Ordinary kriging, multiple linear regression, and artificial neural networks were used to produce spatially distributed TOC maps. Elevation and remote sensing data explained 67% of TOC variability at the Alabama site, while elevation, slope, compound topographic index and electrical conductivity explained 35% of TOC variability at the Georgia site. At both sites, the most accurate TOC maps were produced with the artificial neural network approach (Prediction efficiency = 62% and 49% for Alabama and Georgia, respectively). In Chapter 3, the Environmental Policy Integrated Climate (EPIC) model was used to predict cotton (*Gossypium hirsutum L.*) and corn (*Zea mays L.*) yield and SOC dynamics on different landscape positions of a Coastal Plain soil. Simulated and measured yield were closely related (r^2 = 0.88). Greatest disagreement occurred on the sideslope position, while the best agreement was found in the drainageway. Simulated TOC was moderately related to measured TOC (r^2 = 0.41); highest agreement occurred on the sideslope. The following conclusions can be made: a) on-farm measurement of TOC stocks validated research station data and provided much-needed quantitative information of SOC stocks under pastures; b) terrain attributes and remote sensing data explained TOC variation within pastures; and c) with correct parameterization, EPIC would be an effective tool for evaluating field-scale SOC dynamics affected by short-term management decisions.

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I. SOIL ORGANIC CARBON IN PASTURE AND CROP LANDS OF THE PIEDMONT AND COASTAL PLAIN

ABSTRACT

Quantifying the impact of long-term agricultural land use on soil organic C (SOC) is important to farmers and environmental policy makers. Land use and management affect SOC levels and the magnitude of change depends on tillage practices, soil characteristics, climate and other factors. We measured stocks of SOC under conventional tillage (CvT) row cropping (5-40 years), conservation tillage (CsT) row cropping (5-30 years), and pasture (10-60 years) in 87 fields distributed in the Southern Piedmont and Coastal Plain Major Land Resource Areas of Alabama, Georgia, South Carolina, North Carolina, and Virginia. Across locations, total organic C (TOC) followed the order: pasture (38.9 Mg ha^{-1}) > CsT (27.9 Mg ha^{-1}) > CvT (22.2 Mg ha^{-1}). Variation in TOC was explained by management (41.6%), clay content (5.2%), mean annual temperature (1.0%), and mean annual precipitation (0.1%). Higher soil clay content and precipitation, and slightly cooler temperatures contributed to higher TOC. Management affected TOC primarily at the soil surface (0-5 cm). All soil C fractions were strongly correlated across a diversity of soil types and management systems (r from 0.85 to 0.96). Our results agree with a threshold value of 2 for stratification ratio of C fractions to distinguish previously degraded soils with improved soil quality from degraded soils.

However, stratification ratio as an indicator of soil quality needs further evaluation, especially with respect to determining adequate depth of sampling for calculations and its relationship with other physical, biological and chemical measurements of soil quality. The on-farm measurements of carbon stocks reported in this study complement research station's data and contribute to lessen the dearth of information of carbon stocks under pasture lands in the southeastern USA.

Abbreviations: ASD, aggregate-size distribution; $CMIN_{24}$, potential C mineralization in 24 d; CsT, conservation tillage row cropping; CvT, conventional tillage row cropping; GPS, Geographical Positioning System; MLRA, Major Land Resource Areas; MWD, mean-weight diameter; NT, no-tillage; PET, potential evapotranspiration; POM, particulate organic matter; SCAS, Spatial Climate Analysis Service; SMBC, soil microbial biomass C; SOC, soil organic C; SOM, soil organic matter; TOC, total organic C.

INTRODUCTION

A great research effort has been invested to estimate C sequestration in crop lands of the USA (Lal et al., 1998). Despite this effort, it is difficult to make comparisons among management systems or across regions, because some reports lack bulk density information, unequal soil depths have been sampled, or different analytical procedures have been used. Furthermore, most experiments have been conducted on relatively flat terrain where C losses by erosion are low. A known limitation for comparing C stocks among agricultural systems is the dearth of information from pasture lands, which occupies significant arable land (Census of Agriculture, 2002). Therefore, more research is needed to better characterize potential soil organic C (SOC) sequestration, especially with regard to the diversity of soil types and management in the Southern Piedmont and Coastal Plain Major Land Resource Areas (MLRA).

The long history of exhaustive tillage and subsequent soil erosion has depleted SOC in the southeastern USA. Soil tillage buries residues, disrupts macroaggregates, increases aeration, and stimulates microbial breakdown of SOC (Reeves, 1997). With sound soil and crop management, the warm and humid climate with a long growing season allows for high cropping intensity and biomass production; which translates into high potential for photosynthetic C fixation and soil C sequestration (Reeves and Delaney, 2002). Increasing SOC is appealing because it has a critical role in soil quality and has significant potential to cost-effectively attenuate detrimental effects of rising atmospheric CO_2 and other greenhouse gasses on global warming and climate change (Lal, 1997; Follett, 2001; West and Post, 2002; Sperow et al., 2003).

Franzluebbers (2005) compiled published data comparing conventional tillage versus no-tillage (NT) systems in the Southeastern USA. From those data within the Piedmont and Coastal Plain MLRA, SOC was 21.1 ± 5.9 Mg ha^{-1} under CvT and 24.4 ± 6.9 Mg ha^{-1} under NT. Of the 52 comparisons, 46 had absolute values of SOC greater under NT than CvT. The middle 50 % of observations in ranked order had SOC sequestration rates (NT-CvT) from 0.02 to 0.39 Mg ha^{-1} $year^{-1}$. Recent SOC sequestration estimates from CsT management systems in other regions of the USA include: 0.48 ± 0.59 Mg C ha^{-1} yr^{-1} in the central USA (Johnson et al., 2005), 0.30 ± 0.21 Mg C ha^{-1} yr^{-1} in the southwestern USA (Martens et al., 2005), and 0.27 ± 0.19 Mg C ha^{-1} yr^{-1} in the northwestern USA and western Canada (Liebig et al., 2005). Lal et al. (1998) assumed a value of 0.5 Mg C ha^{-1} yr^{-1} for the entire USA. From an earlier analysis that did not include many of the observations now available, Franzluebbers and Steiner (2002) outlined a geographical area in North America having the highest SOC sequestration potential with adoption of CsT that included the central USA and upper southeastern USA regions. Clearly, adoption of CsT in the Piedmont and Coastal Plain regions has the potential for a high rate of SOC sequestration.

Under similar macroclimatic and soil conditions, the less disturbed the soil, the more C accumulation. The increase in C content in less disturbed soil is attributed to slower decomposition, due to a microclimate in the surface residue layer that is less favorable for microbial activity. Jenny (1941) quantitatively related temperature and precipitation with soil N on grasslands. Soil organic C is closely related to total soil N. At constant temperature, SOC increased logarithmically with increasing precipitation, the rate depending on temperature. If precipitation were constant, SOC declined exponentially with increasing temperature. Franzluebbers and Steiner (2002) compiled 111 pairs of observations from NT and CvT across the USA and Canada and concluded that the greatest potential for CsT systems to sequester SOC was found in climate regions with a mean annual precipitation-to-potential evapotranspiration (PET) ratio of 1.1 to 1.4.

Total SOC content provides no information of the C fraction dimensions. Soil organic matter (SOM), which is estimated to contain 50 to 58 % C (Nelson and Sommers, 1982) is a complex mixture of organic compounds with different turnover times (Christensen, 2001). A distinction among SOM fractions is conceptual and any distinction is merely convenient for modeling of SOC dynamics (Skjemstad et al., 1998). Since the turnover of SOM is a biological process that depends not only on the chemical composition of the substrate but also on the nature of its association with mineral particles (soil structure), methods have been developed to isolate fractions according to size and density of individual soil particles or aggregates (Christensen, 2001). A fraction called particulate organic matter (POM) by Cambardella and Elliot (1992) has been recognized as preferentially depleted when soil management changes from low disturbance to high disturbance (e.g., pastures to croplands or no-till to CvT agriculture). Particulate organic matter is an uncomplexed fraction of SOM composed of particulate (>0.05 mm), partly decomposed plant and animal residues, fungal hyphae, spores, root fragments and seeds. It is also suggested that this fraction is the epicenter for microbial activity and as such an important agent in the formation of macro-aggregates. It is a transitory fraction between litter (fast turnover) and mineral-associated SOM (slow turnover).

We hypothesized that relevant information on the effect of land use and tillage on SOC sequestration in the Piedmont and Coastal Plain could be gained by measuring stocks of SOC under three common management systems (CvT row cropping, CsT row cropping, and pasture) on farms in Alabama, Georgia, South Carolina, North Carolina, and Virginia. Our objectives were to (i) quantify the magnitude and consistency of change in SOC stocks due to management, (ii) determine the effect of climate and soil texture on SOC stocks, and (iii) isolate SOC fractions with depth to better understand the effects of long term management.

MATERIALS AND METHODS

Site Characteristics and Sampling Procedures

The Southern Piedmont and Coastal Plain MLRAs extend along most of the southeastern USA (USDA-NRCS, 1997). Mean annual temperature ranges from 14 °C in the north to 20 °C in the south. Mean annual precipitation typically exceeds 1000 mm, but is more than 1400 mm along the coastlines and in the western section. Dominant soils of both MLRAs are Ultisols (e.g. Kanhapludults, Kandiudults, Hapludults, Paleudults) with loamy to clayey textured argillic and/or kandic horizons, mesic to thermic temperature regimes, udic moisture regime, and a kaolinitic or mixed mineralogy. Most Piedmont soils are residual, developed on rolling landscapes (peneplains) and well drained, at least moderately permeable, and reside at 100 to 400 m above mean sea level. Although most of the land was once cultivated, much of it has been converted to pine (*Pinus sp.*), hardwoods, and pasture. Cash crops include soybean [*Glycine max* (L) Merr.], corn (*Zea mays* L.), cotton (*Gossypium hirsutum* L.), wheat (*Triticum aestivum*

L.) and to a lesser extent tobacco (*Nicotiana tabacum* L.). In contrast, Coastal Plain soils are formed from unconsolidated fluviomarine sediments, and located at 25 to 200 m above mean sea level. Land is dedicated to cash crops such as cotton, peanut (*Arachis hypogaea* L.), corn and soybean. Timber production and livestock farming are important in the Coastal Plain, and pastures are used mostly for beef cattle.

Sites for this investigation were chosen with the help of District Conservationists from the Natural Resources Conservation Service (NRCS) and/or local University Extension Service personnel. A total of 30 locations on farms in the Piedmont and Coastal Plain MLRAs of Alabama, Georgia, South Carolina, North Carolina and Virginia were sampled between January 2004 and April 2005. Three sites (3-5 ha each) differing in land use and tillage management were sampled from the same soil map unit (order II NRCS soil surveys) at a particular location. Because soils were sampled within the same map unit, it is inferred that drainage class, slope, and soil texture were similar across the three sites at each location, ensuring that land use and tillage management were the primary factors influencing SOC. However, it is recognized inclusions can and do occur within map units. Three management systems were investigated: (1) CvT cropland, defined as a system with inversion tillage that buried crop residue. Common practices included moldboard or chisel plowing (primary tillage) and disking prior to seedbed preparation (secondary tillage). (2) CsT cropland, consisting of minimum soil inversion with >30 % residue cover on the surface. Farms that incorporated cover crops (e.g., oats) in the rotation were preferentially sampled. No-tillage and strip-tillage practices were common. (3) Pastures consisting of perennial grass species that were grazed or hayed. Sites were long-established under a particular management, i.e., 5-40 years under CvT, 5-

30 years under CsT, and 10-60 years under pasture. The 30 locations (5 states x 2 MLRAs x 3 replicate farms) were evenly distributed along the study area. Three locations fell outside the Coastal Plain polygon (Atlantic Coastal Flatwoods), but these were included since soils are also found on the Coastal Plain (Fig. 1).

Previous to sampling, sites were evaluated to determine representative areas; obvious sources of unusual variability were avoided. On each site, 8 randomized soil core samples (5cm diameter, 20 cm depth) were composited. At the time of sampling, information was collected on crop management history and positions were determined with a Geographical Positioning System (GPS). Climate data (precipitation and temperature) were obtained by matching the site's coordinates with data (30 year normals) from the Spatial Climate Analysis Service (SCAS, 2005).

Sample Preparation and Laboratory Analyses

Soil cores were cut at 0-5, 5-12.5 and 12.5-20 cm, and air dried. Oven dry bulk density was determined for each depth by calculating mass per unit volume. Air dry samples were then gently crushed and passed through a 4.75 mm screen. Stones (>4.75 mm) were removed from soil samples. A sub-sample was oven dried (105 ºC, 24 h) to obtain a correction factor and express analytical results on an oven-dried basis.

Particulate organic C (POC), soil microbial biomass C (SMBC), and mineralized C (CMIN) were determined with a procedure similar to Franzluebbers et al. (2000a). Duplicate sub-samples (35 and 65 g for 0-5 and 5-20 cm depths, respectively) were moistened to 50 % water-filled pore space and incubated at 25±1 ºC in 1 L canning jars containing vials with 10 mL of 1.0 M NaOH to absorb CO_2, and small vials containing water to maintain humidity. Alkali traps were replaced at 3 and 10 d, and removed at 24 d for C mineralization determination. Carbon dioxide evolved was determined by titration of alkali with 1.0 M HCl. At 10 d, one sub-sample was removed, fumigated with chloroform and incubated separately for another 10 d under the same conditions to determine the flush of CO_2 representing microbial biomass C according to the equation (Voroney and Paul, 1984):

$$\mathrm{SMBC} = (\mathrm{mg\ CO_2 - C\ kg^{-1}\ soil})_{\mathrm{fumigated}} / \mathrm{k_c} \qquad \text{Eq. [1]}$$

where $k_c = 0.41$. The particulate organic fraction was determined on the fumigated sub-samples at the end of the 10 d incubation period. Sub-samples were shaken in 100 mL of 0.1 M $Na_4P_2O_7$ for 16 h; the suspension diluted to 1 L with distilled water and allowed to settle for 5 h, when clay content was determined with a hydrometer. The soil suspension was then passed through a 0.053-mm screen and the retained sand-sized material transferred to a drying bottle and weighed after oven drying at 55 ºC for 72 h. Soil C was determined on this fraction.

For soil C, 25 g subsamples were finely grand (<250 µm) on an apparatus similar to Kelley (1994). Determinations followed the dry combustion method of Nelson and Sommers (1982) using a LECO® carbon analyzer. Each batch contained 49 samples; precision and accuracy were calculated by duplicate analysis on 10 % of the samples and by introducing a LECO® Reference Standard and a check soil in each batch. Calculated errors were <5 %, therefore it was not necessary to repeat analysis on any batch. It was assumed that total C was equivalent to organic C, as these are acid soils without carbonates.

Dry-stable and water-stable aggregate distribution were determined on the 0-5 cm samples following a procedure similar to Franzluebbers et al. (2000b). Dry-stability was determined by placing a 100 g soil sample on the uppermost of a set of sieves (20 cm diameter), shaking for 1 minute at Level 6 on a scale of 0-10 on a vibrating CSC Scientific Sieve Shaker (Catalogue no. 18480, CSC Scientific, Fairfax, VA), and weighing soil retained on the 1.0, 0.25, and 0.053 mm screens and that passing the 0.053 mm screen.

Water-stable aggregate distribution was determined by placing the same soil sample used for dry-stable aggregate distribution on the uppermost of two sieves (17.5 cm diameter with openings of 1.0 and 0.25 mm), immersing directly in water, and oscillating for 10 min (20 mm stroke length, 31 cycles min^{-1}). After the 10 minute period, the two sieves were removed and oven dried (55 ºC, 24h). Water containing soil passing the 0.25 mm screen was poured over a 0.053 mm screen and the soil washed with a gentle stream of water. The soil retained was then transferred into a drying tray with a small stream of water. The <0.053 mm fraction was calculated as the difference between initial soil weight and summation of the other fractions. All fractions were oven dried at 55 ºC until constant mass. Mean-weight diameter of both dry- and wet-stable aggregates was calculated by summing the products of aggregate fraction weight and mean diameter of aggregate classes.

Calculation of SOC Stocks

The SOC concentrations were converted to mass per unit area for a fixed depth (0-20cm) by calculating the product of concentration, bulk density, and thickness. To account for variation in soil mass between samples, “equivalent soil depths” were calculated following the method described by Ellert and Bettany (1995). Additional thickness of the subsurface layer required for attaining equivalent soil mass was computed as follows:

$$T_{add} = \frac{(M_{soil,equiv} - M_{soil,surf}) * 0.0001 \ ha\, m^{-2}}{\rho_b} \qquad \text{Eq. [2]}$$

where:

T_{add} = additional thickness of layer being adjusted required to attain the equivalent soil mass (m)

$M_{soil,\ equiv}$ = mass of heaviest layer (Mg ha^{-1})

$M_{soil,\ surf}$ = mass of layer being adjusted (Mg ha^{-1})

ρ_b = bulk density of layer being adjusted (Mg m^{-3})

Calculation of Stratification Ratio

Franzluebbers (2002) defined stratification ratio as a soil property at the soil surface divided by the same soil property at a lower depth, such as the bottom of the tillage layer. Stratification ratios were calculated from soil properties at 0–5 cm depth divided by those at 12.5-20 cm depth.

Statistical Analysis

After examination of laboratory results, one location in North Carolina was considered an outlier. The location was known to be geographically situated on the Atlantic Flat Woods MLRA, but at the time of sampling a decision was made to include the observations in the Coastal Plain cluster. The main reason for declaring the location as an outlier was its exceptionally high C content on the 0-20 cm layer (122-169 Mg ha^{-1}) compared to the other 14 locations in the Coastal Plain (14-47 Mg ha^{-1}). Furthermore, initial statistical analyses showed that inclusion of this location misrepresented comparisons between the Piedmont and Coastal Plain, and quadrupled standard errors by management in the Coastal Plain when compared to similar management in the Piedmont. Therefore, only 87 sites (29 locations) out of the 90 sampled sites (30 locations) were included in the reported statistical analyses.

Soil properties were analyzed for variance (one-way ANOVA) using PROC GLM in SAS (SAS 9.1, 2003 SAS Institute Inc., Cary, NC) with MLRA, locations nested within MLRA and management as independent variables, and soil properties as dependent variables. When indicated, an analysis of covariance (ANCOVA) with clay as covariable was performed to account for the effect of clay content on SOC. The effect of mean annual temperature and annual precipitation on C was analyzed using PROC RSREG to test for the significance ($P=0.05$) of climate variables and examine the structure of the estimated response surface.

RESULTS AND DISCUSSION

Soil Organic C Stocks

Pasture and CvT soils tended to have lower bulk densities than CsT soils (0-20 cm) so that an additional 0-9.4 cm layer (avg. = 2.4 cm) was required to attain the equivalent soil mass. However, total organic C (TOC) calculated on an equal mass basis (i.e., adjusted using Eq. 2) did not change the comparative values in relation to TOC on an equal volume basis. Variation in TOC was explained by management (41.6%), clay content (5.2%), mean annual temperature (1.0%), and mean annual precipitation (0.1%). Higher soil clay content and precipitation, and slightly cooler temperatures contributed to higher TOC.

Total organic C in the 0-20 cm layer was affected by MLRA (i.e., 32.2 and 27.0 Mg ha^{-1} in the Piedmont and Coastal Plain, respectively, P≤0.002), and by management (i.e., 38.9, 27.9 and 22.2 Mg ha^{-1} under pasture, CsT and CvT, respectively, P≤0.001). The interaction between MLRA and management was not significant. These C stock calculations agree well with published data. From Franzluebbers (2005), C stocks for the Piedmont and Coastal Plain averaged 24.4 and 21.1 Mg ha^{-1} in CsT and CvT systems, respectively (18 cm average depth). Data on SOC stocks under pasture are scarce, yet our results agree well with the 37.8 and 35.3 Mg ha^{-1} reported by Franzluebbers et al. (2000) and Fesha et al. (2002) for long term pastures (20 cm depth) in the Piedmont of Georgia and in the Coastal Plain of Alabama, respectively. The use of conservation tillage and pastures should be considered an effective strategy for restoring C stocks in agricultural systems in these MLRAs. There is a direct relationship between SOC and SOM; restoration of higher levels of SOM is crucial for improvement of soil structure, soil fertility and crop production, and would ensure long-term sustainability of agricultural production. Furthermore, increasing SOC is a sink for atmospheric CO_2, and therefore a way to mitigate potentially detrimental effects of greenhouse gasses.

Surface (0-20 cm) texture of Coastal Plain soils was mostly sand, loamy sand or sandy loam; while texture of Piedmont soils was mostly sandy loam, sandy clay loam or clay (Fig. 2). When clay was included as a covariate, the difference in SOC between MLRAs was not significant (P=0.9), while differences in TOC among management systems remained significant (P≤0.0001). Clay content explained 35 % of TOC variability in CsT systems, 33 % in CvT systems, and only 7 % under pastures (Fig. 3). All sampled soils except two were upland, well drained Ultisols, the exception were upland Alfisols (Aquic Haploxeralfs and Ultic Hapludalfs) in the Coastal Plain of Alabama and Virginia, respectively (Appendix 1). Most of these soils are highly weathered with clay mineralogical suites dominated by kaolinite, hydroxyl interlayered vermiculite, gibbsite and iron oxides. Greater clay concentration could improve water relations, and therefore, soil fertility to allow greater input of C, resulting in overall greater SOC. The mechanism by which clay particles stabilize SOC has not been well elucidated. Some research indicates that the clay mineralogy may influence the mechanisms for C stabilization. For example, in soils with kaolinitic mineralogy, the interaction between positive charges associated with oxides and negative charges of clay minerals formed strong aggregates that can physically protected organic matter (van Veen et al., 1984). In soils with mixed or smectitic mineralogy, organic matter may act as the primary binding agent for soil aggregates where the negative surface charges of soil organic matter and clay minerals are mutually bound to positively charged polyvalent metal cations (Edwards and Bremner, 1967). In contrast, Wattel-Koekkoek et al. (2001) concluded that the total amount of organic C in the clay-size fraction was independent of the clay mineralogy.

Mean annual temperature and precipitation influence C stocks at the regional scale (Jenny, 1941; Franzluebbers and Steiner, 2002). With clay content as a covariate, temperature ($P \leq 0.0001$) and precipitation ($P \leq 0.03$) significantly affected TOC (Fig. 4). The combined effect of temperature and precipitation explained 35 % of the variation in TOC. Mean annual temperature had a more marked effect on TOC than mean annual precipitation. At constant precipitation, TOC increased with decreasing temperature; and, at constant temperature, TOC increased with increasing precipitation.

Soil Organic C Fractions

Pastures contained significantly greater TOC than cropland (0-5 cm) (1.9 times greater than CsT and 3.1 times greater than CvT), but there were no differences among management systems at lower depths (5-20 cm). A similar management effect was observed for POC, SMBC, and CMIN (Fig. 5). Pastures and CsT had minimal soil disturbance that allowed soil C fractions to accumulate at the surface. Above-ground residues would have decomposed more slowly than incorporated residues, because minimal contact with the soil would have increased drying/rewetting and reduced interactions with soil fauna and microbes. Average concentration of TOC, POC, SMBC and CMIN within the surface 20 cm followed the order: pasture > CsT > CvT (12.3 vs 8.3 vs 6.7 g kg^{-1}, $P \leq 0.0001$, LSD=1.3 for TOC; 7.6 vs 5.2 vs 4.1 g kg^{-1}, $P \leq 0.0001$, LSD=1.0 for POC; 0.45 vs 0.29 vs 0.23 g kg^{-1}, $P \leq 0.0001$, LSD=0.04 for SMBC; 0.39 vs 0.22 vs 0.17 g kg^{-1}, $P \leq 0.0001$, LSD=0.04 for CMIN). Franzluebbers and Stuedemann (2002) found similar results comparing long-term pastures with long-term CsT in the Piedmont of Georgia. Greater TOC, POC, SMBC, and CMIN under pastures compared with croplands could have been due to a variety of factors, including greater overall rate of photosynthetic activity resulting in greater C inputs throughout the year (because of the growth capabilities of perennial versus annual plant species), and less C exported via cattle production compared with grain harvest. The POC-to-TOC ratio decreased with soil depth in pasture and CsT, but remained fairly constant in CvT. There were no statistical differences in POC-to-TOC between management systems (data not shown).

Across all management systems, depths of sampling and soils of the Piedmont and Coastal Plain, there was a strong relationship among all SOC fractions (Table 1). The relationship between TOC and POC (TOC = 0.36+1.02 POC; R^2=0.80, n=261) indicates that C accumulation in this warm and humid region was largely due to increases in the POC fraction; i.e., for every unit of TOC accumulated, 62% consisted of POC. Franzluebbers and Stuedemann (2002) reported 57% POC for every unit of TOC under long-term pastures in the Southern Piedmont.

Potential C mineralization during 24 d (CMIN) decreased with depth and showed significant difference between management systems (in the order pasture > CsT > CvT) (Fig. 5d). The response in CMIN was similar to those observed for SMBC and was strongly related to all soil organic C (Table 1). At the 0-5 cm depth, C mineralization under pasture doubled that of CsT and almost quadrupled that of CvT. Carbon mineralization rates decreased with increasing depths and followed the order pastures > CsT > CvT. Greater C mineralization under pastures suggests that less disturbed systems (perennial species, no tillage) have increased the potential biological activity of soil organic matter compared with cultivated land.

In soils of the Piedmont, Franzluebbers (1999) observed an inverse relationship between C mineralization and soil clay content; i.e., the clay fraction in soils protected soil organic matter from decomposition. In our study, the relationship between CMIN and clay was not significant.

Aggregate Stability

Mean-weight diameter (MWD) and aggregate-size distribution (ASD) of dry soil at a depth of 0-5 cm was not different among management systems. However, there was a significant impact of management ($P<0.001$) on MWD and ASD in water, with treatments following the order: pasture > CsT > CvT (Fig. 6). Comparing dry to wet

ASD, changes occurred mainly among large macroaggregates (1000-4750 μm). Pasture soils withstood disruptive forces during wet sieving more than cropland soils, with CsT > CvT. Large macroaggregates under CsT were 24% of the whole soil with dry sieving and 17% with wet sieving, while the same aggregate-size class was 22% with dry sieving and 10% with wet sieving in CvT. Disruption of macroaggregates with wet sieving increased the <53 μm aggregate-size class, i.e., silt and clay-size microaggregates. In pasture soils, disruption occurred in the 53-250 μm aggregate-size class, resulting in an increase in the <53 μm aggregate-size class. Our procedure for determining dry or wet MWD did not differentiate between true aggregates and large sand particles that were retained on the screens and therefore the stability of macroaggregates was more reflective of changes in soil structure induced by management.

We did not determine C contents of aggregate-size classes, but the fact that C contents were in the order: Pasture > CsT > CvT (Fig. 5), would suggest that SOC was a major binding agent of large macroaggregates in these soils. Tisdall and Oades (1982) proposed a model that described microaggregates bound together into macroaggregates by microbial- and plant-derived polysaccharides, as well as roots and fungal hyphae. Reduction in aggregation has been associated with loss of SOC with cultivation (Beare et al., 1994, Six et al., 2000).

Slaking, or structural degradation in water, was most prominent in soil under CvT. Dispersed soil particles can seal pores, reduce infiltration, and cause water runoff. Soil structural degradation has been associated with physical disturbance and continual exposure of new soil to wet-dry cycles and to a change in soil micro-climatic conditions that increases SOM decomposition (Paustian et al., 1997; Balesdent et al., 2000). In contrast, CsT and pasture systems not only avoid these negative effects, but promote plant root and fungal hyphae proliferation, responsible for macroaggregate formation (Beare et al., 1993). Resistance of soil to structural degradation is particularly important under the climatic conditions of the Piedmont and Coastal Plain where intense storms are common during the summer.

Clay content explained 77% of the variation in MWD of dry aggregates, but only 26% of the variation in MWD of wet aggregates (Fig. 7). Total organic C explained minimal variation in MWD of dry aggregates and 21% of the variation in MWD of wet aggregates. These data indicated that clay-sized particles played a major role in holding dry aggregates together, but that TOC was more important in wet aggregates. Shaw et al. (2003) found that Fe oxides play a more significant role in clay aggregation than soil organic matter in Rhodic Paleudults. Yet, soil organic matter has a significant role for reducing clay dispersion in these highly weathered southeastern USA soils (Shaw et al., 2002). Electrostatic attraction would occur among oxides and 1:1 clay minerals. Electrostatic attraction are at maximum in close proximity. Wetting the soil produces ion hydration and swelling draws water in between clay platelets, pushing them apart and reducing electrostatic attraction. Clay (phyllosilicates and oxides) and organic matter are binding agents of soil aggregates (Tisdall and Oades, 1982; Kemper and Rosenau, 1984). Management systems that maximize TOC would help maintaining favourable soil structure in the southeastern USA.

Soil Organic C Stratification Ratio

Stratification ratio of SOC fractions (e.g., TOC, POC, SMBC and CMIN) differed ($P \leq 0.0001$) among management systems, and was 4.2-6.1 under pastures, 2.6-4.7 under

CsT, and 1.4-2.8 under CvT (Fig. 8). Stratification of SOC fractions is common in natural ecosystems, where high stratification reflects relatively undisturbed soils. Franzluebbers (2002) suggested that stratification ratio of SOC fractions could be used as a simple diagnostic tool to identify land management strategies for restoring critical soil functions, and that among diverse soils, TOC stratification ratio might be a better indicator of soil quality than total TOC content of the entire plow layer. Stratification > 2 are interpreted as an indicator of undisturbed soil condition or of improved quality on previously degraded soils. Greater TOC stratification ratio in pastures and CsT than in CvT was a consequence of TOC accumulation at the soil surface, which would have a positive effect on erosion control, water infiltration and nutrient conservation. In the Southeastern U.S., the warm-humid climate is a limiting factor for SOC accumulation. Therefore, the determination of TOC content may not be the best indicator of improved soil quality when comparing across diverse soil groups. These data supported the proposed threshold stratification ratio of 2 (i.e., most ratios under CvT were ≤ 2, while they were ≥ 2 under CsT and pasture).

The depths we used for calculation of stratification ratios (i.e., 0-5 and 12.5-20.3) were similar to those used by Franzluebbers (2002) in south-central Texas, Alberta and British Columbia. In northeastern Ohio, Jarecki et al. (2005) used the depths 0-5 and 10-20 cm and reported stratification ratios < 2 on a field with 14 years of no-tillage corn. They attributed this low value to the fact that corn root-derived C contributed more C to SOC than stover-derived C. In other regions, the indicator may need definition of depths for calculations. In southwestern Spain, SOC at 0–5 and 5–10 cm divided by that at 10–25 cm resulted in stratification ratio of SOC between CsT and CvT that was not significantly different (Moreno et al., 2006). When the 25–40 cm soil layer was used for the denominator, stratification ratios were >2 for CsT and significantly greater than for CvT.

Stratification ratio of TOC was related to wet MWD (Fig. 9a). Although significant variation occurred (R^2=0.20), stratification ratio of TOC under CvT was <2 and lowest wet MWD (< 1.0) occurred under CvT. Higher values of wet MWD would be desirable, because they indicate soil structural integrity during heavy rainfall events. There was also a significant response of stratification ratio of TOC with years under CsT (Fig. 9b). Lowest values occurred during the first 5 years and the response reach a maximum about 10 years after switching from CvT to CsT. Even under long-term CsT (i.e., 30 years), the surface layer (0-5 cm) was the zone of concentrated TOC. Although Loveland and Webb (2003), after a review of the literature, suggested that there was little quantitative evidence of a threshold for SOC, stratification ratio of SOC fractions may provide a new conceptual framework for evaluating the importance of SOC on soil functions related to aggregation, water-use efficiency, and nutrient cycling.

SUMMARY AND CONCLUSIONS

On-farm measurements of C stocks in the Piedmont and Coastal Plain complemented research station data under cultivated systems and much-needed quantitative information of SOC stocks under pastures. Total organic C in the 0-20 cm layer was greatest under pasture, intermediate under CsT, and least under CvT (38.9, 27.9 and 22.2 Mg ha^{-1}, respectively, P<0.001).

All SOC fractions were strongly correlated (r>0.84) across a diversity of soils and management. The relationship between TOC and POC indicated that SOC accumulation in this warm and humid region was largely composed of increases in the POC fraction; i.e., for every unit of TOC accumulated 0.62 consisted of POC. Climate (mainly temperature) and soil texture influenced SOC stocks within well-drained upland soils. Cooler climate and finer textures resulted in higher SOC.

Management affected SOC primarily at the soil surface (0-5 cm). Stratification ratio of SOC fractions was in the order: pasture > CsT > CvT. Results supported the proposed threshold value for stratification ratio of 2 to distinguish soils with improved soil quality from degraded soils. However, stratification ratio as an indicator of soil quality needs further evaluation, especially with respect of determining adequate depth of sampling for calculations and its relationship with other physical, biological and chemical measurements of soil quality.

Policies that promote sod-based or forage rotations and conservation tillage will lead to significant SOC sequestration throughout the Piedmont and Coastal Plain, resulting in improved soil quality, plant productivity and the potential for mitigating global warming.

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Table 1. Pearson correlation coefficients among carbon fractions. (*** indicates highly significant, $P \leq 0.0001$).

	TOC	POC	SMBC	CMIN
Total organic carbon (TOC)	-	***	***	***
Particulate organic carbon (POC)	0.90	-	***	***
Soil microbial biomass carbon (SMBC)	0.95	0.85	-	***
Carbon mineralized in 24 days (CMIN)	0.94	0.85	0.96	-

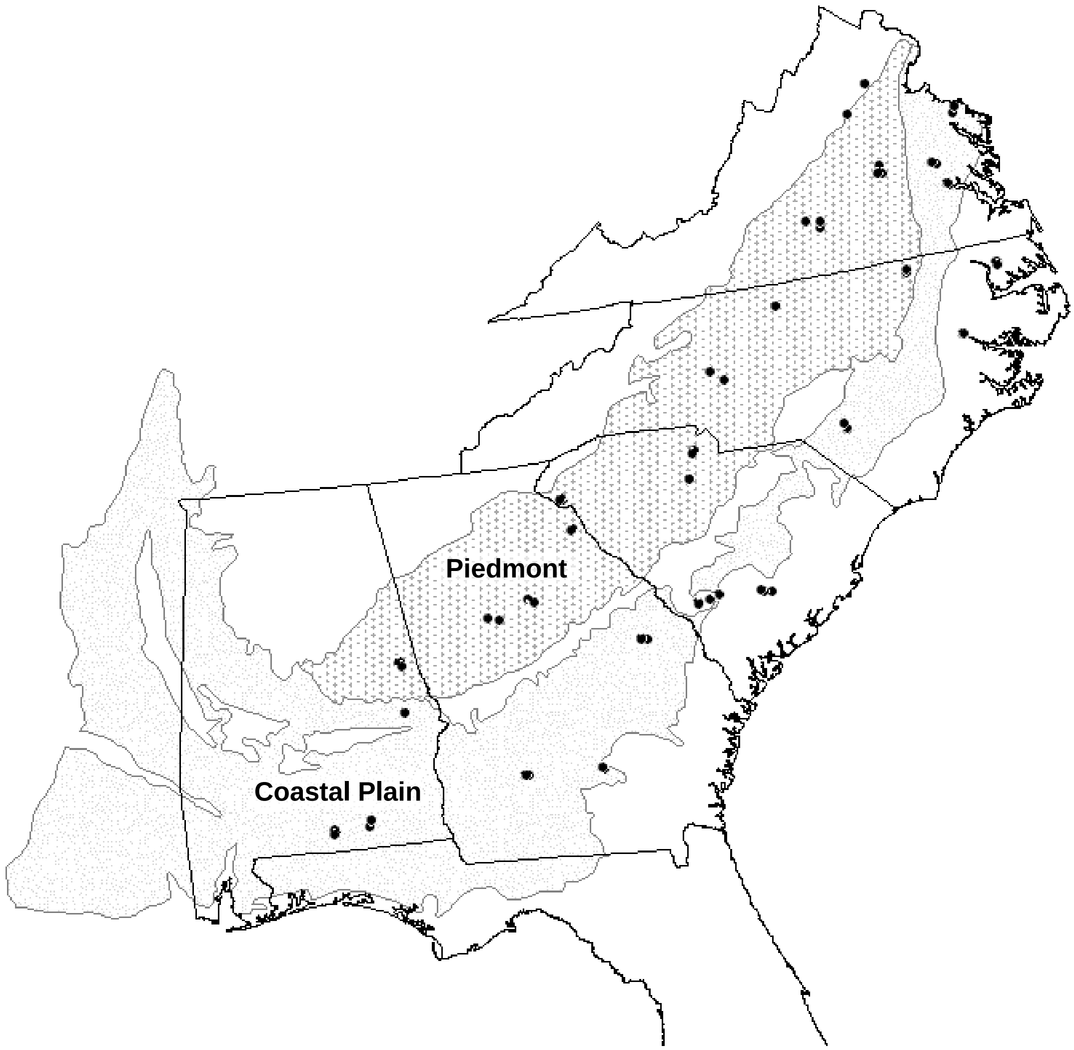


Fig. 1. The Piedmont and Coastal Plain Major Land Resource Areas and sites where soil organic C stocks (0-20 cm) in pasture and crop lands have been measured.

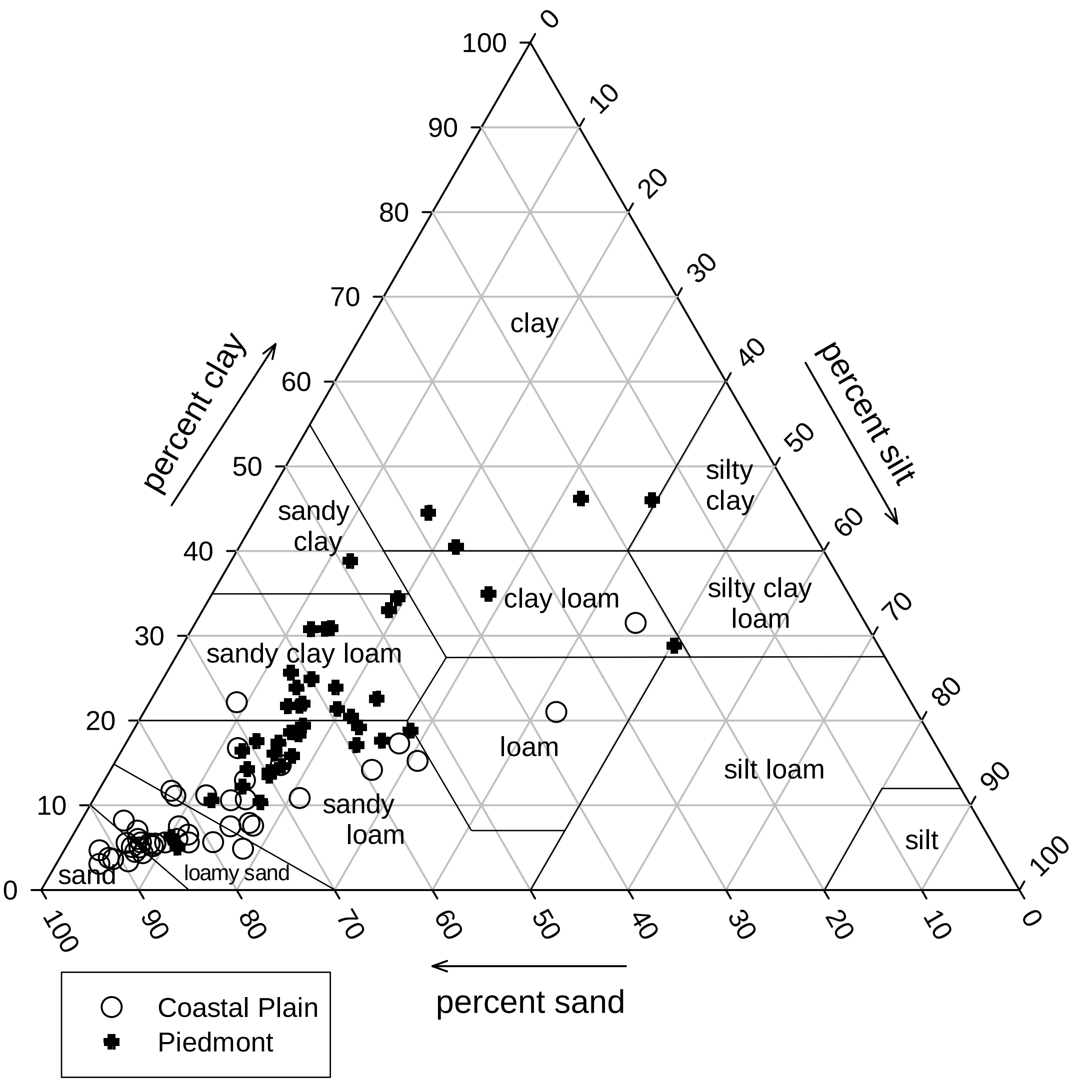


Fig. 2. Surface (0-20 cm) texture of soils sampled in the Coastal Plain and Piedmont Major Land Resource Areas.

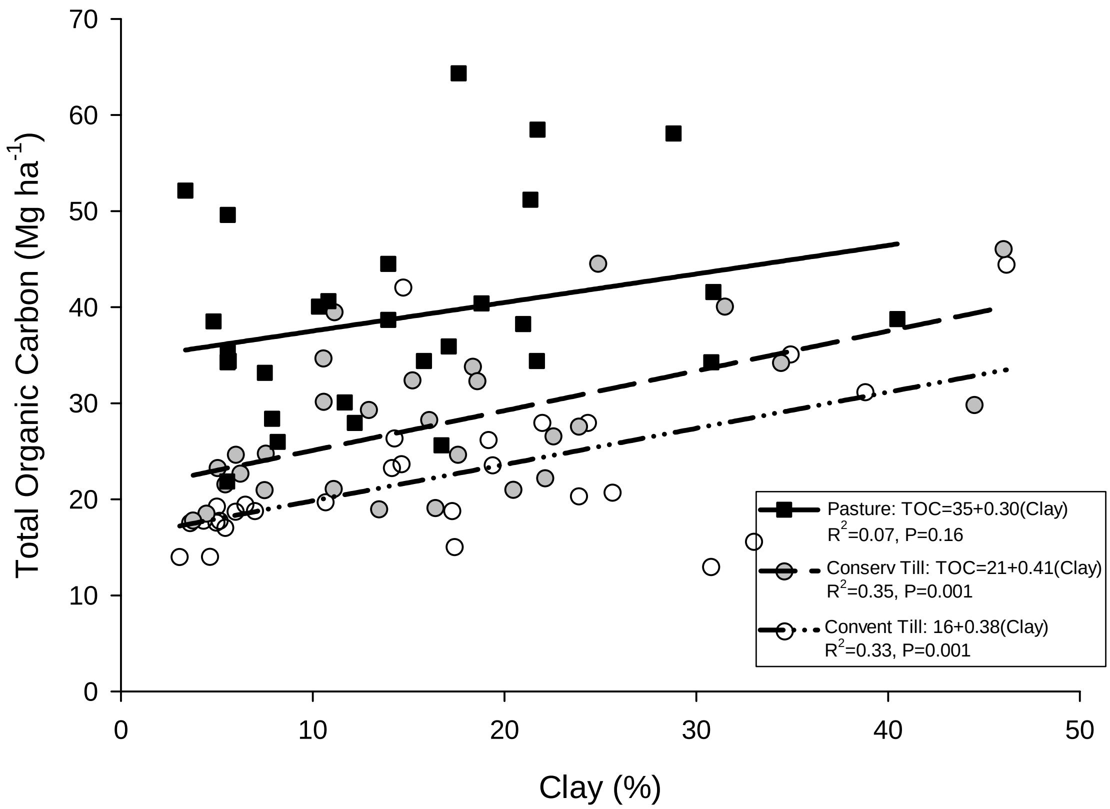
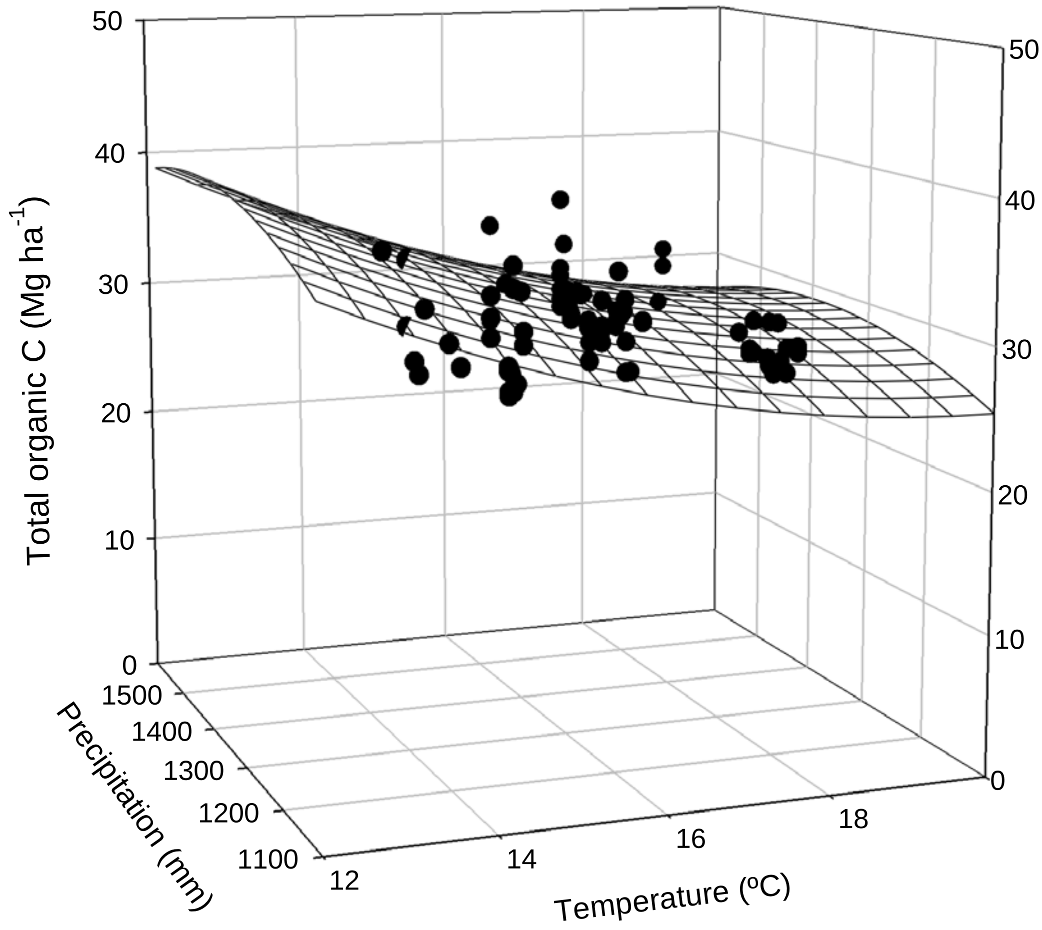


Fig. 3. Effect of clay content on total organic C (0-20 cm) under pasture, conservation tillage and conventional tillage systems.



$C = 1.66-6.01(tmp)+0.13(pcp)+0.16(tmp)^2-0.0003(tmp)(pcp)-0.00004(pcp)^2$

$R^2=0.35$, P>F: tmp$\leq$0.0001, pcp$\leq$0.03

Fig. 4. Mean annual temperature and mean annual precipitation (30 yr normal) effects on total soil organic C stocks (0-20 cm).

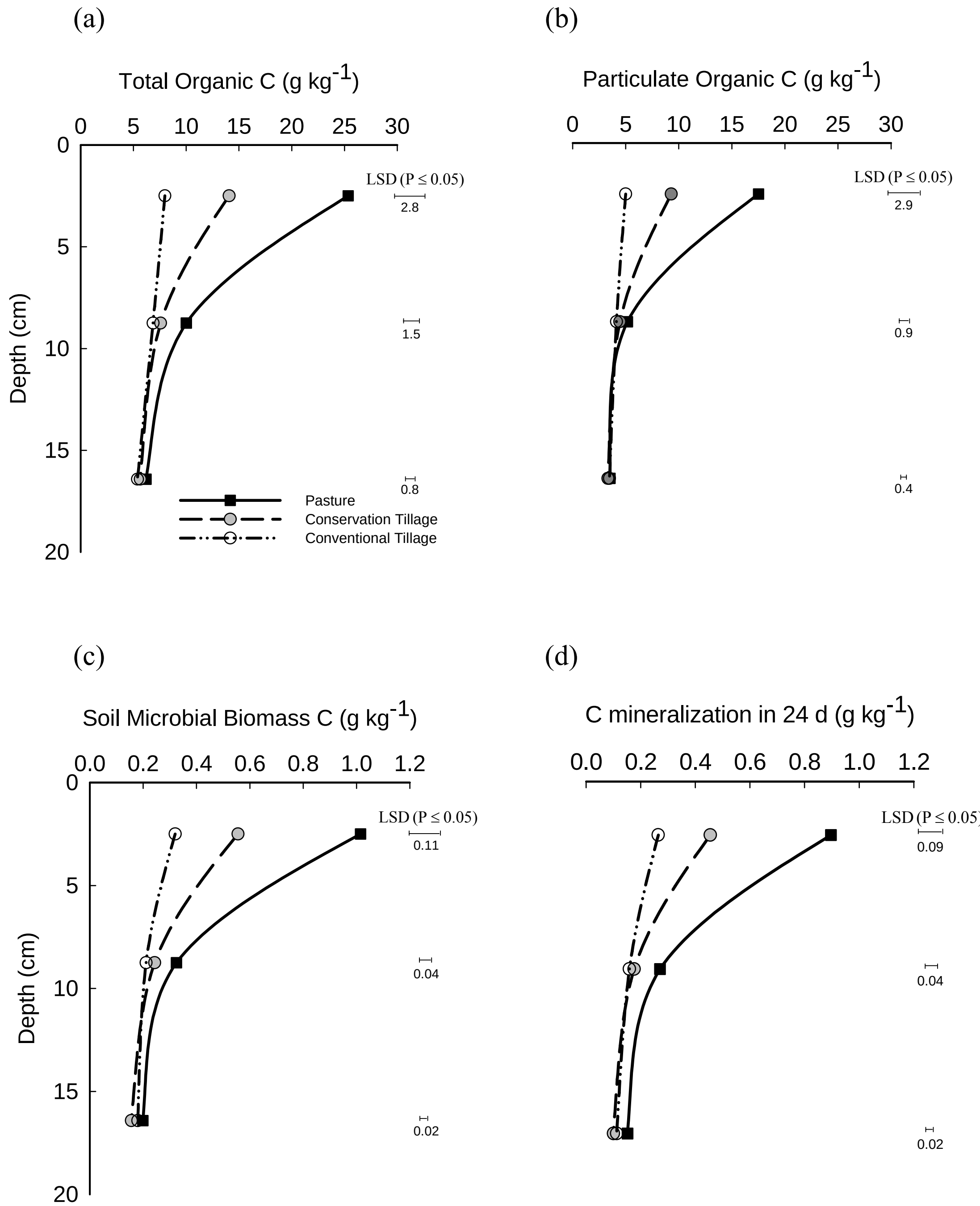


Fig. 5. Depth distribution of (a) total organic C, (b) particulate organic C, (c) soil microbial biomass C, and (d) carbon mineralization in 24 days. Bars are LSD ($P \leq 0.05$) between management systems.

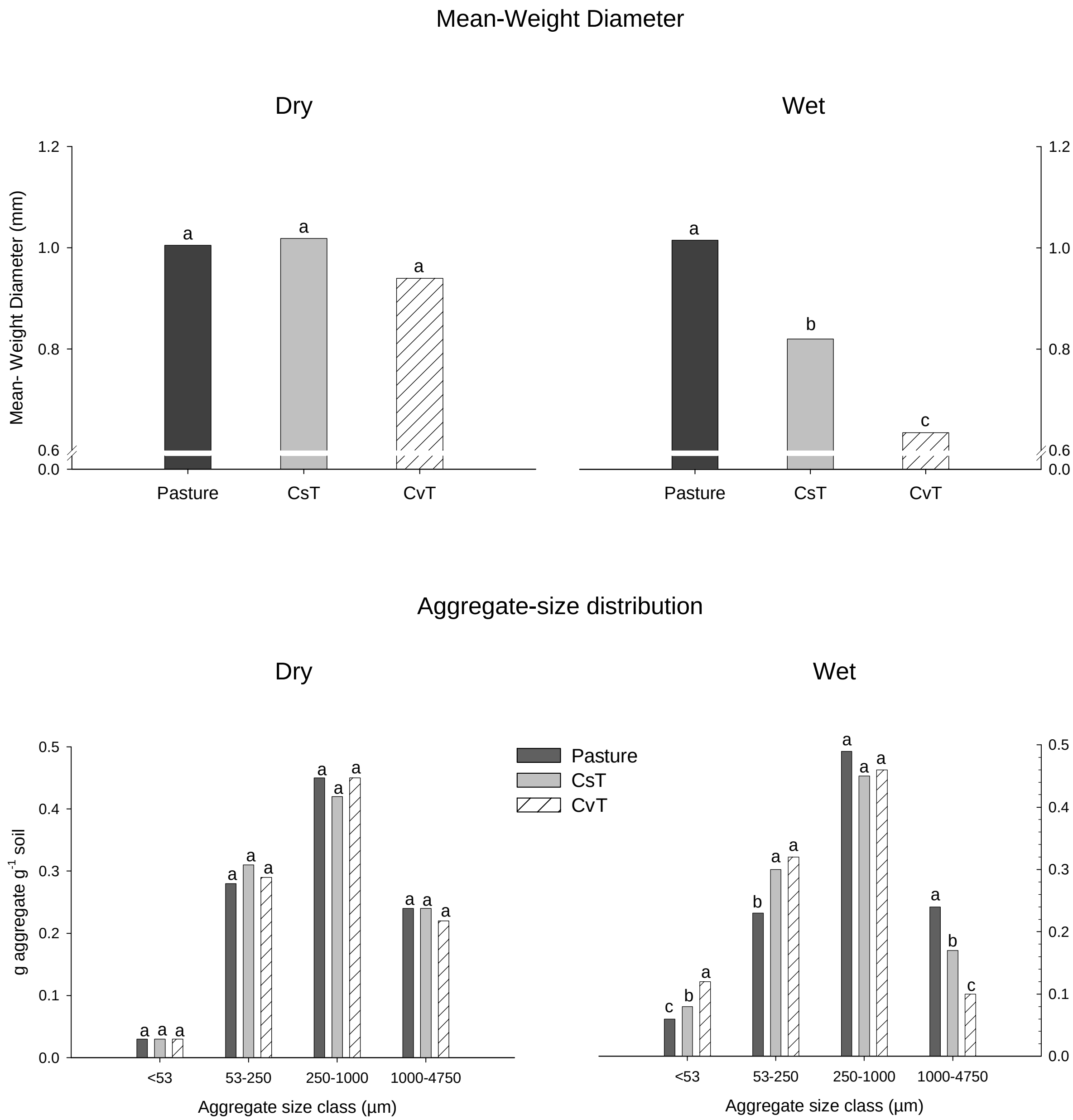


Fig. 6. Dry and wet mean-weight diameter and aggregate-size distribution (0-5 cm) under pasture, conservation tillage (CsT) and conventional tillage (CvT) systems. Bars with different letters indicate significant difference in management at P≤0.05.

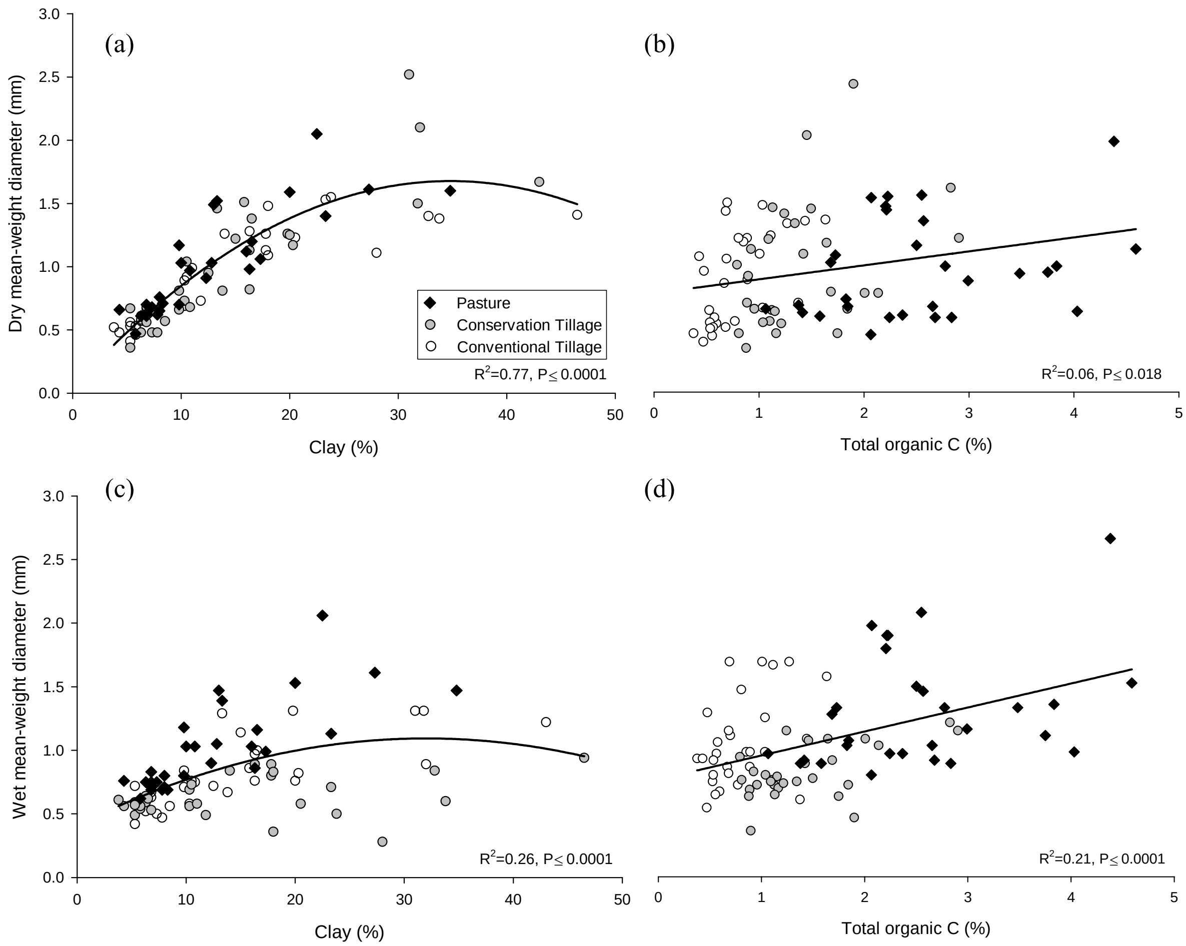


Fig. 7. Effect of clay and total organic C concentration on dry and wet mean-weight diameter of the 0-5 cm layer. Letters (a) and (b) correspond to dry distribution, letters (c) and (d) to wet distribution.

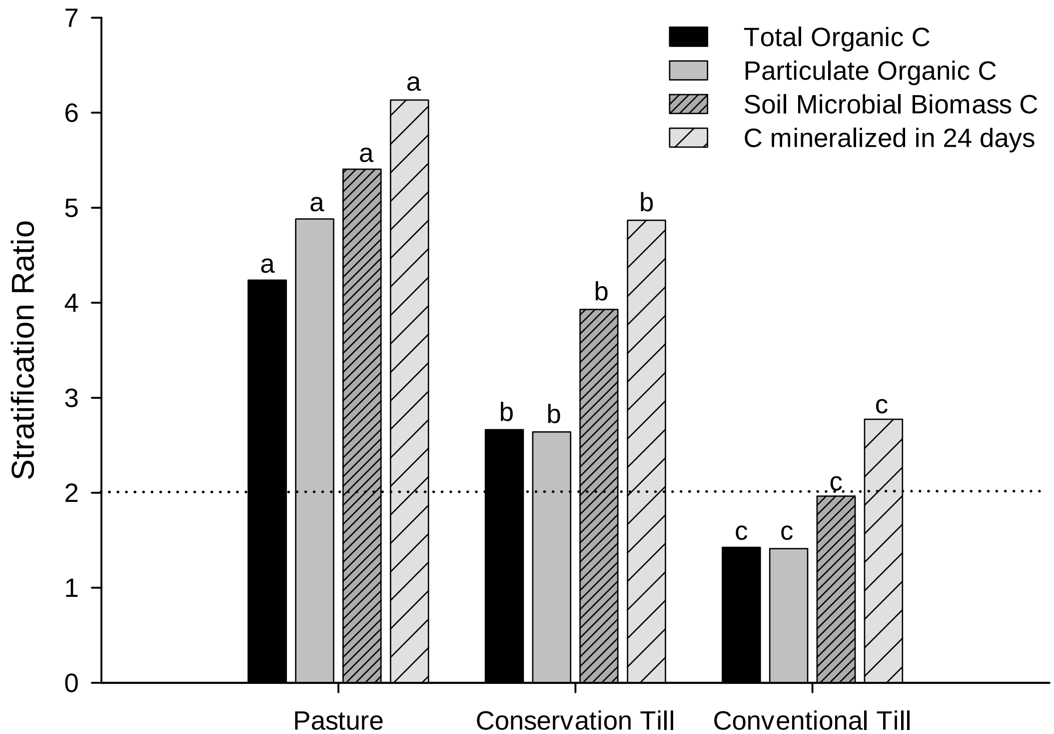
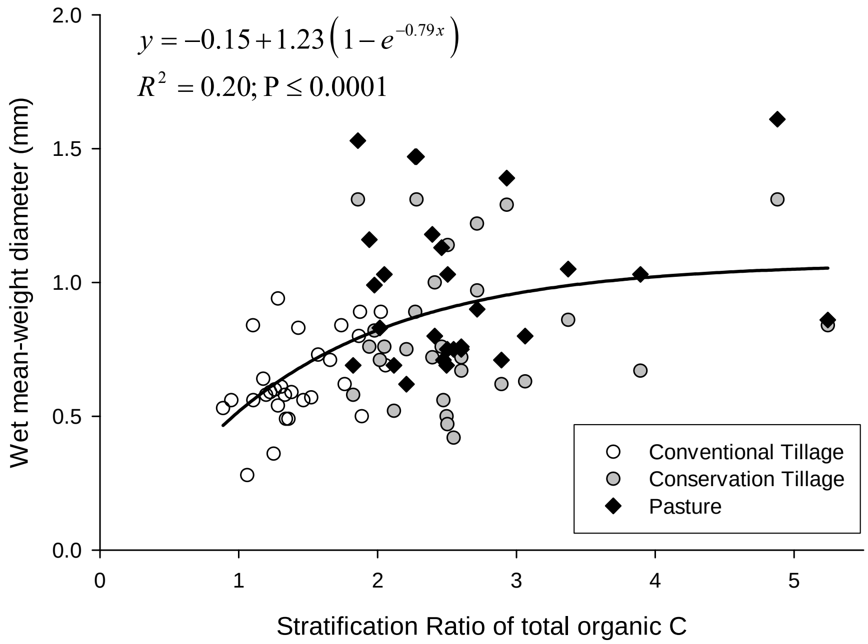


Fig. 8. Stratification ratio of soil organic C fractions under pasture, conservation tillage, and conventional tillage. Bars sharing the same letter within a C fraction are not different at P = 0.05.

(a)



(b)

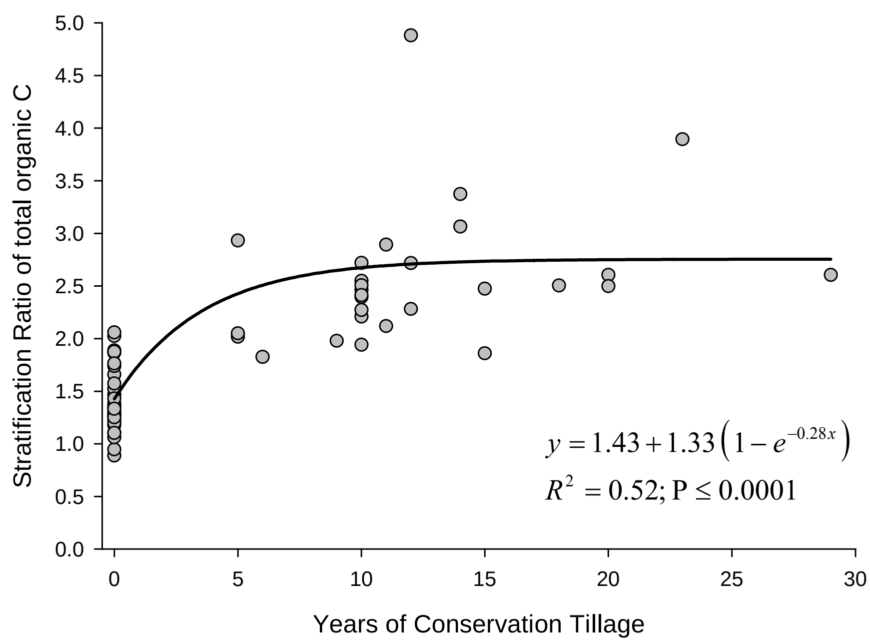


Fig. 9. Relationship of stratification ratio of total organic C to (a) wet mean-weight diameter and (b) number of years under conservation tillage.

II. RELATING SOIL ORGANIC CARBON IN PIEDMONT PASTURES TO LANDSCAPE, ELECTRICAL CONDUCTIVITY AND REMOTE SENSING DATA

ABSTRACT

Landscape characteristics could affect soil organic C (SOC) sequestration in pastures, yet the field-scale spatial distribution of SOC in pastures has been relatively uninvestigated. Our objective was to determine the relationship between SOC and secondary data in two Southern Piedmont pastures. Geo-referenced SOC, soil texture, field-scale electrical conductivity (EC) and terrain attribute (TA) data were collected on two 5.5-ha grazed pastures; one near Watkinsville, GA (Typic Kanhapludults) and the other near Gold Hill, AL (Rhodic Kanhapludults). Near infrared (NIR), red and green reflectance data were obtained from aerial photographs. Elevation and slope explained 26% of SOC variability at Watkinsville, while elevation and the normalized difference vegetation index (NDVI) explained 63% of SOC variability at Gold Hill. Ordinary kriging, multiple linear regression (MLR) and artificial neural networks (ANN) were used to produce SOC maps. In Watkinsville, prediction efficiency with ANN (PE = 49%) was four times greater than with the second best method (kriging), and in Gold Hill (PE = 62%) was 1.5 greater than the second best method (MLR). Factor analysis of multivariate

TA, EC and remote sensing (RS) data followed by fuzzy k-means clustering of scores identified four clusters in Watkinsville, and three clusters in Gold Hill. Soil organic C was statistically different (P≤ 0.01) among clusters at both sites, and its variability was explained by elevation, slope, compound topographic index (CTI), and NIR and red reflectance. Easily obtainable secondary data (i.e., TA, EC and RS) were significantly related to SOC variability and could be used to enhance SOC maps. Using ANN for SOC mapping would be appealing when complex non-linear relationships exist.

Abbreviations: ANN, artificial neural networks; ARS, Agricultural Research Service; CIR, color infrared; CTI, compound topographic index; DEM, digital elevation model; EC, electrical conductivity; FPI, fuzziness performance index; GIS, geographic information system; GPS, global positioning system; MLR, multiple linear regression; NCE, normalized classification entropy; NDVI, normalized difference vegetation index; NIR, near infrared; NRCS, Natural Resource Conservation Service; PE, prediction efficiency; PLANC, plan curvature; PROFC, profile curvature; R, red; RMSE, root-mean square error; RS, remote sensing; RSV, relative structural variability; SOC, soil organic carbon; TA, terrain attributes; VIF, variance inflation factor**.**

INTRODUCTION

The Southern Piedmont Major Land Resource Area has a total land area of 16.7 Mha. It extends from northern Virginia to eastern Alabama, occupying 34, 38, 35, 29 and 9% of the land area in Virginia, North Carolina, South Carolina, Georgia and Alabama, respectively. Most of this land was once cultivated to row crops, but much has reverted to mixed stands of pine and hardwoods, and monoculture pine production; the expansion of major cities has incorporated land for residences and associated urban development (USDA-NRCS, 1997). Currently, large acreage of pasture supporting cattle-grazing production systems exists in the Southern Piedmont (Census of Agriculture, 2002).

Soil organic C plays a critical role in soil quality and has potential to cost-effectively mitigate detrimental effects of rising atmospheric CO_2 and other greenhouse gas emissions on global warming and climate change (Lal, 1997; Reeves, 1997). Evaluation of SOC distribution in pastures at scales comparable to farm management units, which encompass heterogeneous soils and different landforms, has been relatively uninvestigated. Since SOC influences soil quality and plant productivity, it is of interest to characterize its spatial distribution for optimizing agricultural inputs (e.g., manures and fertilizers) and to assess how management practices might alter its distribution. Moreover, understanding the relationship between SOC and landscape variability will be necessary to upscale SOC stocks from field-scale to physiographic region.

The influence of topography on soil properties has long been recognized. Jenny (1941) proposed a conceptual model of soil formation with topography as a state factor. Our understanding of the relationship between topography and soil properties improved with the advent of Geographic Information Systems (GIS) and Global Positioning System

(GPS). Variables describing topography are known as terrain attributes (TA), and are derived from a digital elevation model (DEM). Moore et al. (1993) and Florinski et al. (2002) listed mathematical expressions for calculating several TA (e.g., elevation, slope, aspect, plan and profile curvature).

The relevance of any particular TA on soil properties often depends on the overall landform shape and the redistribution processes operating on the landscape (Pennock, 2003). Martz and De Jong (1991) found that soil erosion on a small Canadian prairie watershed was directly related to the catchment area, except on the midslope where erosion was directly related to steepness. Epipedon SOC generally increases with convergent landscape character, due to soil deposition and difference in net mineralization. Florinsky et al., (2002) defined zones of accumulation, dissipation and transit based on profile (PROFC) and plan (PLANC) curvatures. Basically, concave curvatures (PROFC and PLANC < 0) result in accumulation, convex curvatures (PROFC and PLANC > 0) result in dissipation; and transit zones (no net change) occur when PROFC and PLANC are of opposite sign. Moore et al. (1993), Gessler et al. (2000), and Terra et al. (2004) found strong relationships between the Compound Topographic Index (derived from specific catchment area and slope) and SOC (r from 0.48 to 0.88). Mueller and Pierce (2003) reported high correlation between SOC and elevation (r from -0.68 to -0.77).

Although many studies have shown strong TA-SOC relationships, care must be taken when interpreting relationships, especially in farm-scale studies where management plays an important role (Bergstrom et al., 2000). For example, higher contents of SOC at the toeslope may be attributed to the effect of topography (accumulation zone), or to the fact that it is the zone in the field where animals congregate in response to management routines and hence higher level of organic C input from cattle deposition, which also increase fertility and subsequent forage growth. As indicated by Young and Hammer (2000), Jenny's "factor" approach holds better at the regional scale than at the field-scale.

The sampling intensity required to produce reliable SOC estimation is related to its spatial variability. Variation in SOC may occur on a finer spatial resolution than can be detected with a sampling protocol because of sampling costs. Therefore, secondary data correlated with SOC are sometimes necessary to more accurately characterize field-scale SOC variability. Besides TA, more easily measured soil properties have been used as secondary spatial information to characterize field-scale SOC distribution. Field-scale soil EC is among the most useful and easily obtained measures that depicts soil spatial variability. Rhoades et al. (1989) formulated mathematical models relating EC to soil properties. Basically, EC is a function of soil salinity, saturation percentage, water content and bulk density. Water holding capacity and bulk density are closely associated with soil texture. Temperature also affects EC, since electrolytic conductivity increases at an approximate rate of 1.9% per degree centigrade (Corwin and Lesch, 2003).

Geo-referenced in situ estimates of EC can be made at the field scale using either of two types of sensors, contact sensors that measure resistance and non-contact sensors that rely on electromagnetic induction; measurements from both sensors were strongly correlated with laboratory measurements of EC (Corwin and Lesch, 2003). It is also possible to indirectly relate EC to SOC. Studies have shown significant correlation coefficients, e.g. $r = -0.36$ (Johnson et al., 2001), $r = -0.42$ (Johnson et al., 2003), and $r =$

-0.42 (Terra et al., 2004). Ronnie et al. (2003) found positive correlation (r=0.55) on Histic Humaquepts of the North Carolina Coastal Plain.

Remote sensing data are another source of secondary spatial data. Crop and bare soil spectral responses can be related to crop productivity and surface soil properties. Chen et al. (2000) developed a relationship between surface (0-15 cm) SOC concentration and image intensity values from an aerial photograph using a logarithmic linear equation (R^2 = 0.93) on a Georgia Coastal Plain field. Recently, Sullivan et al. (2005) reported high correlation (r = -0.78) between spectral response remotely sensed by the IKONOS satellite and surface (0-15 cm) SOC of tilled soils in an Alabama Coastal Plain field. Soil organic C was negatively correlated with reflectance, because increasing SOC concentration has a darkening effect that reduces the amount of reflected energy. Soil organic C was detected in the visible and NIR regions of the spectrum, where the relationship was linear or curvilinear (Henderson et al., 1992). We hypothesize that RS imagery may play a role in aiding detection of SOC variability in pastures through the relationship between SOC and forage growth conditions, since the latter has been shown to be highly correlated with RS data (Yang and Everitt, 2002; Blackmer and Shepers, 1996). High sunlight absorption in the red (R, 600-700 nm) would be indicative of high chlorophyll concentration, and high reflectance in the NIR (750-1350 nm) has been shown to be directly related to green leaf density (Knipling, 1970).

In general, soil properties vary continuously over the landscape; contiguous samples would be most similar and not independent. Geostatistics provide the means to analyze spatial dependence among soil samples through variography and kriging or co-kriging interpolation (Goovaerts, 1999). High resolution secondary information such as

TA, EC and RS could be used to give greater detail to less extensive soil measurements like SOC (Bishop and McBratney, 2001). With today's advances in geo-referenced sensor technology, the amount of easily obtainable ancillary information has been steadily increasing. Multivariate statistical procedures exist to reduce dimensionality and weigh data relevancy. Specifically, principal components and principal factor analyses, respectively, may be combined with unsupervised classification methods or cluster analyses to group similar areas on a landscape (Fraisse et al., 2001; Terra et al., 2004; Sullivan et al., 2005).

Multiple linear regression constitutes a less intensive technique to relate SOC and ancillary data (e.g., Moore et al., 1993), but the non-linearity in the relations presents problems. During recent years, artificial neural networks (ANN) have developed as a flexible mathematical tool capable of handling complex non-linear relationships between inputs and output. There have been an increasing number of studies applying ANN to SOC prediction (Levine and Kimes, 1997; Ingleby and Crowe, 2001; Somaratne et al., 2005). In ANN, several transfer functions accommodate the nonlinearity of the input-output relationship. The desired relationship is "learned" by repeatedly presenting examples of the desired input-output relationship to the network, and adjusting the model coefficients (i.e., the weights) to get the best possible agreement between the observed values and those predicted by the model (Demuth et al., 2005).

Piedmont pastures constitute a good arena for studying landscape effects on SOC, because of the relatively undisturbed condition of the soil surface. Our hypothesis was that SOC distribution was related to landscape form, and the prediction of SOC may be improved by incorporating more easily obtainable secondary data. Therefore, the objectives of this study were to (i) characterize SOC spatial distribution, (ii) evaluate various techniques for estimating SOC, and (iii) determine the relationship between SOC and easily obtainable secondary data in two Southern Piedmont pastures.

MATERIALS AND METHODS

Site Characteristics

Two pastures (about 5.5 ha each) were selected for this research. One was owned by the Agricultural Research Service (ARS) and located near Watkinsville in northeast Georgia (83º27’20”W, 33º51’51”N), and the other was a farmer-owned site near Gold Hill in east-central Alabama (85º31’5”W, 32º42’59”N). Mean annual temperature at both locations was about 16 ºC. Mean annual precipitation was 1250 mm in Watkinsville, and 1450 mm in Gold Hill. Both fields were long-term (>30 years) grazed pastures. The Watkinsville field is dominated by bermudagrass (*Cynodon dactylon* L.) with minor contributions from tall fescue (*Lolium arundinaceum* Schreb.) and annual ryegrass (*Lolium multiflorum* Lam.). Grazing was with Angus cattle (cows and cow/calf pairs) periodically during the year to consume available forage. The Gold Hill field was dominated by tall fescue, with some contribution from dallisgrass (*Paspalum dilatatum* Poir.), bermudagrass and bahiagrass (*Paspalum notatum* Fluegge). Grazing was with Herefords cattle to consume available forage. Before pasture establishment, fields were cultivated with annual crops and managed with conventional tillage; agricultural terraces remained. These fields were selected because of their variability in surface soil texture, upland topography, and because they were representative of large areas of the Southern Piedmont Major Land Resource Area.

Soils in the Watkinsville field included Cecil and Pacolet series (fine, kaolinitic, thermic Typic Kanhapludults). These soils were formed in material weathered from gneiss, were well-drained, acidic, and contained argillic and kandic horizons. The surface horizon (Ap) was a sandy loam to sandy clay loam texture, and subsurface horizons were sandy clay loam, clay loam or clay textured. The argillic horizons were sandy clay loam, clay loam or clay. Slopes ranged from 2 to 10%.

Soils in the Gold Hill field belonged to the Gwinnett series (fine, kaolinitic, thermic Rhodic Kanhapludults). These soils were formed in intermingled basic crystalline materials (mainly amphibolite), were well-drained, acidic, and contained argillic and kandic horizons. The surface horizon texture was sandy loam to gravelly sandy loam. The argillic horizons were clay loam or clay. Slopes ranged from 2 to 15%.

Elevation and EC Data Collection

An elevation survey was conducted in November 2003 at the Watkinsville field and in May 2005 at the Gold Hill field. At each field, a Trimble 4600 L.S. Surveyor Total Station (Trimble Navigation, LTD, Sunnyvale, CA)[1] was mounted on an all-terrain vehicle. The vehicle traveled in transects spaced approximately 8-m apart at an approximate speed of 4 km h^{-1}, recording GPS location and elevation every second. The vehicle pulled a VERIS 3100 sensor cart (Veris Tech., Salina, KS)[1], which recorded EC every second at 0 to 30 cm and 0 to 90 cm. Soil moisture during surveys was near field capacity. A second survey of EC was conducted at the Watkinsville field in October

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

2004. Elevation and EC sample density were 1100 readings ha^{-1} at Watkinsville and 1900 readings ha^{-1} at Gold Hill.

Digital Elevation Modeling and Terrain Attribute Computation

A 5-m digital elevation model (DEM) was generated for each field using a finite difference interpolation technique in ArcInfo (ver. 9.0, 2004, ESRI, Redlands, CA). The DEM was used to derive primary terrain attributes from tools in ArcGIS (ver. 9.0, 2004, ESRI, Redlands, CA), which included maximum downhill slope (%), profile curvature (m^{-1}) relating convexity or concavity of the surface in the direction of the slope, plan curvature (m^{-1}) relating convexity or concavity in the direction perpendicular to the slope, flow direction, and flow accumulation. Secondary terrain attributes (e.g. catchment area and compound topographic index) were derived from flow accumulation and slope, respectively (Moore et al., 1993):

$$CA = cell\ area \cdot Fa \qquad \text{Eq. [1]}$$

$$CTI = \ln\left(\frac{SCA}{\tan\beta}\right) = \ln\frac{(cell\ dim \cdot Fa)}{Slp\ /\ 100} \qquad \text{Eq. [2]}$$

where: CA = catchment area, Fa = flow accumulation, CTI = compound topographic index, SCA = specific catchment area, cell dim = x or y cell dimension, β = slope in degrees, Slp = slope in percentage.

EC Mapping

Isotropic exponential semivariogram models were fit to EC data using GS+ (ver. 7.0, 2005, Gamma Design Software, Plainwell, MI). The nugget was a small portion of the semivariance (<10%), indicating strong spatial dependence. High R^2 (>0.95) of isotropic models to semivariance data were indicative of a high goodness of fit. Electrical conductivity was interpolated to a 5-m grid using kriging with weights based on semivariogram models.

Remote Sensing Data

A color infrared (CIR) aerial photograph (1-m spatial resolution) of the Watkinsville field acquired on January 1999 was obtained from the Natural Resource Conservation Service (NRCS). A CIR aerial photograph (0.15-m spatial resolution) of the Gold Hill field acquired in January 2005 was obtained from the City of Auburn. The Gold Hill photograph was resampled to 1-m using ArcGIS. Digital counts from both photographs, representing the spectral reflectance for each pixel, were derived using ERDAS Imagine (Leica Geosystems GIS and Mapping, Atlanta, GA). The digitized images had three bands: Band 1 was NIR reflectance (maximum sensitivity ≈ 730 nm), Band 2 was red reflectance (650 nm), and Band 3 was green reflectance (550 nm). Because differences in spectral sensitivity may offer increased information through the use of a spectral index (Flowers et al., 2003), the Normalized Difference Vegetation Index (NDVI) was calculated as:

$$NDVI = (NIR - R)/(NIR + R) \qquad \text{Eq. [3]}$$

where NIR = near infrared band, R = red band.

Soil Sampling and Laboratory Analyses

At the Watkinsville field, 82 soil samples were collected from the geo-referenced center of 25 m grids in November 2003. After preliminary soil analyses an additional 16 samples were collected to improve variogram structure. Five subsamples (one at the grid point and four within a 2-m radius) were obtained using a 2.5 cm diameter soil core at 0-20 cm depth and composited to make 98 samples. At the Gold Hill field, 90 soil samples were collected from the geo-referenced center of 25 m regular grids in May 2005. Three subsamples within a 2-m radius of the grid point were obtained using a 5-cm diameter soil core and composited.

Soils were air dried, gently crushed and passed through a 2-mm screen. Gravel (>2 mm) was removed. A sub-sample was oven dried to obtain a correction factor and to express analytical results on an oven-dried basis. Subsamples (25 g) were ground (<250 μm) and SOC was determined by dry combustion (Nelson and Sommers, 1982) using a LECO® CN-2000 carbon analyzer (Leco Corporation, St. Joseph, MI). Precision and accuracy were calculated by duplicate analysis on 10% of samples.

Particle size distribution was determined with the pipette method following soil organic matter removal with hydrogen peroxide and dispersion with sodium hexametaphosphate (Kilmer and Alexander, 1949).

Data Analysis

Ancillary data (i.e., TA, EC, RS) were overlaid and data spatially coinciding with soil sampling locations were extracted using ERDAS. A modified jackknifing method was used to split the data set into training (80% of data) and validation (20%) subsets. Points located near the boundary of the field were forced into the training set. Remaining points were randomly assigned to either of the two subsets. The training set was used to create a model, which was then used to estimate validation values, thus providing an independent assessment of the prediction quality.

Three approaches for mapping SOC were evaluated: i) Ordinary kriging, ii) Multiple linear regression, and iii) Artificial neural networks.

Ordinary Kriging

Log transformation of SOC previous to semivariogram analysis was conducted for the Watkinsville data to reduce skewness closer to zero; data were back-transformed to original values for reporting. Contour maps of semivariogram surfaces were created to assess anisotropy. Semivariogram models were described with three parameters: the range or distance where two observations become uncorrelated, the sill or maximum variance of the observations (as a function of separation distance), and the nugget which represents micro-scale variability and measurement error (Goovaerts, 1998). Relative structural variability (RSV) was used as an indicator of the proportion of spatially structured variability (Mueller and Pierce, 2003):

$$RSV = (\text{sill-nugget})/(\text{sill})*100 \qquad \text{Eq. [4]}$$

All semivariogram modeling was performed with GS+ (ver. 7.0, 2005, Gamma Design Software, Plainwell, MI). Soil organic C data were surfaced to 5-m grids using block kriging on a 5x5 local grid.

Multiple Linear Regression

Multiple linear regression (PROC REG, SELECTION = Stepwise; SLENTRY = 0.05; SLSTAY = 0.05) relating SOC to ancillary data (TA, EC, RS) was performed in SAS (ver 9.1, 2003 SAS Institute Inc., Cary, NC). Multicolinearity was assessed with intercept adjusted variance-inflation factors (VIF option).

Artificial Neural Networks

Artificial neural networks were developed in MATLAB (ver 6.1, 2001, The MathWorks, Inc., Natick, MA). The ANN technique provides flexible mathematical structures capable of identifying complex non-linear relationships between input and output data sets. A feed-forward back-propagation ANN was created using built-in functions of the neural network toolbox of MATLAB. Figure 1 shows the network architecture used, consisting of interconnected processing elements arranged in layers: (i) an input layer containing the input variables (i.e. location coordinates, TA, EC, RS), (ii) a hidden layer of neurons associated with the tan-sigmoid transfer function, and (iii) an output layer with the purelin (linear) transfer function. The tan-sigmoid function produced values from -1 to +1 and the linear output layer allowed the network to produce values outside this range. Each layer was connected by weights determined through a learning algorithm; the Levenberg-Marquardt or trainlm. A training set consisting of the inputs and known outputs was presented to the network. The network calculated the prediction error and the learning algorithm used this to modify weights. This procedure was repeated using all the data in the training set until a convergence criterion was met, e.g., error converged at zero. Thus, parameters were automatically estimated from the input data and desired response by means of the training algorithm.

The type of network in Fig. 1 has been recommended as a general function approximator (Demuth et al., 2005), since it can approximate any function equally well given sufficient neurons in the hidden layer (we used 5 neurons). Data were pre-processed before presenting to the network by data normalization (zero mean and unity standard deviation) and principal component analysis. The principal component analysis 1) orthogonalized components of the input vectors, producing uncorrelated variables, 2) ordered resulting orthogonal components so that those explaining the largest variation came first, and, 3) eliminated those components that contributed little to variation (Khattree and Naik, 2000). A similar network architecture and training algorithm was used by Somaratne et al. (2005) for predicting SOC across different land-use patterns and by Melesse and Hanley (2005) for a CO_2 flux simulation study.

Factor Analysis

The Watkinsville multivariate dataset contained 15 variables and the Gold Hill multivariate dataset contained 13 variables (Table 5). To minimize correlation between variables, factor analyses were performed. This technique developed groups of variables so that correlation within a group was enhanced and correlation between groups was minimized. Each factor represented a new variable (latent variable) that could be used as an independent variable in multiple linear regressions (Mallarino et al., 1999; Khattree and Naik, 2000). Factor analysis (principal component method and Varimax orthogonal rotation) was performed with SAS. Regression analysis evaluated the relationships between latent variables and SOC.

Cluster Analysis

Factor scores correlated with SOC were used in a clustering procedure (Fraisse et al., 2001; Terra et al., 2004). Clusters were created by unsupervised classification with the Management Zone Analyst software (Fridgen et al., 2004) using fuzzy k-means clustering. Fuzzy clustering allowed partial membership of pixels to multiple classes. The minimum number of clusters was set at two and the maximum at six. Other parameters were set as suggested by Fridgen et al. (2004): measure of similarity = Mahalanobis (because variables had unequal variances and non-zero covariance); fuzziness exponent = 1.5; maximum number of interactions = 300 and convergence criteria = 0.0001.The optimum number of clusters was decided by evaluating the two performance indices developed by the software, the fuzziness performance index (FPI) and the normalized classification entropy (NCE), as well as consideration of the within zone SOC variance reduction (Fraisse et al., 2001).

Model Validation

The validation data set was used to asses accuracy and precision of all predictions. The root-mean-square error (RMSE) and the prediction efficiency (PE) (Mueller and Pierce, 2003) were used as a measure of prediction quality:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{1}^{n}(y_i - \hat{y}_i)^2}{n}} \qquad \text{Eq. [5]}$$

$$PE = 100\% \cdot \frac{MSE_{avg} - MSE}{MSE_{avg}} \qquad \text{Eq. [6]}$$

where y_i is the measured value, $\hat{y}_i$ is the predicted value, n is the total number of observations, MSE is the square of RMSE, and MSE_{avg} is the MSE obtained by using the average field values.

RESULTS AND DISCUSSION

Correlation between Ancillary Variables and Soil organic C

There were no significant differences in SOC, clay, and sand contents (0-20 cm) between training and validation sets in either field, but differences between fields were highly significant (Table 1). The Watkinsville field had lower mean SOC (0.70 g kg^{-1}) compared to Gold Hill (1.21 g kg^{-1}). Surface soil texture ranged from sandy loam to clay in both fields, but mean clay content was 8 g kg^{-1} less at Watkinsville than at Gold Hill.

Correlation coefficients among ancillary variables, clay and SOC are shown in Table 2. Correlation between any two variables between fields was not consistent, suggesting differences in intrinsic variability of soil properties, historical artifacts, and/or management differences. In the Watkinsville field, only two terrain attributes (elevation and slope) were correlated with SOC. Negative correlation was expected, because SOC tends to accumulate at lower elevations and decreases on steeper slopes due to erosion. Elevation and slope had the strongest correlation with SOC in the Gold Hill field as well, but correlation was positive. Concentration of SOC was greater in the upper portion of the field where surface soil texture was finer. The Gold Hill field had some steep slopes, but the soil was well protected by dense pasture coverage.

In Gold Hill, a positive correlation between SOC and EC also existed, although there was likely not a causal mechanism explaining this correlation. Electrical conductivity has a fundamental relationship with soil texture and water content. Both, clay and water content (not shown) were highly correlated with SOC and EC (Table 2). A positive correlation of SOC with NIR ($r=0.25$) and negative correlation with red ($r=-0.28$) and green ($r=-0.27$) bands of the aerial photograph were also detected. High reflectance in the red was indicative of low chlorophyll concentration, and high reflectance in the NIR has been shown to be directly related to green leaf density (Knipling, 1970).

Geostatistical analyses

No spatial pattern in SOC was evident in Watkinsville (Fig. 2). Semivariogram analysis indicated weak spatial structure, with the range of spatial correlation < 70 m and RSV of 50%. The isotropic semivariogram model had high R^2 (0.8), but cross validation showed poor agreement between estimated and observed values (Table 3). Therefore, kriged values had high error variance.

At Gold Hill, SOC increased from south to north (Fig. 2). Geostatistical analyses were conducted on raw data since deviations from normality were small. Semivariogram analysis indicated strong spatial structure of SOC, with the range of spatial correlation > 250 m and RSV of 86% (Table 3). An isotropic semivariogram was used, because there was not significant anisotropy judged by a semivariogram surface (data not shown). Ordinary kriging was appropriate on this data set. Mueller and Pierce (2003) suggested that strong correlation ($r \geq 0.70$) was necessary for a covariable to be used in cokriging. From our data, elevation was the only ancillary variable meeting this requirement (Table 2), but cokriging did not enhance SOC prediction, as indicated by greater MSE in cross validation compared with ordinary kriging (Table 3). Regression kriging, a method that combines a linear regression model with kriging of the regression residuals (Odeh et al., 1995), was not appropriate because residuals did not exhibit spatial dependence (data not shown). Parameters presented in Table 3 are within the range of published data. From 9 spatial studies of SOC concentration, the range was 40 to 300 m, with 160 m on average, and RSV was 50 to 100 %, with 55% on average (McBratney and Pringle, 1999).

Multiple Linear Regression

Regression models explained 26% of SOC variability in Watkinsville and 63% in Gold Hill (Table 4). There was not significant correlation between independent variables as indicated by very low variance inflation factors of the selected model variables. Elevation was a key contributor to SOC variation in both fields, although it was negatively correlated with SOC in Watkinsville and positively correlated with SOC in Gold Hill. Soil at low topographic positions in Gold Hill had a sandier epipedon formed from alluvial sediments, which explained the low SOC concentration. The second variable in the regression models was slope in Watkinsville and NDVI in Gold Hill. Other studies found significant relationship between terrain attributes and SOC. For example, More et al. (1993) used wetness index, stream power index and aspect as predictors of SOC with R^2 of 0.48. Gessler et al. (2000) explained SOC variability with a combination of slope and log flow accumulation (R^2=0.80), or with compound topographic index as the only regressor (R^2=0.78). Florinsky et al. (2002) reported significant influence of elevation, slope, plan, and profile curvatures with R^2 of 0.37. Terra et al. (2005) reported the significant effect of elevation, slope, compound topographic index, EC, water table depth, sand and silt content on explaining SOC variation. Terra et al. (2005) also reported that elevation and slope became non significant when sampling intensity changed from a 9 x 18 m grid to a 34 x 36 m grid.

Although the contribution of NDVI to explain SOC variability in Gold Hill was small, it was highly significant in the model (P=0.0007). The NDVI has been widely measured as an indicator of plant stress and was positively correlated with crop yield (Shanahan et al., 2001; Yang and Everitt, 2002). In our study, it was likely that better grass growth indicated by higher NDVI values is associated with higher SOC (better plant growth conditions) in the surface soil.

Factor Analyses

There were various degrees of correlation among ancillary variables, e.g., between compound topographic index and ln catchment area, surface and deep EC, and aerial photograph bands. Degree of correlation varied with field (Table 2). Therefore, factor analysis was appropriate to circumvent the problems created by correlated variables and to facilitate the interpretation of complex relationships. Factor loadings, the first six eigenvalues of the correlation matrix, and cumulative variances for each field are shown in Table 5. Highest loadings for each factor (in bold) and the variable with highest influence on a particular factor (latent variable) are also reported. Two or more variables grouped in a latent variable suggest a common factor that made them vary together within a site. Signs of the factor loadings indicate how these variables relate when representing the common factor. Variables with large (positive or negative) factor loadings were more likely to represent a common factor (Mallarino et al., 1999). Although there is no rule for deciding what is large, in our case, decisions were easy because some loadings were clearly distinguishable from the rest. We used factor analysis to form groups of correlated variables and define latent variables that represented the groups. Then we used these latent variables in stepwise multiple regression analyses to explain SOC (Table 6).

In Watkinsville, Factors 1, 3, 4, and 5 were chosen by a stepwise multiple linear regression relating factors to SOC (Table 6). The latent variable derived from Factor 1 represented field-scale EC (Table 5). The negative sign of the latent variable EC with SOC indicated that historical erosion probably exposed clayey subsoil with low SOC. The latent variable derived from Factor 3 represented soil wetness, indicating that areas in the field which collect water leads to higher SOC. Factors 4 and 5 were related to elevation and slope, respectively. Coefficient signs indicated that SOC accumulated at low topographic positions with less steep terrain.

In Gold Hill, Factors 1, 2, 5 and 6 were chosen by the stepwise multiple linear regression procedure (Table 6). The latent variable derived from Factor 1 represented elevation (Table 5), which had the greatest contribution to the model. The positive sign indicated a direct relation between elevation and SOC. The latent variables derived from

Factors 2 and 6 (aerial imagery) indicated that favorable conditions for pasture growth were associated with zones of SOC accumulation. Factor 5 reflected EC, which was related to soil texture.

Soil organic C Maps

Maps of SOC using different methods are shown in Figures 3 and 4. Generally, all models underestimated SOC. Watkinsville maps created with MLR had very low PE and high RMSE. There was a slight improvement of PE using kriging compared with MLR, but the best performance was obtained with ANN.

Gold Hill maps were of higher quality than Watkinsville maps. Kriging and MLR produced similar RMSE and PE, but ANN had the highest PE of 62% (50% higher than with other methods). At both sites, ANN was also the best predictor of the variance of actual observations, i.e., the range of SOC. Mueller and Pierce (2003) obtained a PE of 60% for SOC produced with kriging and regression with terrain attributes (northing, elevation, slope, plan, and profile curvatures) of cropland in Michigan. On cropland in Alabama, Terra et al. (2004) obtained a PE of 63% with kriging and 41% with regression using terrain attributes (elevation, slope, and compound topographic index), EC, water table depth, and clay and sand content. Clay and sand content was not used as regressors in this study, because the objective was to evaluate how more easily obtainable and less expensive ancillary variables (i.e., terrain attributes, electrical conductivity, and aerial photograph data) might perform as SOC predictors.

Comparing map qualities or goodness of fit between prediction techniques was informative. The feed-forward back-propagation ANN outperformed kriging and MLR at both study sites. A more comprehensive study would be required to determine the optimum list of variables for the training of neural networks in predicting SOC concentrations. In future work, it would be important to evaluate the effect of individual variables and their sensitivity in the model.

Cluster Analyses

Cluster analysis was used to group areas in the field with similar characteristics. Variables used for cluster analyses were latent variables correlated with SOC (Table 7). The complete data set (training plus validation) was used. The fuzzy k-means procedure created classes that were discernible, but not completely be attributed to a particular latent variable (Fig. 5, Table 7). While the performance indices (FPI and NCE) did not clearly point to an optimal solution, reducing within-zone SOC variance was also used (Fraisse et al., 2001). The four clusters in Watkinsville were created using Factors 2, 3, 4, and 5, representing the latent variables of aerial photograph data, wetness condition, elevation, and slope, respectively. The two clusters in Gold Hill were created using Factors 1 and 6, representing the latent variables of elevation and NIR (the first band on the aerial photograph), respectively.

Analysis of variance (Proc Mixed) detected significant differences ($P \leq 0.05$) among clusters in both fields. At Watkinsville, the highest SOC concentration was in the cluster with relatively high compound topographic index (wetness index). This was probably the zone in the field where plants had less water constraint during the growing season and therefore produced and returned more biomass to the soil. Although there were no statistical differences among the other clusters, lowest SOC concentration was in the cluster occupying steepest slopes, likely representing the zone in the field with greatest previous erosion. At Gold Hill, highest SOC concentration was in the cluster delimited by high elevation and lowest concentration in the cluster delimited by low elevation. In this particular field, soil at higher elevation had finer texture and although this area had some steep slope, the soil was well protected by a dense pasture biomass. The cluster with medium SOC was delimited by high NIR reflectance, indicative of active growing plant biomass.

SUMMARY AND CONCLUSIONS

There could be causal effects that explain the relationship between SOC and terrain attributes, but relationships between SOC and EC, or between SOC and RS were considered indirect. Indirect relationships should not preclude their importance as easily obtainable ancillary variables capable of depicting field scale soil variability. Regardless of the analytical procedure used, TA, field-scale EC, and RS explained SOC variability. Therefore they can be used to enhance SOC maps. Factor analysis followed by multiple linear regression helped define the most influential variables on SOC at a field scale.

Artificial neural networks are flexible mathematical structures that were able to identify non-linear relationships between input and output data sets. This technique produced better prediction of SOC than other methods (kriging and MLR). A weakness of the ANN was their specificity for the fields we studied.

The quantitative technique for cluster definition was appealing, because it objectively delineated homogeneous soil units, and therefore, would reduce sampling costs to characterize SOC changes in time without sacrificing precision.

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Table 1. Summary statistics and significance test for SOC, clay and sand concentrations (dag kg^{-1}) (0-20 cm) in the training and validation data from Watkinsville, GA and Gold Hill, AL.

Variable	Statistics	Watkinsville (W)		Gold Hill (GH)	
		Training	Validation	Training	Validation
SOC dag kg^{-1}	Minimum and Maximum	0.43~1.49	0.47~1.10	0.54~1.95	0.71~1.83
	Mean	0.70	0.70	1.21	1.27
	Standard Deviation	0.19	0.15	0.31	0.30
	Number of samples (n)	78	20	72	18
	P>F (Ho: train = validation)	0.90		0.48	
	P>F (Ho: W = GH)	<0.0001			
Clay dag kg^{-1}	Minimum and Maximum	5.8~44.5	9.3~42.1	10.2~47.5	21.3~40.6
	Mean	21.6	21.2	29.6	30.3
	Standard Deviation	9.7	9.9	7.4	5.8
	P>F (Ho: train = validation)	0.87		0.71	
	P>F (Ho: W = GH)	<0.0001			
Sand dag kg^{-1}	Minimum and Maximum	39.4~76.5	40.6~74.1	26.04~77.9	35.9~58.9
	Mean	59.9	60.9	47.8	46.5
	Standard Deviation	9.5	10.2	9.6	7.1
	P>F (Ho: train = validation)	0.71		0.60	
	P>F (Ho: W = GH)	<0.0001			

Table 2. Pearson linear correlation coefficients between ancillary variables and SOC concentration (dag kg^{-1}) (0-20 cm) at the Watkinsville, GA (n=78), and Gold Hill, AL (n=72), sampling sites, P≤0.05.

Site/ Var[†]	Eleva	Slope	Plan	Prof	CTI	lnCA	EC_s1	EC_d1	EC_s2[‡]	EC_d2	NIR	Red	Green	Clay
Watkinsville														
Eleva	1													
Slope	-0.45	1												
Plan	NS[*]	NS	1											
Prof	-0.23	NS	-0.22	1										
CTI	NS	-0.24	-0.55	NS	1									
lnCA	NS	NS	-0.62	NS	0.92	1								
EC_s1	NS	NS	NS	NS	NS	NS	1							
EC_d1	NS	NS	0.26	-0.23	-0.26	NS	0.83	1						
EC_s2	NS	NS	0.34	-0.26	-0.25	NS	0.71	0.83	1					
EC_d2	NS	NS	0.31	-0.31	-0.31	-0.27	0.69	0.93	0.88	1				
NIR	NS	NS	NS	NS	NS	NS	NS	-0.25	-0.27	-0.24	1			
Red	NS	NS	NS	NS	NS	NS	-0.24	-0.34	-0.34	-0.32	0.68	1		
Green	NS	NS	NS	NS	NS	NS	-0.23	-0.33	-0.32	-0.33	0.74	0.95	1	
Clay	NS	NS	0.27	NS	NS	NS	0.42	0.43	0.55	0.44	NS	NS	NS	1
SOC	-0.26	-0.27	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS
Gold Hill														
Eleva	1													
Slope	0.64	1												
Plan	0.37	NS	1											
Prof	-0.39	-0.26	-0.27	1										
CTI	-0.54	-0.39	-0.58	0.42	1									
lnCA	-0.31	NS	-0.57	0.35	0.91	1								
EC_s1	0.45	0.25	NS	NS	NS	NS	1							
EC_d1	0.51	0.40	NS	NS	NS	NS	0.57	1						
NIR	NS	0.35	NS	NS	NS	NS	NS	0.28	ND[~]	ND	1			
Red	NS	NS	NS	NS	NS	NS	NS	NS	ND	ND	NS	1		
Green	NS	NS	NS	NS	NS	NS	NS	NS	ND	ND	0.35	NS	1	
Clay	NS	NS	NS	0.28	NS	NS	0.46	NS	ND	ND	NS	-0.28	-0.31	1
SOC	0.71	0.50	NS	NS	-0.29	NS	0.43	0.36	ND	ND	0.25	-0.28	-0.27	0.35

[*]NS = Not significant at P≤0.05 level
[~]ND = No data
[†]Variables: Eleva = Elevation; Plan = Plan curvature; Prof = Profile curvature; CTI = Compound topographic index; lnCA = natural log of Catchment area; EC_s = Electrical conductivity 0-30 cm; EC_d = Electrical conductivity 0-90 cm; NIR = Near infrared; SOC = Soil Organic Carbon
[‡]In watkinsville EC was measured in two occasions

Table 3. Isotropic semivariogram model parameters for SOC (dag kg^{-1}) (0-20 cm) at Watkinsville, GA (n=78) and Gold Hill, AL (n=72) sites.

Data set	Model†	Range (m)	Nugget	Sill	RSV‡ (%)	R^2	Kriging Cross Validation	
							MSE§	R^2
Watkinsville SOC	Exp	68	0.031	0.061	50	0.80	0.03	0.04
Gold Hill SOC	Sph	257	0.015	0.107	86	0.99	0.03	0.69
Gold Hill SOC x Elev¶	Gau	293	0.001	2.010	100	0.99	1.21	0.68

† Exp = Exponential, Sph = Spherical, Gau = Gaussian.
‡ RSV = Relative structural variability, defined in the text.
§ MSE = Mean Square Error, defined in the text.
¶ Elev = Elevation.

Table 4. Stepwise regression parameters relating soil organic C to ancillary variables, partial and model R^2 values, intercept adjusted variance inflation factors (VIF), and significant test for the Watkinsville, GA and Gold Hill, AL sites.

Site	Parameter	Estimate	Partial R^2	Model R^2	VIF	P>F
Watkinsville	Intercept	10.401			0.00	<0.0001
	Elevation	-0.034	0.19	0.19	1.26	<0.0001
	Slope	-0.043	0.07	0.26	1.26	<0.0001
Gold Hill	Intercept	-7.267			0.00	<0.0001
	Elevation	0.0393	0.56	0.56	1.01	<0.0001
	NDVI†	1.200	0.07	0.63	1.01	0.0007

†NDVI = Normalized difference vegetation index, defined in the text.

Table 5. Factor loadings for the first six factors, eigenvalues, cumulative contribution of explained variance, for the Watkinsville, GA and Gold Hill, AL dataset. Latent variable interpretive names, based on the highest loading factors (in bold) are also provided.

Variable / parameter†	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6
Watkinsville						
X coordinate	0.12	-0.06	-0.06	**0.96**	0.07	0.02
Y coordinate	-0.11	0.11	-0.02	0.22	0.05	0.09
Elevation	0.09	0.00	-0.15	**-0.88**	-0.26	-0.15
Slope	0.10	0.04	-0.08	0.23	**0.96**	-0.01
Plan curvature	0.13	0.05	-0.38	-0.01	-0.09	-0.16
Profile curvature	-0.09	0.03	0.21	0.12	-0.01	**0.95**
CTI	-0.17	-0.01	**0.94**	-0.02	-0.23	0.12
Ln Catchment area	-0.14	-0.02	**0.95**	0.07	0.12	0.12
EC_s 2003	**0.88**	-0.08	-0.02	-0.04	0.05	0.03
EC_d 2003	**0.95**	-0.09	-0.16	0.00	0.03	-0.07
EC_s 2004	**0.89**	-0.20	-0.05	0.08	0.02	-0.02
EC_d 2004	**0.94**	-0.10	-0.18	0.03	0.04	-0.09
Near Infra Red reflectance	-0.04	0.67	0.02	-0.10	0.04	-0.02
Red reflectance	-0.18	**0.97**	-0.03	-0.03	0.01	0.02
Green reflectance	-0.13	**0.97**	-0.01	0.00	0.01	0.01
Eigenvalue	4.38	2.72	2.36	1.83	0.98	0.75
Cumulative variance	0.29	0.47	0.63	0.75	0.82	0.87
Latent variable††	EC	Photo	Wetness	Elevation	Slope	Prof. Curv.
Gold Hill						
X coordinate	-0.17	-0.21	-0.01	**0.92**	-0.09	-0.05
Y coordinate	**0.94**	-0.06	-0.07	-0.08	0.16	0.10
Elevation	**0.92**	0.03	-0.16	-0.12	0.16	0.05
Slope	0.53	0.06	-0.05	-0.26	0.13	0.16
Plan curvature	0.20	0.06	-0.33	-0.04	0.06	0.02
Profile curvature	0.00	-0.09	0.18	0.04	0.03	0.02
CTI	-0.23	-0.05	**0.93**	0.06	-0.06	-0.02
Ln Catchment area	-0.01	-0.04	**0.96**	-0.05	-0.02	0.06
EC_s	0.29	-0.09	-0.07	-0.09	**0.92**	0.06
EC_d	0.34	0.08	-0.04	-0.36	0.35	0.05
Near Infra Red reflectance	0.13	0.14	0.04	-0.04	0.06	**0.97**
Red reflectance	0.02	**0.99**	-0.05	-0.09	-0.02	-0.01
Green reflectance	-0.04	**0.96**	-0.03	-0.11	-0.06	0.18
Eigenvalue	4.18	2.27	2.13	1.01	0.81	0.76
Cumulative variance	0.32	0.50	0.66	0.74	0.80	0.86
Latent variable††	Elevation	Photo	Wetness	X Coord.	EC	NIR

† ECs = electrical conductivy at 0-30 cm depth
ECd = electrical conductivity at 0-90 cm depth
CTI = Compound Topographic Index

††Latent variable names: EC = electrical conductivity, Photo = aerial photograph reflectance in the red and green bands, Wetness = indicative of soil water holding capacity, Prof. Curv. = profile curvature, X Coord = easting coordinade, NIR = near infrared reflectance.

Table 6. Stepwise regression relating SOC (dag kg^{-1}) (0-20 cm) to factor scores (latent variables), partial and model R^2 values, and significant test on the training set of the two study sites.

Site	Parameter[†]	Estimate	Partial R^2	Model R^2	P>F
Watkinsville	Intercept	0.70			<0.0001
	Factor 1 (EC)	-0.03	0.03	0.03	0.0657
	Factor 3 (Wetness)	0.07	0.10	0.13	0.0023
	Factor 4 (Elevation)	0.06	0.09	0.22	0.0019
	Factor 5 (Slope)	-0.07	0.13	0.35	0.0002
Gold Hill	Intercept	1.22			<0.0001
	Factor 1 (Elevation)	0.20	0.60	0.60	<0.0001
	Factor 2 (Photo)	-0.06	0.02	0.62	0.0567
	Factor 5 (EC)	0.06	0.03	0.65	0.0076
	Factor 6 (NIR)	0.06	0.02	0.67	0.0349

[†] Latent variable names are given in parenthesis: EC = electrical conductivity, Wetness = indicative of soil water holding capacity, Photo = aerial photograph reflectance in the red and green bands, NIR = near infrared reflectance.

Table 7. Pearson linear correlation coefficients between factor scores and SOC concentration (dag kg^{-1}) (0-20 cm) at the Watkinsville, GA (n=98) and Gold Hill, AL (n=90) sites, P≤0.05.

Factor	Watkinsville†	Gold Hill†
1	NS	0.73 (Elevation)
2	-0.26 (Photo)	NS
3	0.28 (Wetness)	NS
4	0.21 (Elevation)	NS
5	-0.31 (Slope)	NS
6	NS	0.25 (NIR)
7	NS	NS
8	NS	NS
9	NS	NS

† Latent variable names are given in parenthesis: Photo = aerial photograph reflectance in the red and green bands, Wetness = indicative of soil water holding capacity, NIR = near infrared reflectance.

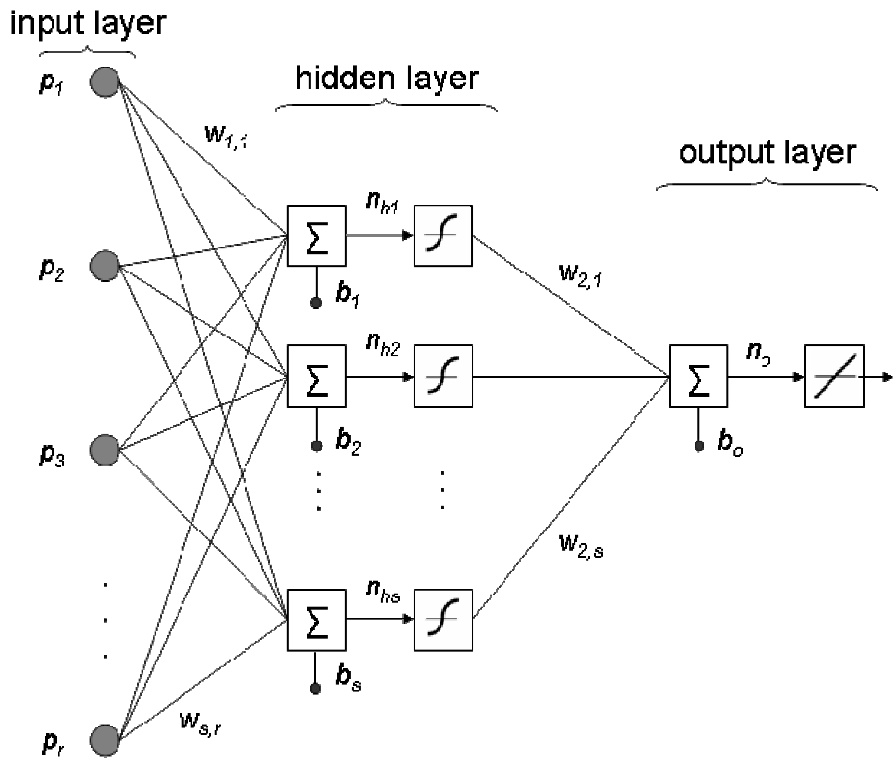

Fig. 1. Architecture of a single-hidden layer feed-forward back-propagation artificial neural network. P = input variable; W = weight; b = prediction error; n_h= hidden layer of networks; n_o = output layer.

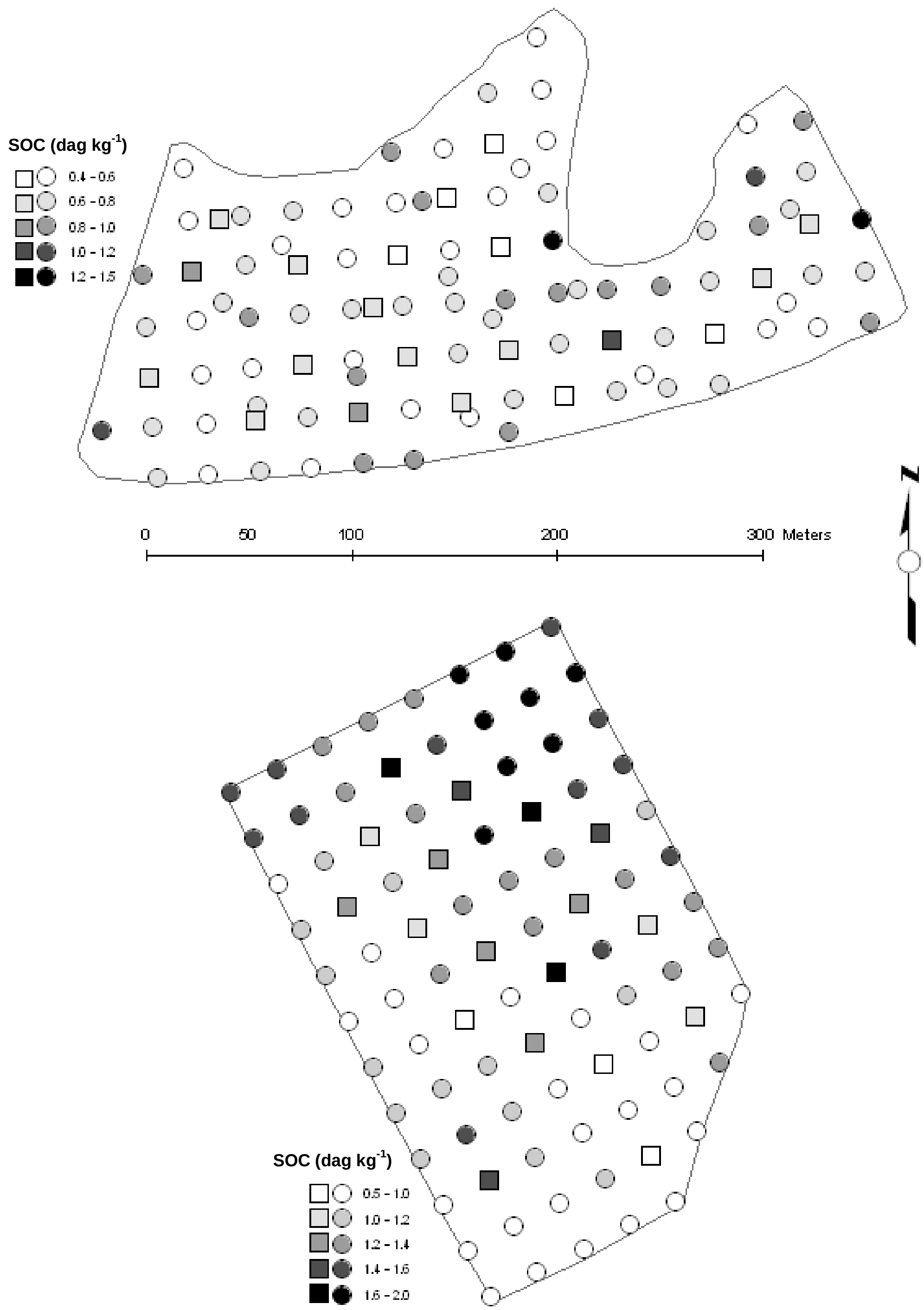

Fig. 2. Layout of sampling points and ranges of SOC (dag kg^{-1}) (0-20 cm) at Watkinsville and Gold Hill. Circles correspond to the training set and squares to the validation set.

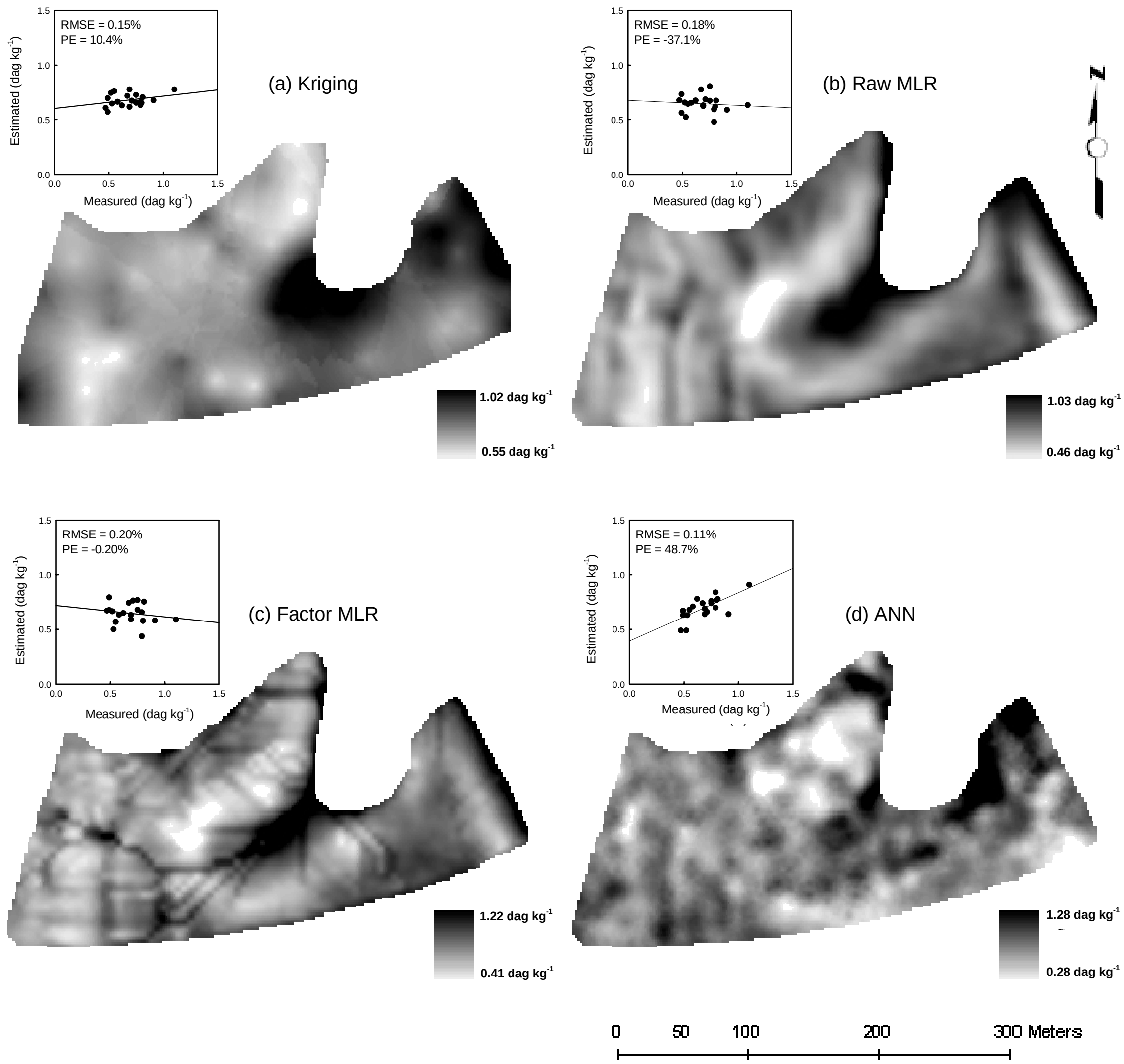

Fig. 3. Soil organic C Maps (0-20 cm) and map quality indices for Watkinsville using: (a) Kriging, (b) Multiple Linear Regression (MLR) with raw data, (c) MLR with factor scores, and (d) Artificial Neural Networks (ANN). Measured versus predicted comparisons were done on the validation set. RMSE = Root mean squared error; PE = Prediction efficiency (defined in the text).

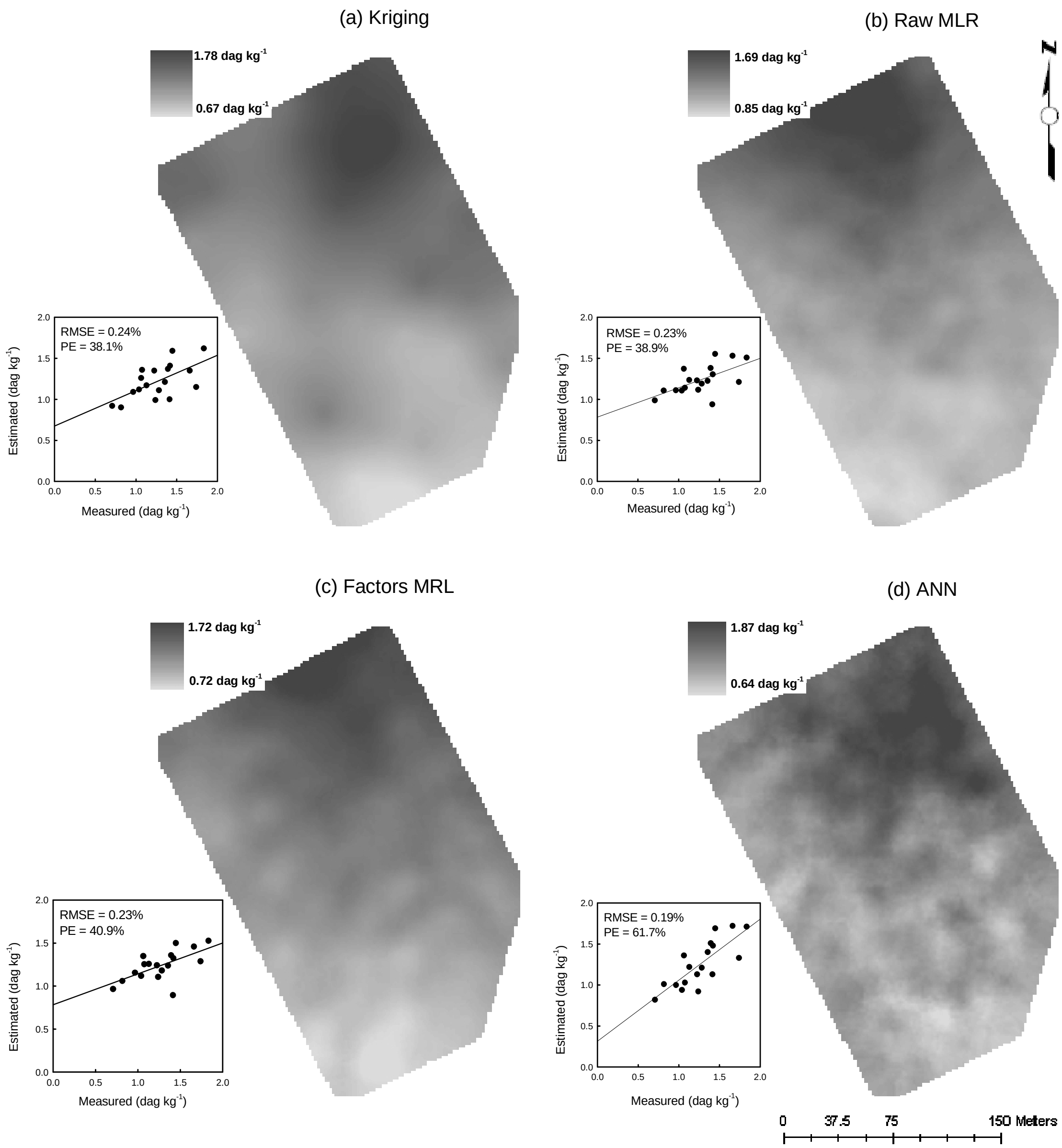

Fig. 4. Soil organic C Maps (0-20 cm) and map quality indices for Gold Hill using: (a) Kriging, (b) Multiple Linear Regression (MLR) with raw data, (c) MLR with factor scores, and (d) Artificial Neural Networks (ANN). Measured versus predicted comparisons were done on the validation set. RMSE = Root mean squared error; PE = Prediction efficiency (defined in the text).

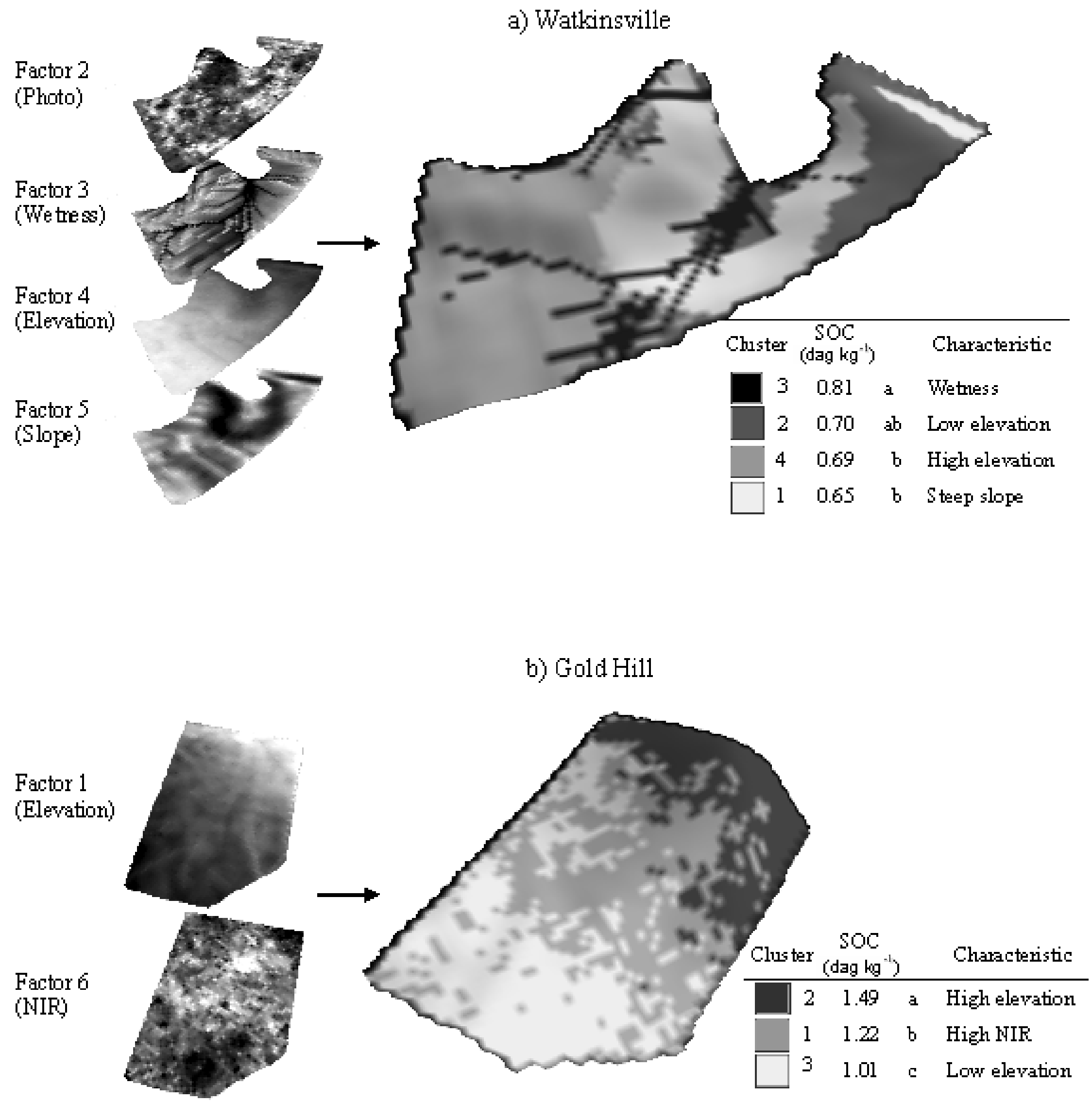

Fig. 5 Clusters generated using fuzzy k-means clustering for a) Watkinsville, and b) Gold Hill. Grid files of factor scores used for the cluster analyses are shown on the left. Tables with soil organic C means and letters separating means (P≤0.05) are shown on the right

III. SIMULATING FIELD-SCALE SOIL ORGANIC CARBON DYNAMICS USING EPIC

ABSTRACT

Simulation models integrate our understanding of soil organic C (SOC) dynamics and are useful tools for evaluating impacts of crop management on soil C sequestration; yet, they require local calibration. Our objectives were to calibrate the Environmental Policy Integrated Climate (EPIC) model, and evaluate its performance for simulating SOC fractions, as affected by landscape and management system. An automatic parameter optimization procedure was used to calibrate the model against results from a site-specific experiment in central Alabama. Model performance in predicting corn (*Zea mays* L.) and cotton (*Gossypium hirsutum* L.) yields and SOC dynamics was evaluated on different landscapes of a Coastal Plain soil (Typic, Oxyaquic and Aquic Paleudults) during the initial adoption of conservation tillage (5 years). Model performance was statistically evaluated with regression and Mean Squared Deviations (MSD). Simulated yield explained 88% of measured yield variation, with greatest disagreement between measurements and simulations at the sideslope position and least disagreement in the drainageway. Simulation of SOC fractions explained about 7, 27 and 41% of the total variation in the data for microbial biomass C (MBC), slow humus C (SHC) and total organic C (TOC), respectively. Lowest errors on TOC simulations (0-20 cm) were found

on the sideslope and in the drainageway. We concluded that the automatic parameterization was successful, although further work was needed to fine tune the SHC and MBC fractions, and to improve EPIC predictions of SOC dynamics with depth.Overall, EPIC was sensitive to spatial differences that resulted from landscape positions in the driving variables. With correct parameterization, EPIC would be a valuable tool for simulating field-scale SOC dynamics affected by short-term management decisions.

Abbreviations: CT, conventional tillage; CTm, conventional tillage + manure; EPIC, Environmental Policy Integrated Climate; FAST, Fourier amplitude sensitivity test; FHP, fraction of humus in passive pool; GIS, geographical information system; GLUE, generalized likelihood uncertainty estimation; HI, harvest index; IM; inequality of means; LC; lack of correlation; MBC, microbial biomass C; MSD, mean squared deviation; MUSLE, modified universal soil loss equation; NT, no tillage; NTm, no tillage + manure; NU; non unity of slopes; PHU, potential heat units; POC, particulate organic C; RUE, radiation use efficiency; SA, sensitivity analysis; SHC, slow humus C; SHWT, seasonal high water table; SOC, soil organic C; SOM, soil organic matter; TOC, total organic C; UA, uncertainty analysis; USLE, universal soil loss equation.

INTRODUCTION

The balance between primary production and decomposition of soil organic mater (SOM) determines the amount of organic C stored in soils. The study of complex mechanisms and interactions, by which soil use and management practices affect the nature and concentration of SOC, is best approached by field experimentation coupled with simulation models. During recent years, SOM simulation models have integrated our understanding of SOC dynamics and have consequently become tools for evaluating SOC sequestration and projecting future impacts of management practices on environmental quality and climate change (Rosenberg et al., 1999).

Soil organic matter, containing 50 to 58% C, is a complex mixture of organic compounds with different turnover time (Nelson and Sommers, 1982). There is no simple analytical technique for qualifying and quantifying SOM fractions. In fact, the distinction between fractions is conceptual and convenient for modeling SOC dynamics. Molina and Smith (1998) listed 33 SOC simulation models, most of which were process-based and multi-compartmental. Soil organic C is subdivided into several pools with unique characteristics and decomposition rates that follow first-order kinetics. Carbon additions from crop residues or animal manures are successively transferred into different pools varying in stability. The multi-compartmental structure of these models provides flexibility and the ability to accommodate control variables (e.g. water content, temperature, erosion). The fundamental equation of C flux between pools is of the form (Polyakov and Lal, 2004):

$$\frac{\partial \mathrm{C}}{\partial t} = -kmpC_{soil} + h \qquad [1]$$

where C_{soil} = concentration of organic C in soil; t = time; k = first-order decomposition coefficient; m, p = correction factors for soil temperature and moisture; h = additional rate (independent of decomposition rate), such as erosion, deposition or net primary production.

A special issue of Geoderma (Volume 81, 1997) reported the performance of nine SOM models across 12 long-term data sets. The Century model (Parton et al., 1987; 1994) successfully simulated SOM across a variety of land use and climates and was among the models that consistently produced low errors and showed the lowest overall bias (Kelly et al., 1997; Smith et al., 1997). Century classifies SOC into three pools based on the rate of mineralization and turnover. First, the labile pool represents easily mineralizable compounds along with microbial and fungal biomass that generally comprises about 5-15% of the total SOC and has a turnover rate of month to years. Second, the slow pool, which represents recently added residues, comprises 20-40% of the total SOC with turnover time of several decades. Third, the stable or recalcitrant pool, comprises the remaining 60-70% and has turnover time of hundreds to thousands of years.

EPIC, developed in the early 1980s, is a process-based model capable of describing interactions among climate, soil and management at a subwatershed scale (1 to 100 ha). The acronym initially stood for the Erosion Productivity Impact Calculator, as it was designed to estimate erosion impacts on crop productivity throughout the USA (Williams, 1990). Later, evolution of the model with incorporation of functions to simulate environmental processes related to water quality and SOC sequestration, merited its name change to the Environmental Policy Integrated Climate model. The EPIC model is flexible in handling a wide array of crop rotations, management systems, and environmental conditions, and has been tested in numerous environments. A comprehensive description of development and application of EPIC was presented by Gassman et al. (2004). The original C cycling routine in EPIC was relatively simple and a function of soil N levels, but EPIC v3060 received major modification of its C routine with concepts derived from the Century model. Detailed description of new C and N algorithms can be found in Izaurralde et al. (2001; 2006).

Model parameters are best determined by experimentation, but spatial variability, measurement errors and budget constraints for field experiments often make it necessary to estimate or modify parameters through calibration. A common calibration approach consists of adjusting model parameters to minimize deviations between simulated and observed values. Manual calibration is subjective and time-consuming, but automated iterative procedures have been developed (Eckhardt and Arnold, 2001; Zhai et al., 2004; Wang et al., 2005). Sensitivity analysis, which provides insight into the relative importance of each parameter in determining model performance can be used to identify key parameters to be optimized. Recently, Wang et al. (2005) performed a sensitivity analysis on EPIC v3060. They adjusted corn yield and SOC related parameters using an automatic parameter optimization procedure. Parameters of major importance were: difference of soil water content at field capacity and wilting point, biomass-energy ratio, potential heat units, harvest index, fraction of organic C in microbial biomass, fraction of humus in the passive pool, and microbial decay rate coefficient.

The newly modified EPIC v3060 is expected to perform well under a range of environmental and management conditions, but further calibration and validation studies are needed. A challenging aspect of site-specific modeling is to account for the transfer of relevant components within and between landscapes. Most process models consider soil losses, but do not account for gains or deposition (Pennock and Frick, 2001; Polyakov and Lal, 2004). The inability of most models to account for soil deposition may impair them from detecting management impacts on SOC at cumulative landscape positions.

Since its establishment in 2000, a site-specific experiment at E.V. Smith research center (Shorter, Alabama) has provided information on the nature and sources of variation in soil properties and crop productivity, as well as soil-landscape relationships (Terra et al., 2004; 2005). Soil properties, field operations, crop yield, and weather data have been documented. This experiment provides a valuable arena for calibrating SOC simulation models for the Southern Coastal Plain Major Land Resource Area, which makes up the major portion of agricultural lands in the southeastern USA. The experiment also provides a unique opportunity to evaluate short-term changes in SOC during the transition to conservation management on degraded Ultisols. To date, there have been no studies of the ability of EPIC v3060 to accurately simulate within-field variability of SOC, and no calibration study of EPIC v3060 has been performed in the Coastal Plain. Our objective was to calibrate EPIC v3060 against results from a site-specific experiment in the Coastal Plain of Alabama and to test model performance in predicting SOC dynamics at different landscape positions. The calibration process focused primarily on the crop growth and C modules.

MATERIALS AND METHODS

EPIC Model Description

EPIC was designed to simulate field-scale crop yield and SOC dynamics. It operates on a daily time-step and can perform long-term simulations (hundreds of years) on watersheds up to 100 ha. Twelve plant species can be modeled simultaneously allowing inter-crop, cover-crop mixtures, and/or similar scenarios to be simulated. The model can account for tillage effects on surface residue, soil bulk density, mixing of residue and nutrients in the surface layer, wind and water erosion, hydrology, soil temperature and heat flow, C, N, and P cycling, fertilizer and irrigation effects on crops, pesticide fate, and economics (Williams, 1990). Simulations are driven by daily weather (input or simulated) including temperature, radiation, precipitation, relative humidity and wind speed. Daily crop growth is simulated from solar radiation and modified by stress factors (e.g., water, temperature, nutrients, and pests).

In EPIC v3060, SOC and N are split into the same three pools as in the Century model (labile, slow and recalcitrant). Carbon and N can also be leached or lost in gaseous forms. Crop residues (including roots) and manure added to the soil are split into two compartments (metabolic and structural) based on lignin and N contents. The basic difference between Century and the new C cycling routine in EPIC v3060 are: i) within EPIC, leaching of organics is estimated by equations that use a linear partition coefficient and soil water content to calculate movement as modified by sorption; while in Century, monthly water leached below the 30-cm depth is modified by soil texture; ii) C transformation rates are based on temperature and water content calculated with equations originally built in EPIC; iii) the surface litter fraction in EPIC has a slow compartment in addition to the metabolic and structural litter components in Century; and, iv) in EPIC, lignin concentration is modeled as a function of plant age, whereas in Century it is modeled as a function of annual precipitation. Apart from the four aspects mentioned, EPIC does not account for soil deposition, while Century does (Polyakov and Lal, 2004). According to R.C. Izaurralde (personal communication), EPIC provides an estimate of soil deposition within the watershed. Soil deposition is obtained by calculating the difference in soil erosion estimated from two equations, the Universal Soil Loss Equation (USLE) and the modified USLE (MUSLE). The latter implicitly accounts for depositional processes that occur in the watershed.

Field Background

We used data from the “Site-Specific Agriculture and Landscape Dynamics” experiment, conducted at the Auburn University E.V. Smith Research and Extension Center in central Alabama (32.4°N 85.9°W, ~68 m above MSL). Background of the experimental site and results obtained during the first three years was provided by Terra et al. (2004; 2005). Briefly, the experiment was started in 2000 on a 9-ha field that had approximately 30 years of previous row cropping; mostly cotton, and conventional soil tillage with moldboard or chisel plowing and disking. Soils were predominantly fine and fine-loamy, kaolinitic, thermic Typic and Aquic Paleudults. Experimental treatments consisted of two tillage systems (conventional and conservation) with and without annual application of dairy manure in a corn (*Zea mays* L.) –cotton (*Gossypium hirsutum* L.) rotation (both phases of the rotation present each year). The conservation system consisted of no-tillage (NT) with non-inversion in-row subsoiling and a winter cover crop mixture of white lupin (*Lupinus albus* L.), crimson clover (*Trifolium incarnatum* L.), and fodder radish (*Raphanus sativus* L.) prior to corn and a mixture of black oat (*Avena strigosa* Schreb.) and rye (*Secale cereale* L.) prior to cotton. Sunn-hemp (*Crotalaria juncea* L.) cover crop was included between corn and the rye-oat cover crop since 2003. Conventional tillage (CT) did not include cover crops, but winter weeds were not controlled. Treatments were established in 6.1-m x 240-m strips crossing the landscape in a randomized complete block design with six replications (Fig. 1).

Model Inputs

Weather, soil and management input files were prepared to conduct 5-year simulations, from January 2001 to December 2005.

Weather

A daily weather file of maximum and minimum temperature, precipitation, radiation, relative humidity, and wind speed was established from weather data collected at the experimental station as part of the Auburn University Mesonet (AWIS, 2005). EPIC provided several options for estimating evapotranspiration with the Hargreaves method chosen (Hargreaves and Samani, 1985). Monthly mean air temperature, solar radiation, and total precipitation during the study period are shown in Fig. 2. During the 5 years of simulation, the site received 1215 mm of annual precipitation and 17.7 °C of mean annual air temperature.

Soil

Three major soil landscapes were identified based on previous work (Terra et al., 2004; 2005). The summit position was an elevated area (70.2 m) of relatively flat topography (0-2% slopes) dominated by well-drained soils (Typic Paleudults) with sandy surface and a deep (>150 cm) seasonal high water table (SHWT). The sideslope position

(2-6% slopes) was eroded and had an exposed argillic horizon (Typic Paleudults). A concave drainageway occupied the lowest elevation in the field (68.3 m) with more poorly drained soil (SHWT = 0.5 to 1m) (Aquic Paleudults) and that accumulated eroded sediment from upslope areas resulting in relatively high SOC. These three soil landscapes were identified as Clusters 2, 3 and 4 by Terra et al. (2005). Model simulations were conducted in these areas, because they typified the landscape variability of the site and region.

Soil properties data used for model calibration and validation were from samples collected in 2001, 2003 and 2005. In 2001 and 2003, an average of 10 soil surface (0-30 cm) samples was collected per landscape position and treatment. In addition, a set of 36 surface (0-20 cm) samples that comprised the three soil landscapes and four treatments (CT, NT, CT + manure, and NT + manure) was collected in 2005 (Fig. 1). The model was initialized with soil surface inputs based on data collected in 2001 for the CT treatment. Other soil properties for different horizons were obtained from soil profiles described and sampled in 2005 (Fig. 1). Selected soils properties used for model initialization are shown in Table 1. Carbon fractions were determined for model evaluation on the 2005 soil samples; i.e., microbial biomass C (MBC), particulate organic C (POC) and TOC. We assumed that the POC fraction corresponded to the SHC fraction in EPIC.

Brief descriptions of the analytical procedures follow. Six soil cores were taken at each sampling location. Soil cores were cut at 0-5 and 5-20 cm, and air dried. Bulk density was determined for each depth by calculating oven dry mass per unit volume. Air dry samples were then gently crushed and passed through a 4.75 mm screen. Particulate organic C and MBC were determined with a procedure similar to Franzluebbers et al. (2000). Sub-samples were moistened to ~50 % water-filled pore space and incubated at 25±1 ºC in 1 L canning jars containing vials with 10 mL of 1.0 M NaOH to absorb CO_2, and small vials containing water to maintain humidity. After 10 d, the sub-sample was removed, fumigated with chloroform for 1 d, and then incubated for an additional 10 d under the same conditions to determine the flush of CO_2 representing MBC according to the equation (Voroney and Paul, 1984):

$$\text{SMBC} = (\text{mg CO}_2 - \text{C kg}^{-1}\text{ soil})_{\text{fumigated}} / k_c \qquad [2]$$

where k_c is an efficiency factor of 0.41.

Carbon dioxide evolved was determined by titration of the alkali with 1.0 M HCl. The particulate organic fraction was determined on the same sub-sample at the end of 21 d of incubation. Soil was shaken in 100 mL of 0.1 M $Na_4P_2O_7$ for 16 h; the suspension was then diluted to 1 L with distilled water and allowed to settle for 5 h, and clay content was determined with a hydrometer. The soil suspension was then passed through a 0.053-mm screen and the retained sand-sized material transferred to a drying bottle and weighed after oven drying at 55 ºC during 72 h. Soil C was determined on this fraction. For TOC, 25 g subsamples were finely ground and measurements followed the dry combustion method of Nelson and Sommers (1982) using a LECO® CN-2000 analyzer (Leco Corporation, St. Joseph, MI). Precision and accuracy were calculated by duplicate analysis on 10% of the samples.

On soil profile samples, particle size distribution was determined with the pipette method following SOM removal with hydrogen peroxide and dispersion with sodium hexametaphosphate (Kilmer and Alexander, 1949). In-situ saturated hydraulic conductivity was measured with a compact constant head permeameter (Ksat Inc, Raleigh, NC). Water content at field capacity (−33 kPa) and permanent wilting point (−1500 kPa) were determined on soil cores taken from 0-5 and 5-20 cm depth with values for deeper depths estimated by EPIC.

Landscape characteristics (e.g., watershed area, slope length and gradient) were obtained with ArcGIS (ver. 9.0, 2004, ESRI, Redlands, CA).

Crop Management

Tillage, planting, fertilization, harvesting and other operation dates and fertilizer amounts were based on experimental records. Corn in 2001, 2003 and 2005 was fertilized at planting with 56, 45 and 30 kg ha^{-1} of N, P_2O_5 and K_2O, respectively. At the V6-V8 stage, another application of 112 kg ha^{-1} of N was made. Cotton in 2002 and 2004 was fertilized at planting with 100, 45 and 56 kg ha^{-1} of N, P_2O_5 and K_2O, respectively. The CT and NT with manure treatments (i.e., CTm and NTm) received dairy bedding manure at an approximate rate of 10 Mg ha^{-1} yr^{-1} (dry basis) prior to cover crop planting. Overall, manure composition on dry weight basis for C, N, P, and K, averaged over 5 years, was 280 g kg^{-1}, 10.5 g kg^{-1}, 2.8 g kg^{-1} and 3.3 g kg^{-1}, respectively. Cover crops on the NT treatment were fertilized to compensate for residual nutrients that NTm treatments received from dairy manure applications.

Model Calibration

The calibration process on the SOC and crop growth modules used data from the CT treatment on the summit landscape position (Fig. 1). Since the summit position was a relatively stable and level to convex area at the upper part of the field, it was assumed that a steady-state condition considered necessary for initializing the simulation was reached in this area under long-term CT. Even though evaluation of the C module was of primary interest, accurate modeling of crop yield would be required for correct quantification of C additions and their subsequent transformations (Izaurralde et al., 2006).

A sensitivity analysis (SA) was performed to assess the relative importance of crop growth and soil parameters. Based on Wang et al. (2005), the following crop growth parameters were included: a) biomass-energy ratio (WA), defined as the potential growth rate per unit of intercepted photosynthetically active radiation; b) harvest index (HI) or ratio of economic yield to above-ground biomass; c) Water stress-harvest index (PARM 3), representing the fraction of the growing season when water stress affects harvest index; and d) Soil Conservation Service curve number index (PARM 42), which regulates the effect of potential evapotranspiration on runoff volume. Different from Wang et al. (2005), we did not include the potential heat unit parameter, because it was estimated as the accumulation of daily mean air temperature above the plant's base temperature (10ºC for cotton and 8 ºC for corn) from planting to maturity.

Soil parameters included for sensitivity analysis were: a) fraction of humus in passive pool (FHP); b) microbial decay rate coefficient (PARM 20); and c) a coefficient that adjusts microbial activity in the topsoil (PARM51). Wang et al. (2005) included FHP, PARM20 and FBM (fraction of organic C in the microbial biomass pool) in their SA and found that FBM was not influential. For that reason and because we had analytical data to estimate FBM we did not include this parameter. We included PARM51 because we were interested in evaluating EPIC's ability to simulate vertical distribution of SOC. Table 2 lists parameters included in the SA, their ranges, and sources.

Sensitivity Analysis

The SA identified relevant parameters for subsequent optimization. The procedure ascertained how variation in EPIC outputs was apportioned to different sources of variation related to the parameters. We used the extended FAST method (Saltelly et al., 1999; Ratto et al., 2001). This method is model independent, and allows the determination of not only the main effect of input parameters, but also the total effect of each parameter in combination with all others (i.e., interactions).

The extended FAST was based on the estimation of fractional contribution from each input parameter to the variance of the model output. The main effect or first order sensitivity index (S_i) represented the average output variance reduction that could be achieved, if the parameter (X_i) were fully known and fixed (Saltelly et al., 1999):

$$S_i = \frac{V[E(Y \mid X_i)]}{V_Y} \qquad [3]$$

where S_i is the first order sensitivity index, $V[E(Y \mid X_i)]$ is the expected reduction of total output variance, if the true value of X_i were known, and V_Y is the output variance.

The total sensitivity index (S_{Ti}) for X_i was defined as the average output variance that would remain as long as X_i stayed unknown, and collected in one single term all the interactions involving X_i

$$S_{Ti} = \frac{E[V(Y \mid X_{-i})]}{V_Y} \qquad [4]$$

where S_{Ti} is the total sensitivity index, $E[V(Y \mid X_{-i})]$ is the expected output variance that would remain unexplained if X_i were unknown, but all other parameters were known, (X_{-i} indicates all the parameters but X_i).

Estimation of the pair S_i, S_{Ti} would be important to determine, if the overall impact of the parameter X_i on Y were through its main effect or through interaction with other parameters.

In general, the SA involved four steps: a) selection of a range for each input parameter (Table 2); b) generation of 1500 parameter sets from the ranges specified in the first step (using a triangular distribution); c) evaluation of the model for each parameter set; and d) calculation of sensitivity indices. The second and fourth steps were performed using the public domain software SIMLAB (ver. 2.2, 2003, Joint Research Center, European Commission). The third step was facilitated by i-EPIC (ver. 1.1, 2005, CARD, IA), a public domain software that managed input and output of multiple EPIC simulations within a single database. We first conducted the SA for crop growth parameters and then SA for SOC parameters.

Uncertainty Analysis

After the most influential parameters were identified by the SA, another array of 1500 parameter sets was generated, and their respective simulations were conducted. The uncertainties associated with EPIC outputs were estimated with the GLUE technique of Beven and Binley (1992). On the basis of comparing predicted and observed responses, each parameter set was assigned a likelihood of being an accurate simulator of the system. For our purposes, likelihood was defined as:

$$L(\theta_i \mid X) = \exp\left(-\frac{MSD_i}{\min(MSD)}\right), (i = 1,2,3,...,N) \qquad [5]$$

where X is the observation vector, N is the total number of simulations, MSD_i is the mean squared deviation for the *i*th model run, and min(MSD) is the minimum MSD. The MSD was calculated as:

$$MSD = \frac{1}{n}\sum_{i=1}^{n}(Y_i - X_i)^2 \qquad [6]$$

where Y_i and X_i are predicted and observed values, respectively. The likelihood measures were weighted [$L_w(\theta)$] using:

$$L_w(\theta) = \frac{L(\theta_i \mid X)}{\sum_i^N L(\theta_i \mid X)} \qquad [7]$$

Weighted likelihood measures had a sum of 1 and yielded a relative probability of acceptability for the parameter sets (Beven, 1993). From this, the uncertainty estimation was performed by computing the model output cumulative distribution and the prediction quantiles. Weighted likelihood measures were calculated using the public domain software GLUEWIN (ver. 1.0, 2001, Joint Research Center, European Commission).

Determination of Parameter Values

At the conclusion of the uncertainty analyses, multi-objective functions were defined for crop yields and C pools, respectively as:

$$F_{yields} = \sqrt{\frac{1}{2}\mathrm{L}(\theta_i \mid \overline{Y}_{\mathrm{cotton}})^2 + \frac{1}{2}\mathrm{L}(\theta_i \mid \overline{Y}_{\mathrm{corn}})^2} \qquad [8]$$

$$F_{carbon} = \sqrt{\frac{1}{3}L(\theta_i \mid TOC)^2 + \frac{1}{3}L(\theta_i \mid POC)^2 + \frac{1}{3}L(\theta_i \mid MBC)^2} \qquad [9]$$

where $L(\theta_i \mid \overline{Y}_{\text{cotton}})$ and $\mathrm{L}(\theta_{\mathrm{i}} \mid \overline{\mathrm{Y}}_{\text{corn}})$ are the average cotton (2002 and 2004) and corn (2001, 2003 and 2005) yield likelihood weights, respectively; and $L(\theta_i \mid TOC)$, $L(\theta_i \mid POC)$, and $L(\theta_i \mid MBC)$ are the TOC, POC, and MBC likelihood weights, respectively; calculated using Eq. 7.

The largest F_{yields} and F_{carbon} among the 1500 measurements were identified and the corresponding set of parameter values were used as the calibrated parameters for the site.

Model Validation

The validation process focused on the crop growth and C modules using data corresponding to the three landscape positions (summit, sideslope and drainageway) with the four treatments; i.e., CT, NT, CTm, and NTm.

Statistical Evaluation of Model Performance

The agreement between simulated (Y) and observed (X) values after model calibration was assessed with a combination of the following criteria: a) linear regression of simulated to observed values that had intercept not significantly different from zero and slope not significantly different from unity, and b) MSD and its components.

The MSD was simply the sum of squared deviations between *X* and *Y*, divided by the number of observations (Eq. 6). On perfect equality, with Y=X, MSD=0. The MSD statistic was partitioned into three components (Kobayashi and Salam, 2000; Gauch et al., 2003): a) inequality of means,

$$IM = (\overline{X} - \overline{Y})^2 \qquad [10]$$

If the slope *b*=1, then *IM*>0 if and only if the intercept $a \neq 0$; b) non unity mean square, defined as

$$NU = (1-b)^2 \times (\sum x_n^2 / N) \qquad [11]$$

where b is the slope of the least-squares regression of Y on X and $x_n = X_n - \overline{X}$. Measures the degree of rotation of the regression line, *NU*>0 if and only if $b \neq 1$; and, c) lack of correlation mean square,

$$LC = (1-r^2) \times (\sum y_n^2 / N) \qquad [12]$$

where r^2 is the square of the correlation and $y_n = Y_n - \overline{Y}$, *LC*>0 if and only if $r^2 \neq 1$.

RESULTS AND DISCUSSION

Model Calibration

Sensitivity Analysis

Scatter plots for parameter values and selected output variables are shown in Fig. 3. Clearly, WA and HI were directly related to corn and cotton yields. Also, FHP and PARM20 were the most influential parameters on TOC. Other parameters (e.g., PARM3 and PARM42, and PARM51) had unclear effects on model outputs. Scatter plot diagrams were good for preliminary assessment, but interaction effects among parameters could not be assessed.

The extended FAST sensitivity indices for crop yield and SOC parameters are shown in Tables 3 and 4, respectively. The first order index for a particular parameter indicates the expected amount of variance that would be removed from the total output variance, if the true value of that parameter were known. Therefore it shows the relative importance of an individual parameter. For cotton and corn, WA and HI explained >99% of the output variance. For the C module, FHP and PARM20 explained most of the variance; FHP was the most influential parameter for SHC, while PARM20 was for MBC and TOC. First order indices were consistent with scatter plot diagrams.

The total order index for a particular parameter (X_i) represents the expected amount of output variance that would remain unexplained if X_i, and only X_i, is left free to vary over its uncertainty range assuming all other parameters are known. Indicates those parameters that are not important, neither singularly or in combination with others (interaction effect); therefore, all parameters having low total index can be fixed to any value within their range of uncertainty. Total order indices for parameters of the crop growth module were similar to first order indices, indicating no interaction. However, total order indices for the C module underline an interaction effect among PARM51 and the other parameters affecting MBC.

According to the SA, parameters WA and HI for corn, WA and HI for cotton, and the three parameters for the C module (FHP, PARM20 and PARM51) were chosen as the most influential on model outputs. Parameter selection for the crop growth and SOC modules agreed with Wang et al. (2005).

Uncertainty Analysis

Distribution of predicted average crop yields (corn and cotton) and SOC fractions (MBC, SHC, TOC) are shown in Fig. 4. The height of the bars is given by the sum of likelihood weights of model runs. Distributions were approximately normal. Observed crop yields, except corn in 2005, were within the 90% CI of simulated values. Overall, EPIC simulated cotton yield effectively with differences between observed and predicted yields of 53 and -29 kg ha^{-1} in 2002 and 2004, respectively. Simulation of corn yield was not as good as with cotton, with differences between observed and predicted yields of -552, 120 and -1941 kg ha^{-1} in 2001, 2003 and 2005, respectively. There was a dry period at the time of corn silking and pollination in 2005 that could have reduced actual corn yield, but that was not accounted for by EPIC. Guerra et al. (2004) pointed out that EPIC tended to overestimate low yields, especially under conditions of pronounced water stress. In spite of the poor agreement between observed and predicted average yield in 2005, all simulated crop yields fell within the range of observed yields (minimum and maximum observed yields are not shown).

In 2005, measured MBC and TOC were within the 90% CI of simulated values but SHC was not. EPIC simulated values for MBC and TOC on the 0-20 cm layer were 67 and 157 kg ha^{-1}, respectively, lower than measured values. Simulated values for SHC were 1860 kg ha^{-1} lower than measured values. Initialization of SHC (controlled by the FHP parameter) posed a problem, because of the complex analytical method needed to characterize this C fraction (Izaurralde et al., 2006). We assumed that our analytical results for POC were related to SHC, but this may not have been true. Carbon dating with ^{13}C or long-term soil incubation techniques has been used to characterize SHC (Paul et al., 1995).

Parameter Estimation

From the uncertainty analysis and the use of aggregated likelihood functions for crop yields and SOC fractions (Eq. 8 and 9), the values for each parameter were set at 32.42 kg ha^{-1} MJ^{-1} for WA and 0.50 for HI in corn and 13.00 kg ha^{-1} MJ^{-1} for WA and

0.54 for HI in cotton. Parameter values for the C module were set at 0.32 for FHP, 0.32 for PARM20, and 0.49 for PARM51.

The value for WA was consistent with reports in the literature. Sinclair and Muchow (1999) summarized 11 studies on radiation use efficiency (RUE) in corn at different locations around the world and found a great deal of consistency (16 to 17 kg ha^{-1} MJ^{-1}), which converted into values of WA of 32 to 34 kg ha^{-1} MJ^{-1}. Wang et al. (2005), using a similar EPIC calibration procedure in a corn field of south central Wisconsin, reported WA as 35.4 kg ha^{-1} MJ^{-1}. Our value for HI of corn was close to values reported in many agronomic trails across 9 states in the USA (Kiniry et al., 1997) and the value of 0.48 reported by Wang et al. (2005). The value for WA in cotton was similar to the average of three cotton cultivars (14.43 kg ha^{-1} MJ^{-1}) reported by Rosenthal and Gerik (1991). The value determined for HI in cotton was higher than the average HI measured in our study field (0.32), but we expected a higher value to reflect minimal stress and allow the crop to attain its yield potential, which was not the condition in the field experiment.

Non-hydrolysable C has been considered the extractable fraction most closely related to the passive SOC pool (Wang et al., 2005), represented by the parameter FHP. The FHP value we identified was lower than the average value of 0.51 reported by Paul et al. (1997) for non-hydrolysable C in a cultivated soil profile of the central USA. The value for PARM 20, which can be related to the potential transformations of the various C pools, was higher than the value of 0.13 identified by Wang et al. (2005). This could be related to a climate effect, since the warmer and more humid conditions in this study would favor an increase in C transformation rates. The value for PARM51 was half the default value for this parameter in EPIC (Izaurralde et al., 2006). Overall, the automatic calibration procedure succeeded in identifying the most influential parameters and their values for our experimental site.

Model Validation

Crop Yields

Measured and simulated yields are compared in Fig. 5. In 2001, first year treatments were imposed, neither tillage systems nor manure application impacted measured crop yields. Two possible explanations exist; it was a dry year with corn receiving 441 mm of rain during the growing period (Fig. 2) and it was the first year of no tillage and manure application (following decades of conventional tillage). EPIC reproduced variations among landscape positions, but mostly underestimated measured yields.

The effect of tillage system on measured cotton yields was apparent in 2002. This was the driest year for cotton, receiving only 354 mm during the growing season. Water use efficiency was maximized under NT resulting in higher yield than under CT, especially at summit positions with sandy and well drained soils and at the sideslope where less infiltration occurs due to runoff. EPIC underestimated yield and failed to adequately show the difference between tillage systems and landscape positions. Manure application did not have a clear effect on either measured or simulated yields.

Corn received 774 mm of rain during the growing season in 2003 (wettest year). There were only small differences in measured corn yields among management systems and landscape positions. The greatest difference between tillage systems occurred at the drainageway. Perched water over compacted subsoil under CT at the drainageway reduced yield. EPIC underestimated corn yields, especially at the summit and sideslope positions, but simulated a positive NT effect. There was no clear effect of manure application on measured or simulated corn yields.

The best fit between measured and simulated yields occurred in 2004. The effect of landscape position on cotton yield was well simulated. In 2005, EPIC overestimated corn yield at the summit and sideslope, but adequately simulated yield at the drainageway. Although the amount of rainfall received by the crop (435 mm) was similar to that in 2001, the driest period happened when corn was at the stage of silking, and pollination, which are critical stages for corn grain development. The driest period most likely affected the crop at summit and sideslope positions, because soil would have less water holding capacity than the drainageway position.

Overall, 48% of the simulated yields were within 20% of measured yields (60 simulations were run). Simulated yield explained 88% of the variation in measured yield (Fig. 6). However, the regression had a slope of 0.74 and an intercept of 0.77, which were significantly different from 1 and 0, respectively. EPIC has been characterized as a model that reproduces accurately long-term mean yields, but may be inaccurate for reflecting year-to-year variability (Kiniry et al., 1995). Greater disagreement between simulated and measured yields occurred in very wet or very dry years, suggesting the model needs further adjustments on parameters controlling soil hydrology and water use by plants

Mean Squared Deviations of Crop Yields

Mean squared deviations of crop yield and its components as affected by management and landscape position are shown in Fig. 7. Lowest MSDs were found in the drainageway, followed by the summit and sideslope positions. Within a particular landscape position, the greatest MSD occurred with manure application. The highest contributing component of MSD was different at different landscape positions. At the summit position, lack of correlation between measured and predicted yield was the major component of MSD. Equality between measured and predicted means was greatest at the summit position. At the sideslope position, the major component of MSD was difference in unity of the slope of the regression between measured and predicted yield, although lack of correlation was also important. Although lowest MSD was at the drainageway position, the major component of MSD in this area was inequality of means.

Kobayashi and Salam (2000) introduced the MSD approach to distinguish the source of error in simulation models. They claimed that MSD and its components were better suited to the X-Y comparison than regression and easier to interpret than regression. The main objective in evaluating model performance should be to compare predicted with measured values, rather than fitting of the model to measurements. The three MSD components were additive (all constituents of the MSD) and provided further insight into model performance. For example, the MSD values indicated that more emphasis needs to be placed on parameters that control rate of soil and nutrient loss on sloping landscapes, in addition to the hydrology parameters mentioned before.

Soil Organic C Fractions

Measured and simulated fractions of SOC are presented in Figs. 8, 9 and 10. There was good agreement between measured and EPIC simulated MBC at 0-5 cm. However, at 5-20 and 0-20 cm depths, EPIC overpredicted MBC (Fig. 8) and did not estimate variations due to tillage. Most probably at 5-20 cm depth, the substrate for microbial activity was lower in NT and NTm than in CT and CTm, because residues were left on the surface. There is need for a better adjustment of modeled vertical distribution of MBC, a fact generally overlooked in model reports. The analytical method used to characterize MBC was similar to the method of Jenkinson and Powlson (1976), which was suggested by Izaurralde et al. (2006) as an appropriate method to initialize the MBC fraction in EPIC. Adjustment of other model parameters is suggested, rather than altering MBC methods.

Simulations of SHC were mostly lower than measured POC[1] at 0-5 cm (Fig. 9). At the 5-20 cm depth, differences between measured and simulated values were small, but EPIC did not estimate variations due to tillage adequately. Higher SHC at lower depths of CT and CTm soils was expected, because tillage operations mix residues into lower depths. A possible explanation for the disagreement between measured and simulated SHC may have been that the analytical procedure used (POC) was not necessarily the fraction simulated by EPIC. In addition to define a protocol for SHC determination, more calibration work is needed for sound estimations of SHC.

The best agreement between measured and simulated SOC fractions was obtained for TOC at a depth of 0-20 cm (Fig. 10). Accuracy in estimation of TOC at the 0-20 cm depth has been the strength of Century (Kelly et al., 1997; Pennock and Frick, 2001). Simulations of TOC at the 0-20 cm layer were satisfactory at the sideslope position, but poorer at the summit and drainageway positions. EPIC appeared to accurately simulate SOC mineralization in the drier sideslope, but overestimated mineralization in the moister drainageway position under CT and underestimated mineralization under NT. These

[1] As a remainder, we analyzed soils for particulate organic C (POC) and assumed this fraction represents the slow humus C (SHC) in the EPIC model.

results underscore the need for further calibration work to make the newly modified EPIC (v3060) more accurately account for vertical distribution of SOC fractions.

Mean Squared Deviations of Soil Organic Fractions at the 0-20 cm Depth

The MSD for each landscape position was calculated to evaluate how well EPIC had captured the spatial-temporal dynamics of SOC fractions (i.e., MBC, SHC and TOC) at different positions (Fig. 11). Most of the error associated with the prediction of MBC was associated with inequality of means, followed by the lack of correlation. Slope of the regression between measured and simulated values was close to unity (small NU error).

The largest discrepancy between measured and simulated SOC fractions was noted for SHC, especially at the sideslope position. Inequality of means accounted for most of the variation in SHC at the three landscape positions. Error due to lack of correlation was small at all landscape positions.

Largest MSD for TOC was at the drainageway and smallest at the sideslope. Although there was good agreement between measured and simulated TOC means (very small IM error), correlation between measured and simulated values was poor (LC was the largest component of MSD).

Overall, simulations of SOC fractions explained about 7, 27 and 41% of the total variation in MBC, SHC and TOC, respectively. EPIC simulated up to 91% of total variation in soil C at uniform landscape and management conditions in Izaurralde et al. (2005).

Temporal Changes in Total Organic C

Comparison between simulated and measured temporal changes in TOC is shown in Fig. 12. Data from 2001 and 2003 were from intensive sampling of the 0-30 cm depth.

Data from 2005 were assembled with the 0-20 cm surface sampling and the 20-30 cm depth from profile description. Addition of dairy manure and conservation tillage practices increased TOC but measured C stocks at the 0-30 depth of these degraded soils are still low. EPIC tended to overestimate TOC, but mimicked variations with time. Izaurralde et al. (2006) reported EPIC overpredictions at low TOC and suggested that continued development of the model is needed. Fifteen of the 36 simulations were within the standard error of measured means. Best agreement between simulation and measurements was obtained on the sideslope and in the drainageway, with the CT treatments. The reason why EPIC did not perform well on the summit is not clear; we suggest that parameters controlling water runoff and soil erosion should be included in future calibration works. In addition, model overestimation on the NT treatments suggests that parameters controlling residue transformation rates need further investigation.

SUMMARY AND CONCLUSIONS

Automatic parameter optimization procedures can be applied to EPIC. Our results suggest that when research results are not available, the integration of meaningful ranges of parameters and a numerical optimization routine have the potential to identify crop and SOC parameter values accurately.

Simulated crop yields were lower than measured crop yields in most years. However, temporal management effects on crop yields were adequately simulated. Greater disagreement between simulated and measured yields occurred in the wettest and in the driest season, suggesting EPIC needs further adjustments on parameters controlling soil hydrology and water use by plants.

As tested, EPIC accurately explained the variability of total organic C (0-20 cm) on the calibration year. However, agreement between measured and simulated microbial biomass C and slow humus C was poor; we suggest that more research is needed to define methods for their analytical determination and their estimation in EPIC, especially with respect to SHC.

Further studies are needed to improve EPIC predictions of SOC dynamics with depth. Parameters regulating root distribution and residue decomposition with depth should be considered during the calibration process.

Overall, EPIC was sensitive to spatial differences that resulted from landscape positions in the driving variables. With correct parameterization, EPIC would be a valuable tool for simulating field-scale SOC dynamics affected by short-term management decisions.

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Table 1. Selected soil input data used in the 5-year (2001-2005) simulations

Summit						
Layer Depth (m)	0.05	0.20	0.30	0.46	1.04	1.42
Bulk Density (Mg m^{-3})	1.59	1.65	1.55	1.36	1.36	1.37
Wilting Point (m^3 m^{-3})	0.11	0.11	0.11	0.14	0.15	0.15
Field Capacity (m^3 m^{-3})	0.18	0.18	0.18	0.31	0.32	0.30
Sand (da kg^{-1})	58.37	54.50	53.72	44.90	41.85	45.16
Silt (da kg^{-1})	19.97	26.83	24.63	21.60	20.02	16.24
Clay (da kg^{-1})	21.66	18.67	21.65	33.50	38.13	38.60
Soil organic C (da kg^{-1})	0.70	0.53	0.53	0.33	0.28	0.26
Saturated Conductivity (mm h^{-1})	1.20	1.20	1.20	1.48	0.15	0.15
Sideslope						
Layer Depth (m)	0.05	0.20	0.28	0.46	0.80	1.00
Bulk Density (Mg m^{-3})	1.64	1.60	1.37	1.40	1.37	1.35
Wilting Point (m^3 m^{-3})	0.09	0.09	0.13	0.17	0.19	0.19
Field Capacity (m^3 m^{-3})	0.20	0.20	0.32	0.33	0.34	0.35
Sand (da kg^{-1})	59.53	50.00	41.21	37.96	35.18	32.45
Silt (da kg^{-1})	18.20	28.00	25.87	23.45	21.55	22.38
Clay (da kg^{-1})	22.27	22.00	32.92	38.59	43.27	45.17
Soil organic C (da kg^{-1})	0.58	0.47	0.32	0.28	0.27	0.27
Saturated Conductivity (mm h^{-1})	6.25	6.25	1.68	0.20	0.08	0.08
Drainageway						
Layer Depth (m)	0.05	0.20	0.40	0.62	0.98	1.20
Bulk Density (Mg m^{-3})	1.58	1.69	1.44	1.46	1.34	1.30
Wilting Point (m^3 m^{-3})	0.05	0.05	0.08	0.14	0.18	0.20
Field Capacity (m^3 m^{-3})	0.18	0.18	0.27	0.32	0.35	0.36
Sand (da kg^{-1})	62.90	57.07	52.66	40.92	31.46	28.27
Silt (da kg^{-1})	21.23	30.13	34.31	28.08	22.44	19.31
Clay (da kg^{-1})	15.87	12.80	13.03	31.00	46.10	52.42
Soil organic C (da kg^{-1})	0.76	0.55	0.38	0.29	0.31	0.31
Saturated Conductivity (mm h^{-1})	1.96	1.96	3.19	3.33	0.17	0.07

Table 2. EPIC parameters included in the sensitivity analyses.

Parameter	Description	Range
Yield related		
WA	Biomass-energy ratio (kg ha^{-1} MJ^{-1})	30-45 (corn)† 11-20 (cotton)‡
HI	Harvest index	0.45-0.60 (corn)† 0.30-0.60 (cotton)§
PARM3	Water stress-harvest index	0.3-0.7†
PARM42	SCS curve number index	0.5-2.0†
Soil organic C related		
FHP	Fraction of humus in passive pool	0.3-0.9†
PARM20	Microbial decay coefficient	0.05-1.50†
PARM51	Microbial activity, top layer	0.1-1.0§

†Wang et al. (2005)
‡Rosenthal and Gerik (1991)
§EPIC default range

Table 3. First and total sensitivity indices for crop yield related parameters.

Parameter	First order indexes		Total order indexes	
	Cotton	Corn	Cotton	Corn
WA for Corn	0.00	0.51	0.01	0.50
HI for Corn	0.00	0.49	0.01	0.47
WA for Cotton	0.37	0.00	0.36	0.01
HI for Cotton	0.62	0.00	0.60	0.01
Parm3	0.00	0.00	0.01	0.01
Parm42	0.00	0.00	0.01	0.01

Table 4. First and total sensitivity indices for SOC related parameters.

Parameter	First order indexes†			Total order indexes†		
	MBC	SHC	TOC	MBC	SHC	TOC
FHP	0.30	0.77	0.25	0.25	0.75	0.26
Parm20	0.63	0.23	0.73	0.60	0.24	0.70
Parm51	0.08	0.00	0.02	0.14	0.01	0.03

†MBC, microbial biomass C; SHC, slow humus C; TOC, total organic C

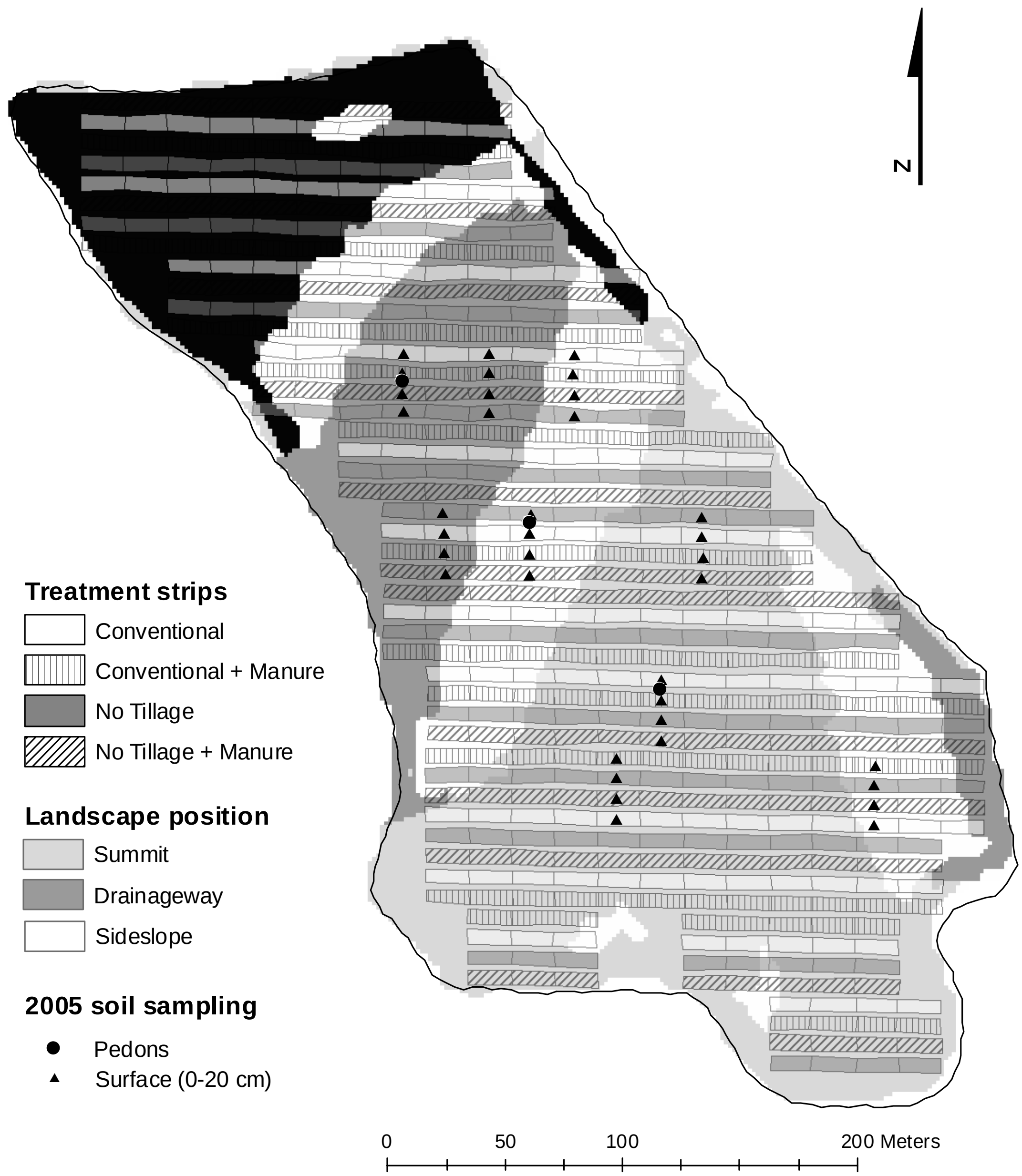

Fig. 1. Experiment layout. Black area at the north was not included in the simulations (explained in the text). East-west rectangles represent strips with different treatments; gray shading in the background represents the three landscape positions; triangles indicate 2005 soil sampling locations and the three circles show locations where soil profiles were described.

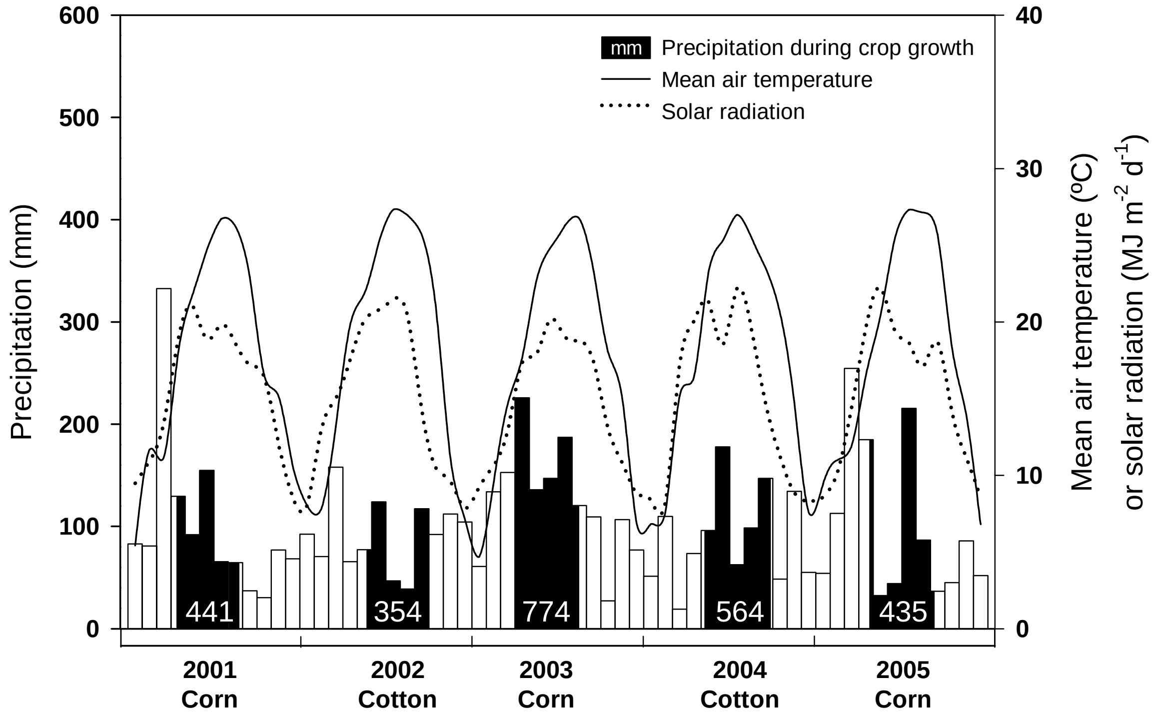

Fig. 2. Monthly total precipitation, mean air temperature and solar radiation for 2001-2005. Total rainfall during crop growth is shown with white numbers on black bars.

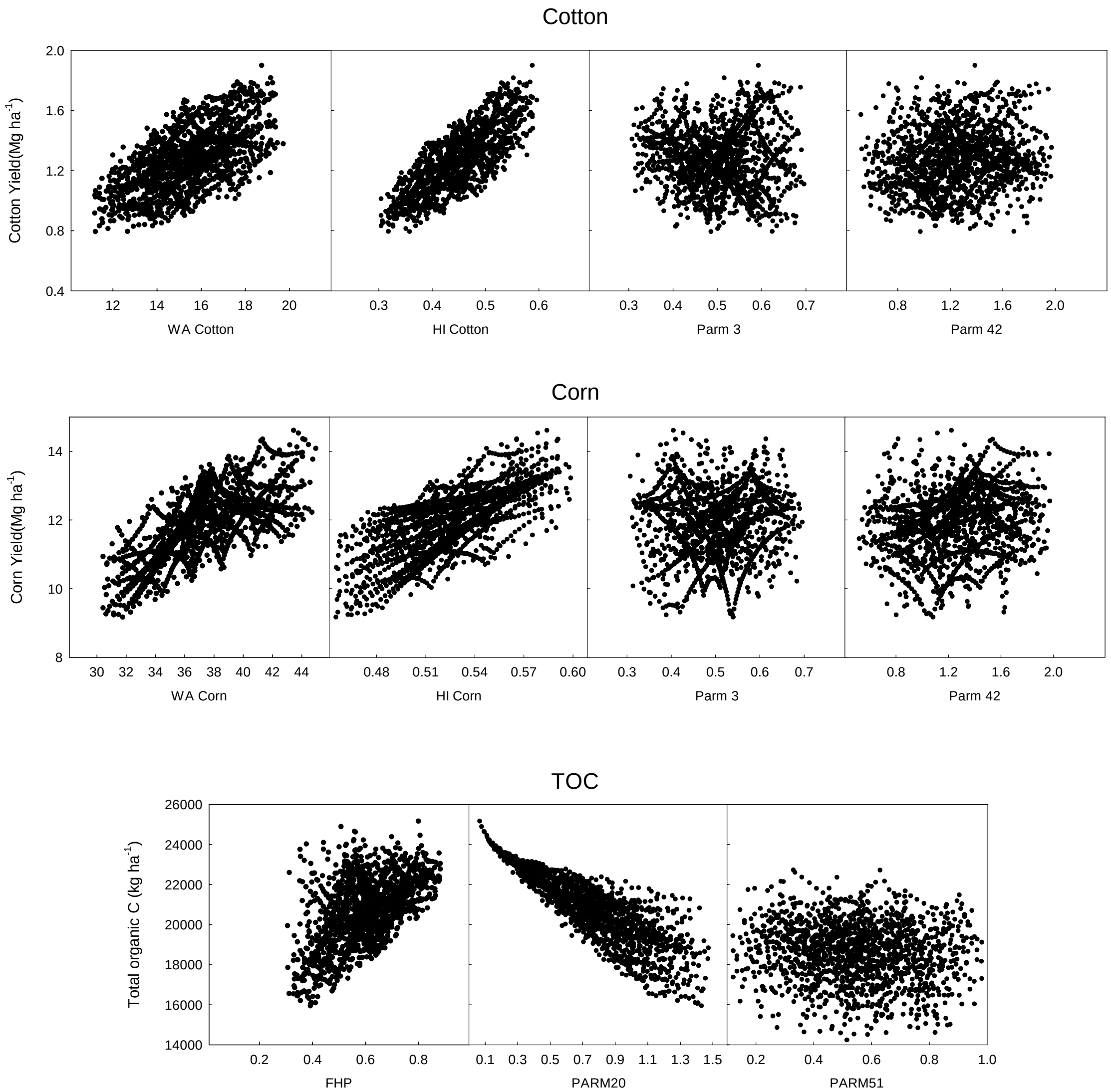

Fig. 3. Scatter plots of model parameters vs. model outputs (cotton yields, corn yields and total organic C). WA = Biomass-energy ratio, HI = Harvest index, PARM 3 =Water stress-harvest index, PARM 42 = The Soil Conservation Service curve number index, FHP = Fraction of humus in passive pool, PARM 20 = Microbial decay rate coefficient, PARM51 = coefficient that adjusts microbial activity in the top soil.

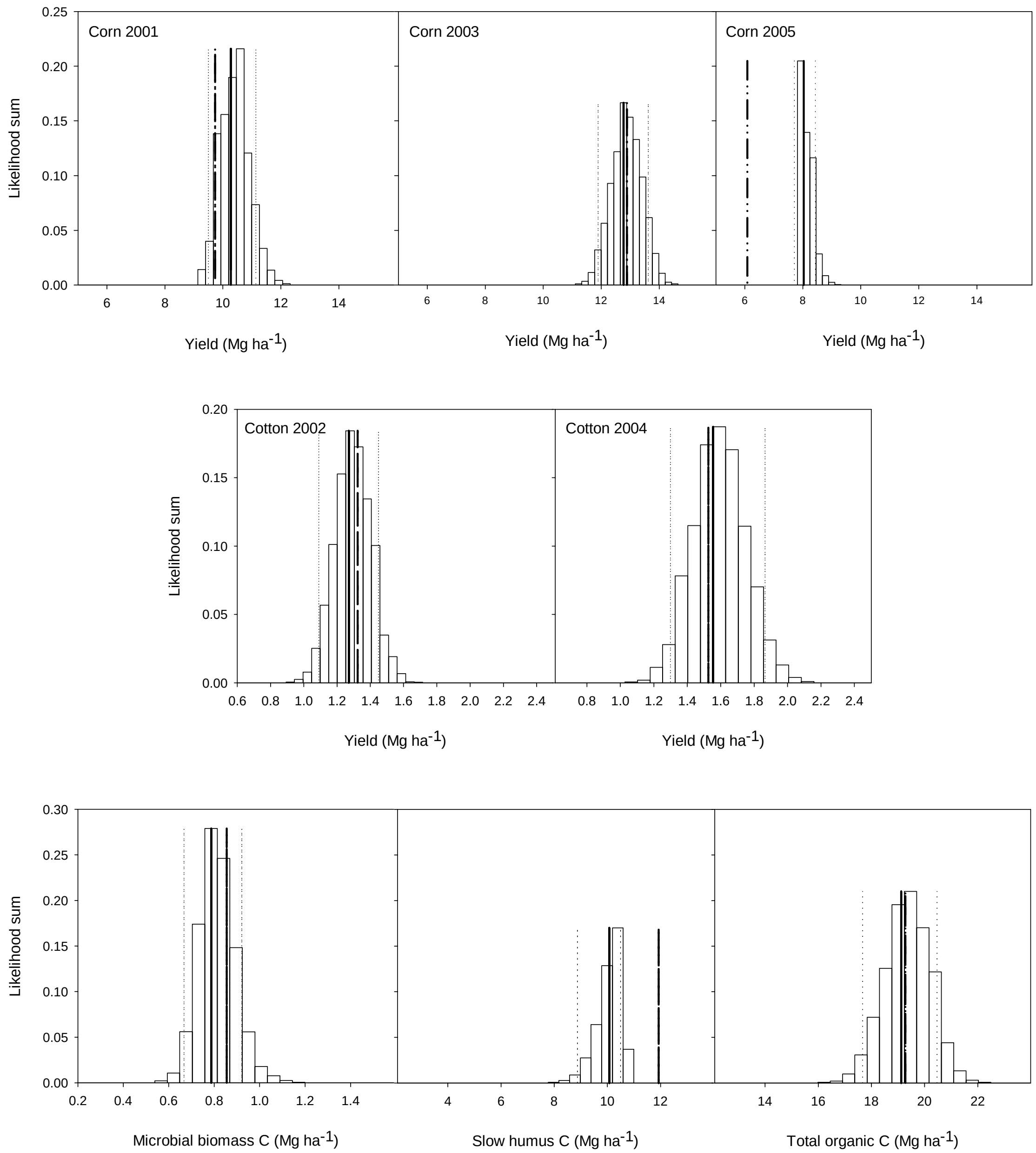

Fig. 4. Probability distribution of predicted crop yields and soil organic C fractions. The 5% and 95% quantiles are shown as vertical dotted lines; the mean of predictions over the 1,500 simulations is represented by a vertical solid line, and the corresponding measured value is shown as a vertical dashed line.

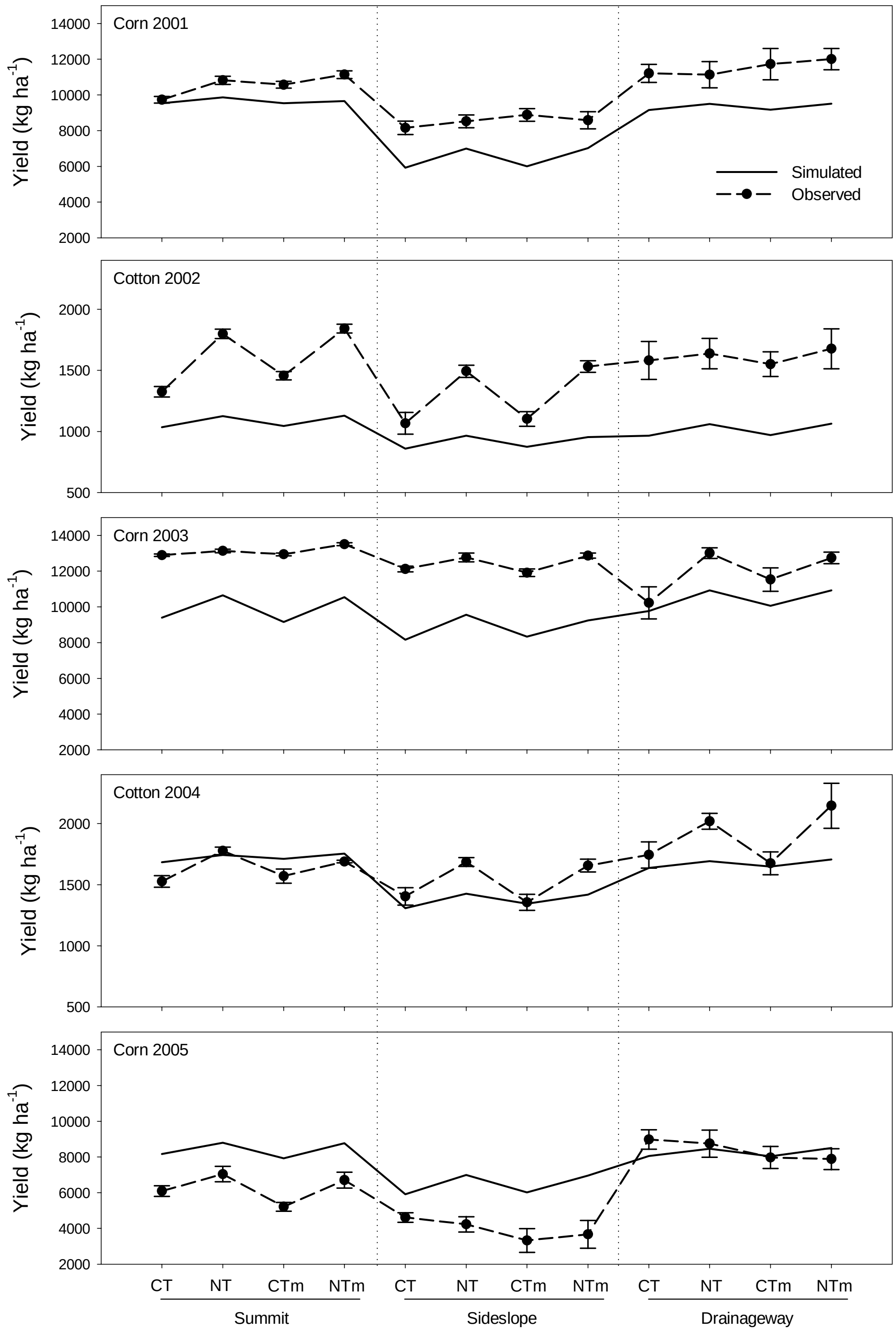

Fig.5. Measured and simulated yields affected by landscape position and treatment. CT = conventional tillage; NT = no tillage; CTm = conventional tillage + manure; NTm = no tillage + manure.

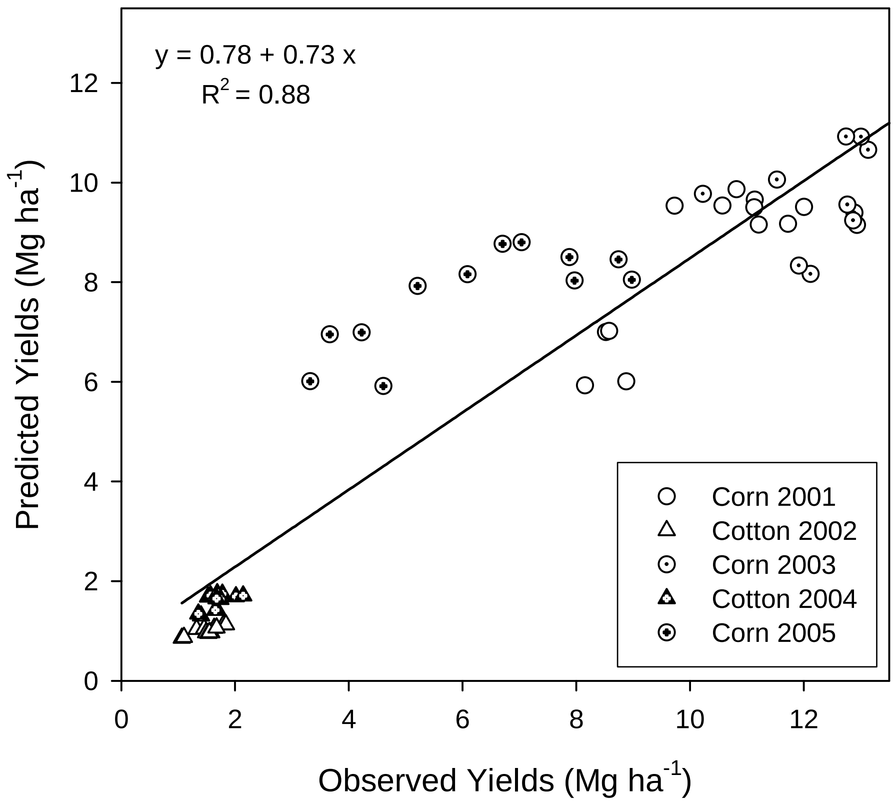

Fig. 6. Comparison of simulated and measured average yields of corn and cotton during the period 2001-2005. The slope and intercept of the regression line were significantly different from 1 and 0, respectively.

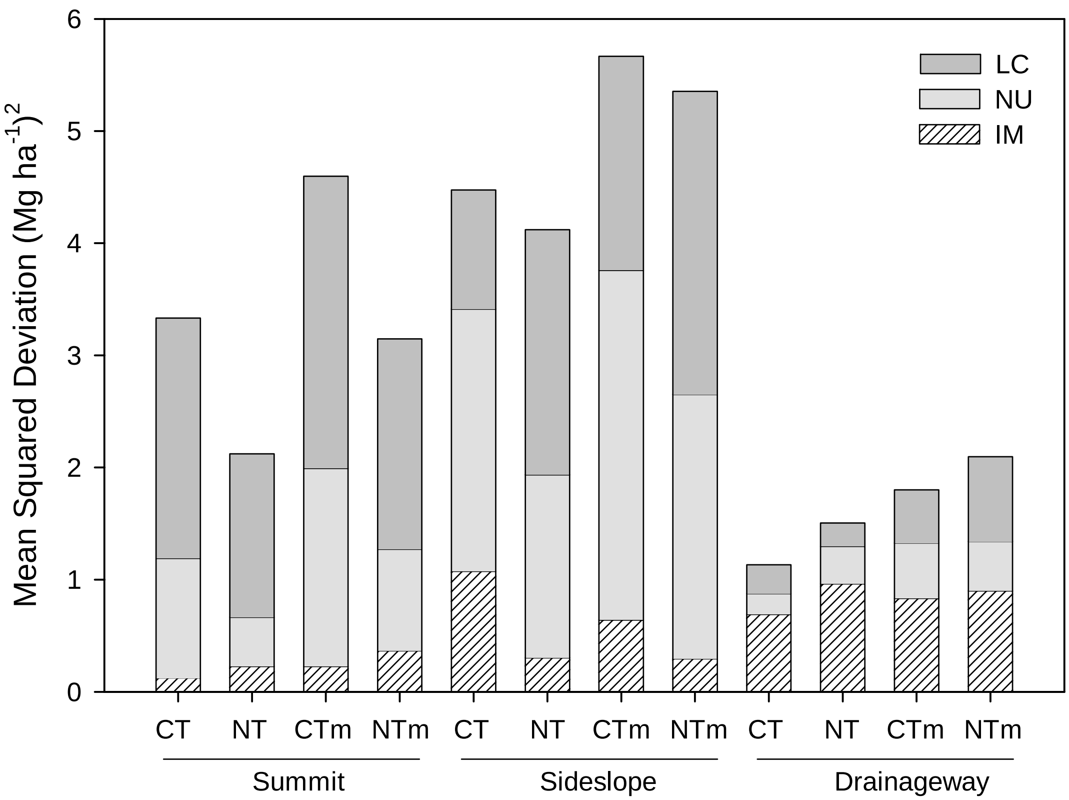

Fig. 7. Comparison of mean squared deviations (MSD) among 12 simulations of crop yields over a 5-year period on three landscape positions. MSD components explained in the text. LC = lack of correlation; NU = non unity mean square; IM = inequality of means; CT = conventional tillage; NT = no tillage; CTm = conventional tillage + manure; NTm = no tillage + manure.

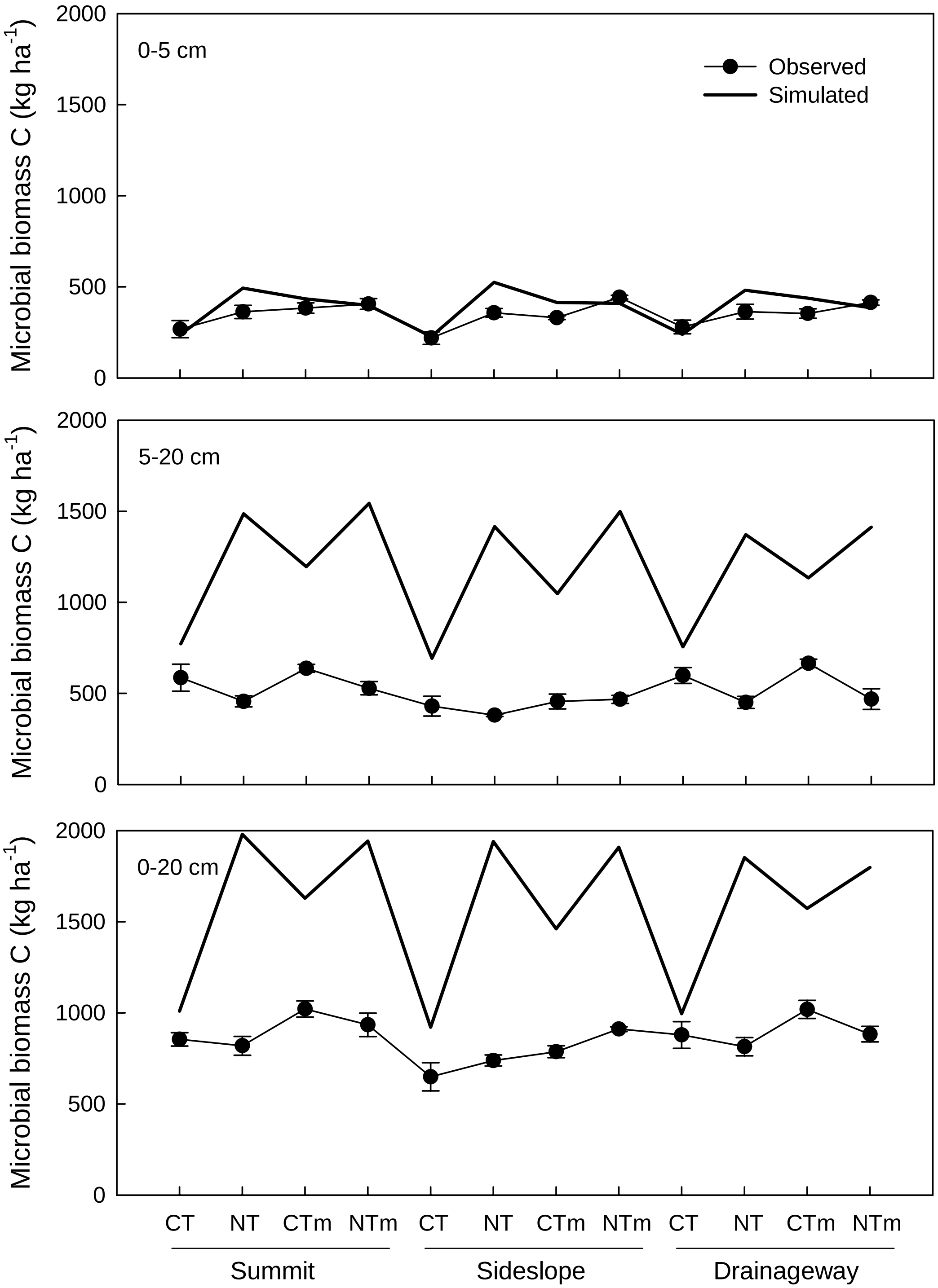

Fig. 8. Measured and simulated soil microbial biomass C affected by landscape positions and treatments (2005 data) at 0-5, 5-20 and 0-20 cm depths. CT = conventional tillage; NT = no tillage; CTm = conventional tillage + manure; NTm = no tillage + manure.

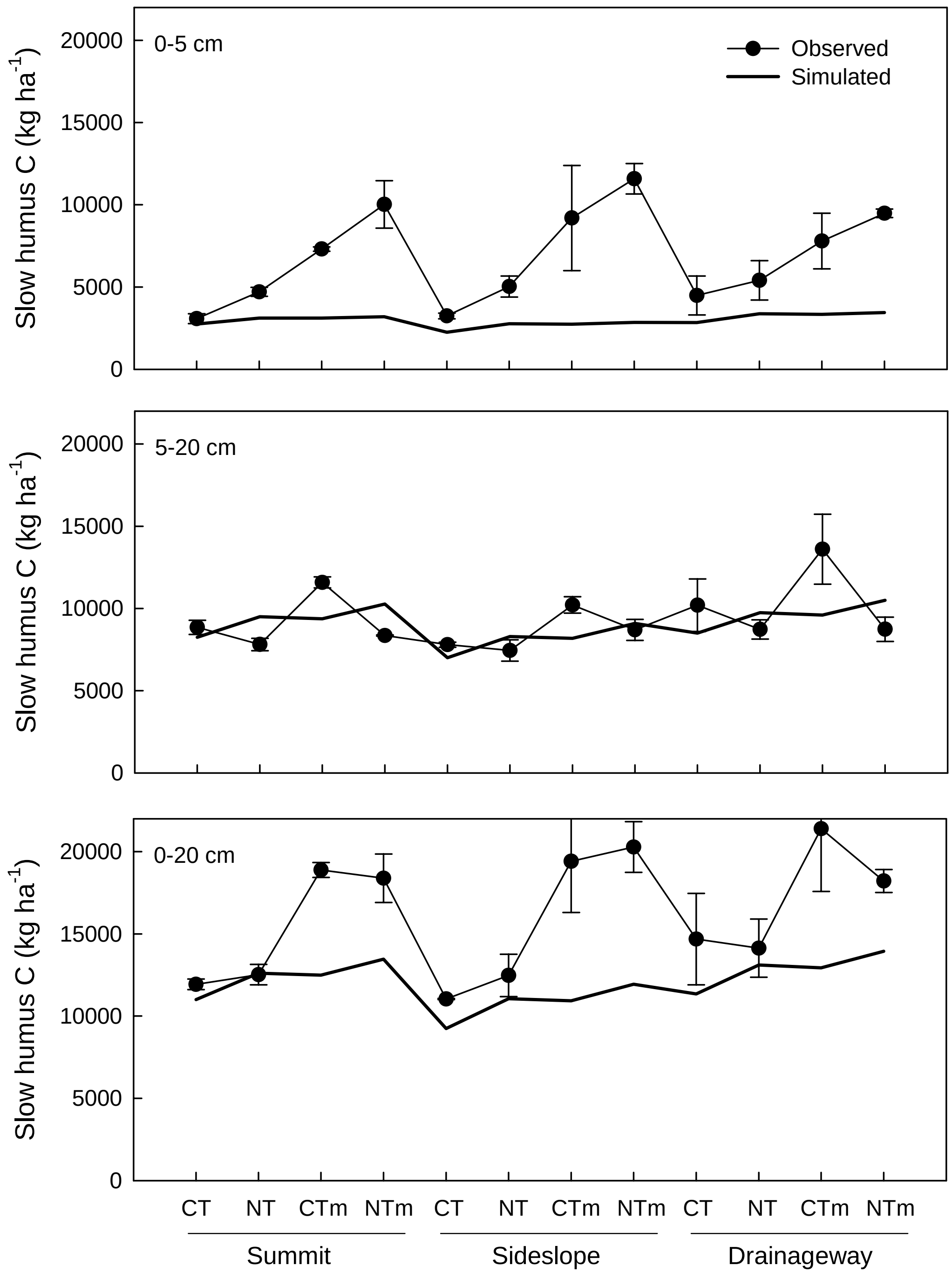

Fig. 9. Measured and simulated slow humus C affected by landscape positions and treatments (2005 data) at 0-5, 5-20 and 0-20 cm depths. CT = conventional tillage; NT = no tillage; CTm = conventional tillage + manure; NTm = no tillage + manure.

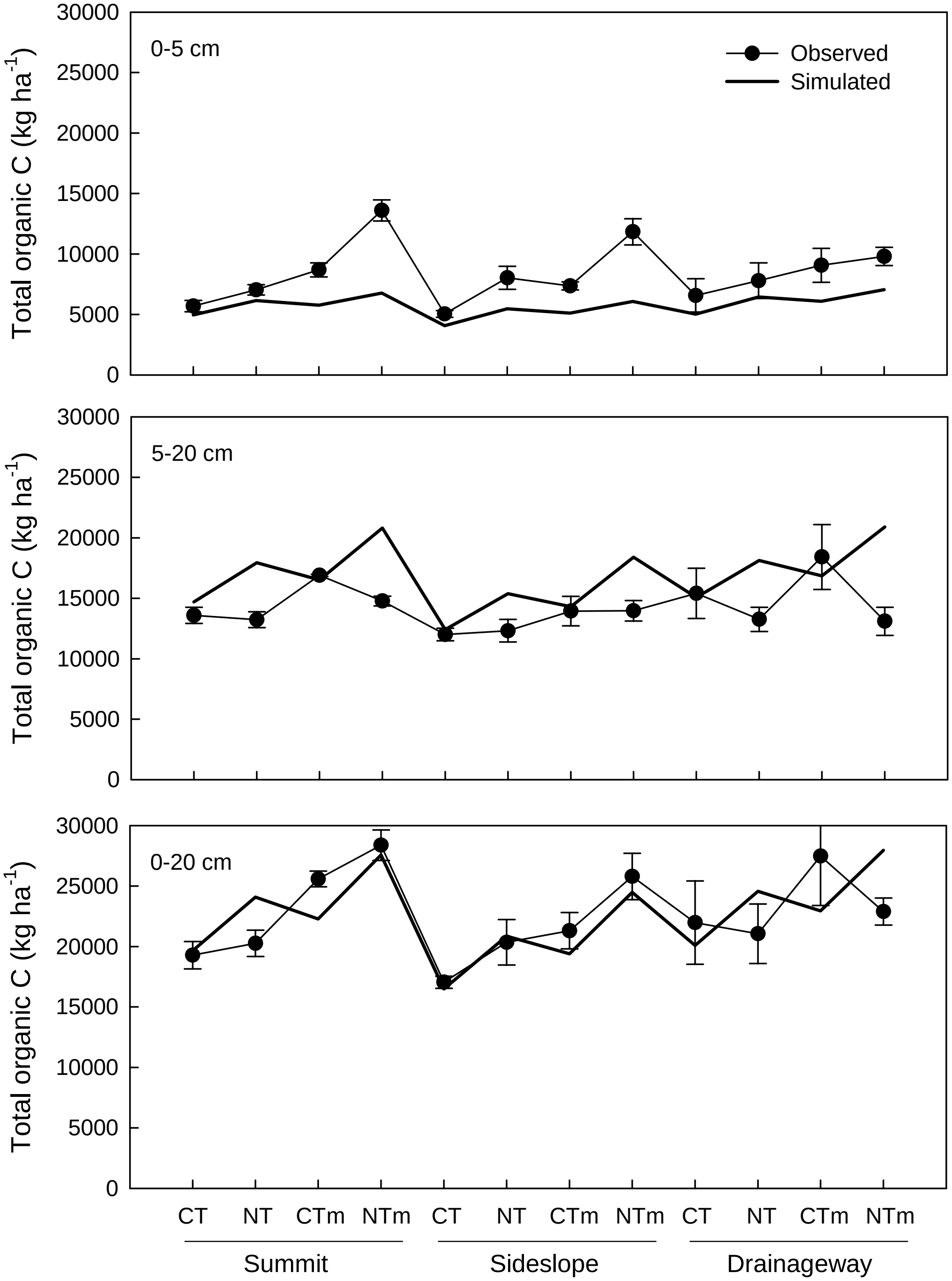

Fig. 10. Measured and simulated total organic C affected by landscape positions and treatments (2005 data) at 0-5, 5-20 and 0-20 cm depths. CT = conventional tillage; NT = no tillage; CTm = conventional tillage + manure; NTm = no tillage + manure.

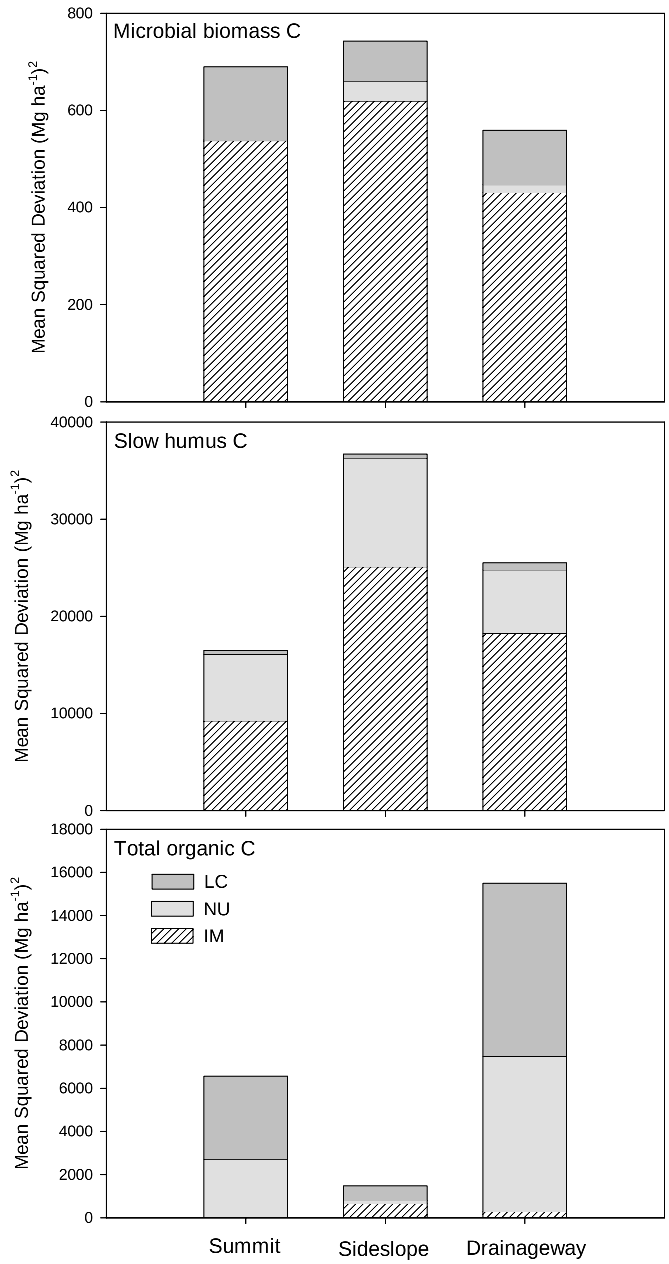

Fig. 11. Comparison of mean squared deviations (MSD) among 4 simulations of microbial biomass C, slow humus C and total organic C (0-20 cm) at the end of 5 years. MSD components explained in the text. LC = lack of correlation; NU = non unity mean square; IM = inequality of means.

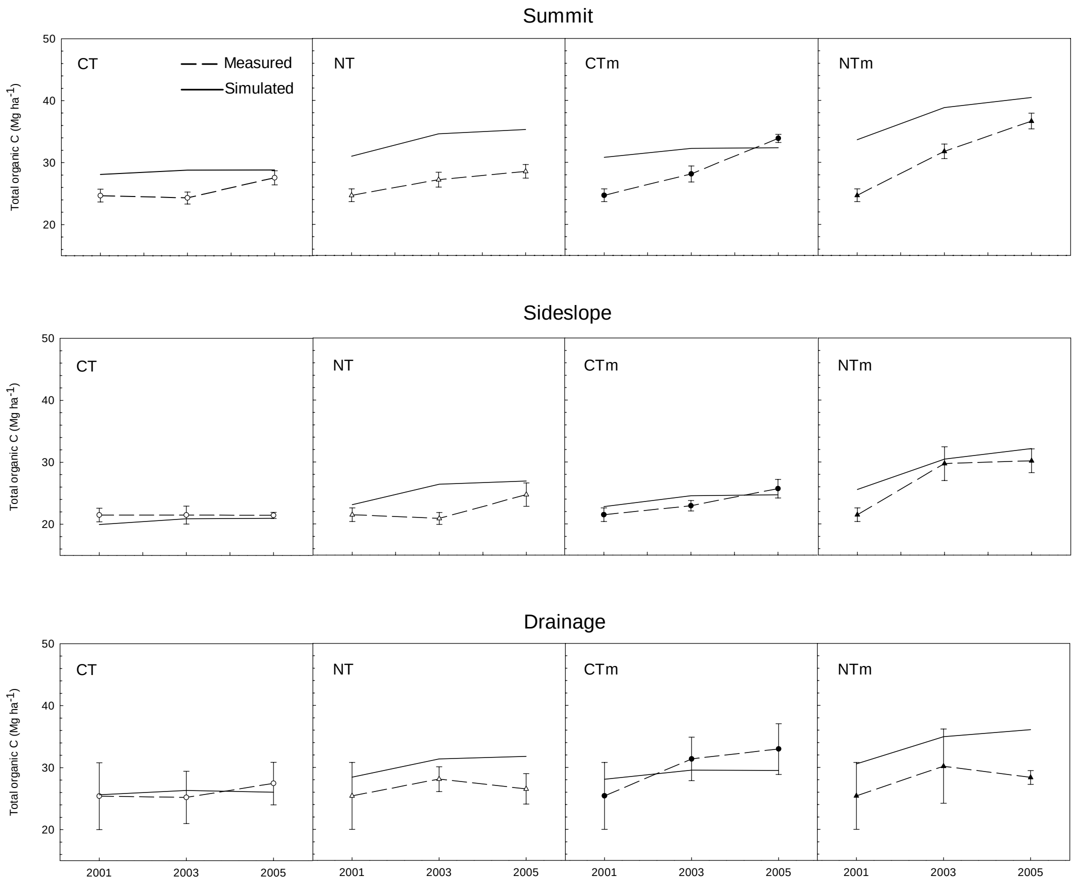

Fig. 12. Measured and simulated total organic C affected by landscape positions and treatments (0-30 cm) in 2001, 2003 and 2005. CT = conventional tillage; NT = no tillage; CTm = conventional tillage + manure; NTm = no tillage + manure.

IV. APPENDIX. Sampling sites within the Southern Piedmont and Coastal Plain and information related to land use and management, soil taxonomy, laboratorial analysis results and climate.

Longitude	Latitude	MLRA†	State	Use‡	Location	Rotation§	Soil Taxonomy	Nº Years	BD¶	Soil Organic C fractions#				Sand	Clay	Pcp. ††	Tmp. ‡‡
										TOC	POC	CMIN	SMBC				
									Mg m^{-3}	-- dag kg^{-1}		--- mg kg^{-1} ---		-- dag kg^{-1} --		mm	ºC
86.50	34.21	CP	AL	CsT	Andalusia	CO-RY-CO-RY-PE-CO	Plinthic Kandiudults	11	1.39	1.5	1.0	466.4	444.0	88.9	6.1	1558	17.8
86.51	34.21	CP	AL	Pas	Andalusia	Grazed Pasture	Plinthic Kandiudults	20	1.39	1.1	0.8	369.4	361.1	88.5	6.1	1560	17.7
86.52	34.21	CP	AL	CvT	Andalusia	CO-RY-PE-RY	Plinthic Kandiudults	20	1.44	1.0	0.7	395.8	404.0	83.4	10.3	1562	17.8
86.06	34.21	CP	AL	CvT	Samson	PE-CO/SmG	Typic Kandiudults	20	1.53	1.1	0.7	416.8	454.3	77.0	15.8	1489	18.4
86.03	34.21	CP	AL	Pas	Elba	Grazed pasture	Typic Kandiudults	20	1.39	1.6	1.0	646.4	602.0	76.4	14.2	1487	18.5
86.03	34.21	CP	AL	CsT	Elba	PE-CO/SmG	Typic Kandiudults	9	1.43	1.4	0.9	565.2	501.1	78.4	9.9	1487	18.5
85.43	34.21	CP	AL	Pas	Opelika	Hayed Pasture	Aquic Haploxeralfs	40	1.37	1.2	0.8	503.4	418.4	78.3	8.0	1380	17.2
85.43	34.21	CP	AL	CsT	Opelika	CO/RY	Aquic Haploxeralfs	20	1.53	0.8	0.5	349.9	303.2	79.5	9.4	1380	17.2
85.43	34.21	CP	AL	CvT	Opelika	CO	Aquic Haploxeralfs	40	1.65	0.7	0.5	289.5	234.8	83.2	9.0	1380	17.2
83.98	34.21	CP	GA	CsT	Sylvester	CO-CO-PE/WF	Plinthic Kandiudults	6	1.66	0.9	0.5	401.7	345.4	85.8	8.2	1283	18.5
83.91	34.21	CP	GA	CvT	Sylvester	PE-CO/WF	Plinthic Kandiudults	30	1.61	1.1	0.6	401.1	378.4	87.2	6.8	1256	18.6
83.95	34.21	CP	GA	Pas	Sylvester	Grazed pasture	Plinthic Kandiudults	20	1.66	0.9	0.5	291.8	294.4	89.1	5.7	1269	18.5
82.94	34.21	CP	GA	CsT	Douglas	CO-RY or WH-PE	Plinthic Kandiudults	29	1.51	2.0	1.8	654.7	729.9	89.7	4.6	1260	18.7
82.93	34.21	CP	GA	CvT	Douglas	PE-CO/WF	Plinthic Kandiudults	10	1.48	2.0	1.8	725.8	783.8	88.4	5.1	1260	18.7
82.94	34.21	CP	GA	Pas	Douglas	Grazed pasture	Plinthic Kandiudults	20	1.38	2.4	1.9	888.4	893.9	85.8	6.0	1260	18.7

Longitude	Latitude	MLRA†	State	Use‡	Location	Rotation§	Soil Taxonomy	Nº Years	BD¶	Soil Organic C fractions#				Sand	Clay	Pcp. ††	Tmp. ‡‡
										TOC	POC	CMIN	SMBC				
									Mg m^{-3}	-- dag kg^{-1}		--- mg kg^{-1} ---		-- dag kg^{-1} --		mm	ºC
82.12	34.21	CP	GA	CsT	Millen	CO-WH-SO-RY-CO	Plinthic Kandiudults	11	1.49	1.5	1.0	541.5	502.6	85.7	6.5	1160	17.7
82.20	34.21	CP	GA	Pas	Midville	Grazed Pasture	Plinthic Kandiudults	10	1.51	1.3	0.8	475.8	435.5	76.9	13.0	1163	17.7
82.20	34.21	CP	GA	CvT	Midville	CO	Plinthic Kandiudults	14	1.47	1.2	0.7	431.4	378.6	72.0	16.4	1159	17.8
83.63	34.21	P	GA	CvT	Madison	CO	Rhodic Kanhapludults	40	1.39	1.9	1.1	616.9	584.8	65.4	20.7	1222	16.3
83.57	34.21	P	GA	CsT	Madison	SG-SO	Rhodic Kanhapludults	10	1.34	2.2	1.5	781.8	726.3	67.7	17.7	1211	16.4
83.56	34.21	P	GA	Pas	Madison	Grazed pasture	Rhodic Kanhapludults	20	1.43	1.9	1.3	698.4	668.7	69.9	15.8	1211	16.4
82.91	34.21	P	GA	Pas	Centerville	Grazed pasture	Typic Kanhapludults	40	1.43	1.4	0.9	528.7	514.1	70.9	14.5	1277	15.9
82.91	34.21	P	GA	CsT	Centerville	CO	Typic Kanhapludults	5	1.48	1.1	0.6	375.9	436.8	73.2	13.3	1277	15.9
82.94	34.21	P	GA	CvT	Centerville	CO	Typic Kanhapludults	15	1.43	1.2	0.6	399.8	494.8	71.7	14.1	1254	15.8
84.05	34.21	P	GA	CvT	Locust Grove	WH or OA	Typic Kanhapludults	10	1.35	1.9	1.1	544.9	718.8	72.3	13.3	1246	16.1
84.19	34.21	P	GA	CsT	Locust Grove	WH-CO-OA	Typic Kanhapludults	10	1.37	1.6	0.9	444.2	586.8	79.2	10.6	1266	16.1
84.20	34.21	P	GA	Pas	McDonough	Grazed pasture	Typic Kanhapludults	11	1.41	1.3	0.8	410.6	513.0	85.7	7.8	1266	16.1
81.40	34.21	CP	SC	CvT	Barnwell	MI	Plinthic Kandiudults	26	1.50	0.9	0.5	290.3	380.7	90.4	6.0	1202	18.1
81.38	34.21	CP	SC	Pas	Barnwell	Hayed Pasture	Plinthic Kandiudults	20	1.52	1.0	0.6	326.7	450.7	88.7	6.6	1202	18.1
81.38	34.21	CP	SC	CsT	Barnwell	CO	Plinthic Kandiudults	10	1.64	0.9	0.5	222.4	359.1	88.5	6.2	1204	18.1
81.22	34.21	CP	SC	CsT	Olar	SO-CO	Typic Kanhapludults	20	1.58	1.1	0.7	352.1	465.2	87.5	6.9	1210	18.0
81.12	34.21	CP	SC	CvT	Bamberg	PE-CO	Typic Kanhapludults	20	1.54	1.4	0.8	403.3	513.9	84.5	7.3	1221	17.8
81.10	34.21	CP	SC	Pas	Bamberg	Grazed pasture	Typic Kanhapludults	20	1.50	2.0	1.0	524.9	728.1	83.1	7.4	1221	17.8

Longitude	Latitude	MLRA†	State	Use‡	Location	Rotation§	Soil Taxonomy	Nº Years	BD¶	Soil Organic C fractions#				Sand	Clay	Pcp. ††	Tmp. ‡‡
										TOC	POC	CMIN	SMBC				
									Mg m^{-3}	-- dag kg^{-1}		--- mg kg^{-1} ---		-- dag kg^{-1} --		mm	ºC
80.40	34.21	CP	SC	CsT	Harleyville	CO-SO	Aquic Paleudults	18	1.56	1.8	1.0	428.1	645.7	78.6	9.0	1257	17.9
80.50	34.21	CP	SC	Pas	Harleyville	Grazed Pasture	Aquic Paleudults	20	1.49	2.5	1.4	611.1	914.6	73.3	12.3	1242	18.2
80.54	34.21	CP	SC	CvT	St. George	CO	Aquic Paleudults	20	1.46	2.5	1.5	701.3	990.2	72.9	12.7	1242	18.0
82.99	34.21	P	SC	Pas	Westminster	Grazed Pasture	Typic Kanhapludults	20	1.35	2.2	1.4	672.6	944.2	66.9	20.3	1361	15.6
83.01	34.21	P	SC	CsT	Westminster	WH-SO-WF-SO-WH-MI	Typic Kanhapludults	7	1.37	1.9	1.2	648.5	810.4	67.6	19.8	1368	15.4
83.04	34.21	P	SC	CvT	Westminster	WH-SO	Typic Kanhapludults	20	1.46	1.5	0.9	596.2	659.3	67.5	20.0	1368	15.4
81.24	34.21	P	SC	CsT	Chester	SmG-CO or MI	Typic Kanhapludults	23	1.40	2.2	1.5	840.6	916.6	71.4	14.1	1204	15.9
81.24	34.21	P	SC	CvT	Chester	VE	Typic Kanhapludults	30	1.32	3.0	2.0	1101.3	1347.1	68.1	13.3	1204	15.9
81.24	34.21	P	SC	Pas	Chester	Grazed pasture	Typic Kanhapludults	30	1.40	2.7	1.7	946.5	1185.5	65.1	13.5	1204	15.9
81.12	34.21	P	SC	Pas	Rock Hill	Grazed pasture	Typic Kanhapludults	20	1.59	1.6	1.0	595.6	773.5	60.6	18.2	1219	16.2
81.14	34.21	P	SC	CsT	Rock Hill	CO	Typic Kanhapludults	14	1.59	1.2	0.6	339.3	448.0	66.5	16.8	1214	16.1
81.15	34.21	P	SC	CvT	Rock Hill	CO	Typic Kanhapludults	15	1.58	1.1	0.5	250.3	363.8	75.0	12.1	1213	16.1
77.23	34.21	CP	NC	CsT	Greenville	SO-WH-CO-SO	Typic Quartzipsamm	10	1.49	1.5	0.8	392.8	548.2	81.6	7.0	1246	16.0
77.21	34.21	CP	NC	CvT	Greenville	TO-CO-PE	Typic Quartzipsamm	20	1.45	1.4	0.8	433.9	629.3	82.5	6.2	1246	16.0
77.21	34.21	CP	NC	Pas	Greenville	Grazed pasture	Typic Quartzipsamm	20	1.43	1.2	0.7	394.3	593.2	82.4	6.0	1246	16.0
77.83	34.21	P	NC	CsT	Littleton	PE-WH-CO	Typic Kanhapludults	14	1.40	1.6	0.9	517.6	805.9	77.9	7.4	1162	14.5
77.83	34.21	P	NC	CvT	Littleton	CO-PE	Typic Kanhapludults	14	1.46	1.7	1.1	599.5	887.0	64.8	17.2	1162	14.5
77.82	34.21	P	NC	Pas	Littleton	Grazed Pasture	Typic Kanhapludults	11	1.41	2.1	1.6	779.4	1037.5	51.0	27.6	1160	14.5

Longitude	Latitude	MLRA†	State	Use‡	Location	Rotation§	Soil Taxonomy	Nº Years	BD¶	Soil Organic C fractions#				Sand	Clay	Pcp. ††	Tmp. ‡‡
										TOC	POC	CMIN	SMBC				
									Mg m^{-3}	-- dag kg^{-1}		--- mg kg^{-1} ---		-- dag kg^{-1} --		mm	ºC
80.73	34.21	P	NC	CsT	Cleveland	CO-SO-WH-SO	Typic Kanhapludults	12	1.39	1.7	1.3	592.9	751.4	40.9	33.7	1142	14.4
80.73	34.21	P	NC	Pas	Cleveland	Grazed pasture	Typic Kanhapludults	12	1.40	2.1	1.5	670.0	934.3	47.9	28.7	1142	14.4
80.55	34.21	P	NC	CvT	China Grove	WH-SO	Typic Kanhapludults	70	1.36	2.4	1.5	780.9	1041.8	53.8	26.1	1117	14.9
79.70	34.21	P	NC	CsT	Reidsville	OR+CL-CO-RY+VH+CL-OA+CL	Typic Kanhapludults	12	1.36	2.0	1.2	696.6	928.0	61.4	21.8	1172	14.3
79.70	34.21	P	NC	Pas	Reidsville	Grazed Pasture	Typic Kanhapludults	18	1.47	1.2	0.7	405.5	509.8	71.9	14.7	1172	14.3
79.70	34.21	P	NC	CvT	Reidsville	VE	Typic Kanhapludults	18	1.60	0.9	0.5	204.5	289.7	78.4	9.6	1172	14.3
79.02	34.21	CP	NC	CvT	Lumber Bridge	CO	Typic Kandiudults	20	1.50	1.3	0.6	303.8	388.5	80.2	7.2	1215	16.2
79.03	34.21	CP	NC	CsT	Lumber Bridge	CO-CO/RY	Typic Kandiudults	5	1.31	2.7	1.7	727.3	958.0	71.0	8.7	1215	16.2
79.05	34.21	CP	NC	Pas	Lumber Bridge	Hayed pasture	Typic Kandiudults	10	1.29	2.3	1.5	621.3	863.1	64.2	16.1	1210	16.4
79.08	34.21	P	VA	Pas	Gladys	Grazed pasture	Typic Kanhapludults	20	1.43	1.6	1.1	506.5	688.8	64.0	17.6	1127	13.1
78.90	34.21	P	VA	CvT	Brookneal	TO	Typic Kanhapludults	26	1.59	0.9	0.5	308.3	395.1	63.0	19.2	1135	13.4
78.88	34.21	P	VA	CsT	Brookneal	SO	Typic Kanhapludults	10	1.60	1.3	0.8	517.2	564.2	62.2	16.6	1135	13.3
77.91	34.21	P	VA	CsT	Powhatan	CO-SO-SmG	Typic Kanhapludults	5	1.57	1.2	0.7	443.1	512.1	58.8	18.7	1117	13.6
77.89	34.21	P	VA	Pas	Powhatan	Grazed Pasture	Typic Kanhapludults	20	1.35	2.4	2.6	830.1	997.4	42.8	20.2	1104	13.6
77.96	34.21	P	VA	CvT	Powhatan	TO	Typic Kanhapludults	5	1.25	2.9	4.0	887.3	1118.7	26.1	29.9	1096	13.6
77.90	34.21	P	VA	Pas	Culpeper	Grazed pasture	Typic Hapludults	40	1.25	2.8	3.7	849.5	1045.8	17.6	39.3	1100	13.0
77.90	34.21	P	VA	CsT	Culpeper	CO-WH-SO	Typic Hapludults	12	1.32	2.4	2.3	839.9	973.5	37.4	31.6	1100	13.0

Longitude	Latitude	MLRA†	State	Use‡	Location	Rotation§	Soil Taxonomy	Nº Years	BD¶	Soil Organic C fractions#				Sand	Clay	Pcp. ††	Tmp. ‡‡
										TOC	POC	CMIN	SMBC				
									Mg m^{-3}	-- dag kg^{-1}		--- mg kg^{-1} ---		-- dag kg^{-1} --		mm	ºC
78.22	34.21	P	VA	CvT	Somerset	SO-WH-SO	Rhodic Kandiudults	20	1.34	2.1	1.2	824.2	892.3	51.2	20.9	1142	12.9
76.75	34.21	CP	VA	Pas	Montross	Grazed Pasture	Typic Hapludults	30	1.39	1.6	0.7	650.0	677.3	60.1	13.4	1115	14.3
76.72	34.21	CP	VA	CsT	Mt. Holly	SmG/SO-CO	Typic Hapludults	10	1.49	1.3	0.5	469.1	446.4	64.5	11.9	1120	14.2
76.72	34.21	CP	VA	CvT	Mt. Holly	SmG/SO-CO	Typic Hapludults	30	1.59	1.0	0.4	368.9	339.6	74.0	8.9	1120	14.2
77.11	34.21	CP	VA	Pas	Quinton	Hayed grass	Typic Hapludults	60	1.59	1.0	0.5	404.7	391.6	77.9	7.6	1135	14.4
77.19	34.21	CP	VA	CvT	New Kent	CO-WH-SO	Typic Hapludults	3	1.46	1.3	1.2	487.2	479.5	57.3	16.7	1131	14.3
77.17	34.21	CP	VA	CsT	Mechanicsville	CO-WH-SO	Aquic Hapludults	15	1.35	1.8	1.5	793.5	650.2	41.0	21.2	1131	14.3
77.00	34.21	CP	VA	CsT	Spring Grove	CO-WH-SO	Ultic Hapludalfs	15	1.41	1.5	1.2	697.7	544.0	39.8	21.9	1173	14.7
77.04	34.21	CP	VA	Pas	Spring Grove	Grazed pasture	Ultic Hapludalfs	25	1.61	1.0	0.7	475.2	412.1	54.3	18.5	1166	14.7
77.01	34.21	CP	VA	CvT	Spring Grove	CO-WH-SO	Ultic Hapludalfs	25	1.64	1.3	0.8	509.8	596.5	65.6	16.1	1166	14.7
85.44	34.21	P	AL	CvT	Lafayette	VE	Rhodic Kanhapludults	15	1.54	1.6	1.0	543.3	716.1	61.6	21.6	1389	16.5
85.44	34.21	P	AL	Pas	Lafayette	Grazed pasture	Rhodic Kanhapludults	40	1.43	1.8	1.1	685.5	878.2	65.9	18.1	1389	16.5
85.44	34.21	P	AL	CsT	Lafayette	CO	Rhodic Kanhapludults	10	1.58	1.2	0.7	457.3	598.6	70.1	15.1	1389	16.5
85.44	34.21	P	AL	Pas	Lafayette	Hayed pasture	Typic Kanhapludults	30	1.65	1.1	0.6	426.3	557.8	73.8	12.4	1389	16.5
85.44	34.21	P	AL	CvT	Lafayette	VE	Typic Kanhapludults	15	1.68	1.0	0.5	341.9	458.7	72.1	12.8	1389	16.5
85.43	34.21	P	AL	CsT	Lafayette	CO	Typic Kanhapludults	10	1.70	1.0	0.5	340.9	463.2	73.7	12.0	1389	16.5
85.44	34.21	P	AL	CvT	Lafayette	VE	Typic Kanhapludults	15	1.60	1.5	0.9	505.5	548.9	72.2	12.8	1389	16.5
85.40	34.21	P	AL	CsT	Lafayette	CO	Typic Kanhapludults	10	1.68	1.3	0.8	387.0	410.8	77.5	10.4	1393	16.5

Longitude	Latitude	MLRA†	State	Use‡	Location	Rotation§	Soil Taxonomy	Nº Years	BD¶	Soil Organic C fractions#				Sand	Clay	Pcp. ††	Tmp. ‡‡
										TOC	POC	CMIN	SMBC				
									Mg m^{-3}	-- dag kg^{-1}		--- mg kg^{-1} ---		-- dag kg^{-1} --		mm	ºC
85.40	34.21	P	AL	Pas	Lafayette	Hayed pasture	Typic Kanhapludults	30	1.69	1.1	0.7	282.3	328.3	82.5	8.1	1393	16.5

†Major Land Resource Areas: CP = Coastal Plain, P = Southern Piedmont.
‡Soil Use/Management: CvT = Conventional Tillage Row Crops, CsT = Conservation Tillage Row Crops, Pas = Pastures (Hayed or Grazed).
§ CL = clover, CN = corn, CO = cotton, MI = millet, OA = oats, OR = orchad, PE = peanut, RY = rye, SG = sorghum, SmG = small grains, SO = soybean, TO = tobacco, VE = vegetables, VH = vetch, WF = winter fallow, WH = wheat.
¶Bulk density.
#TOC = total organic C, POC = particulate organic C, CMIN = C mineralized in 24-d, SMBC = soil microbial biomass C.
††Mean annual precipitation (30-y normals).
‡‡Mean annual temperature (30-y normals).