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RESEARCH ARTICLE

Associations between soil carbon and ecological landscape variables at escalating spatial scales in Florida, USA

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Abstract The spatial distribution of soil carbon (C) is controlled by ecological processes that evolve and interact over a range of spatial scales across the landscape. The relationships between hydrologic and biotic processes and soil C patterns and spatial behavior are still poorly understood. Our objectives were to (i) identify the appropriate spatial scale to observe soil total C (TC) in a subtropical landscape with pronounced hydrologic and biotic variation, and (ii) investigate the spatial behavior and relationships between TC and ecological landscape variables which aggregate various hydrologic and biotic processes. The study was conducted in Florida, USA, characterized by extreme hydrologic (poorly to excessively drained soils), and vegetation/land use gradients ranging from natural uplands and wetlands to intensively managed forest, agricultural, and urban systems. We used semivariogram and landscape indices to compare the spatial dependence structures of TC and 19 ecological landscape variables, identifying similarities and establishing pattern–process relationships. Soil, hydrologic, and biotic ecological variables mirrored the spatial behavior of TC at fine (few kilometers), and coarse (hundreds of kilometers) spatial scales. Specifically, soil available water capacity resembled the spatial dependence structure of TC at escalating scales, supporting a multi-scale soil hydrology-soil C process–pattern relationship in Florida. Our findings suggest two appropriate scales to observe TC, one at a short range (autocorrelation range of 5.6 km), representing local soil-landscape variation, and another at a longer range (119 km), accounting for regional variation. Moreover, our results provide further guidance to measure ecological variables influencing C dynamics.

Keywords Soil carbon · Scale · Variogram · Spatial variation · Spatial autocorrelation

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Introduction

Soil and ecological processes and spatial patterns are linked across many scales, mutually influencing the spatial and temporal distribution of one another. In order to understand regional soil patterns it is necessary to identify the underlying ecological processes responsible for those patterns. This requires assessing multiple scales of variation in soil and ecological variables representing those underlying processes and elucidating how they interact in space and time.

This type of scaling analysis requires assessing factors that may affect observations and conclusions about the spatial behavior of soil and ecological variables. Some of the commonly recognized scale factors are grain (or resolution), extent, observation density and arrangement (sampling design), and sample dimensions (support). Additional factors to consider are range, magnitude, and distribution of attribute values, and spatial auto- and cross-correlations among soil-ecological variables. These factors were included in the broad definition of scale proposed by Blöschl (1999), and have been used in various contexts, including up- and downscaling, investigations of scale-dependent behavior, and scaling within different domains of space and time (e.g., Blöschl and Sivapalan 1995; Moody and Woodcock 1995; McBratney 1998; Hay et al. 2001).

Geostatistics, more specifically variogram analysis, has been used to describe the spatial dependence structure of many soil and ecological variables, including soil carbon (C) (e.g., Vasques et al. 2010a, b). The semivariogram (or simply variogram) characterizes this spatial dependence structure by modeling the semivariance as a function of lag distance (Eq. 1) (Chilès and Delfiner 1999; Grunwald 2006).

$$\gamma(h) = \frac{1}{2m(h)} \sum_{i=1}^{m(h)} [z(x_i) - z(x_i + h)]^2 \qquad (1)$$

where $\gamma(h)$ is the observed semivariance at lag distance h; $m(h)$ the number of paired data at lag distance h; and $z(x_i)$, $z(x_i + h)$ the measurements separated by a lag distance h.

The spatial dependence of an ecological variable can be characterized by the parameters of variogram models, i.e., the nugget and sill variances, and the range (or autocorrelation range), and also by their shapes. These parameters depend on the magnitude and spatial distribution of the variable, sampling design (including the number of observations), and landscape configuration. Importantly, the variogram parameters are the result of the processes that generated the spatial dependence structure.

Many studies have quantified the spatial dependence of soil C using variogram analysis. McBratney and Pringle (1999), for example, identified an average spatial autocorrelation range of 310 m among nine investigations of soil C in agricultural fields. Mueller and Pierce (2003) found ranges for soil total C (TC) between 118 and 249 m within a 13-ha field (corn-soybean rotation) in Michigan, USA, depending on the number of samples. Terra et al. (2004) identified ranges for soil organic C (SOC) varying from 63 to 73 m, also depending on the number of samples, in a 9-ha field (cotton and other crops) in central Alabama, USA. And more recently Simbahan et al. (2006) identified ranges for SOC varying from 89 to 450 m at three fields (diverse crops) of 49 to 65 ha in Nebraska, USA. Commonly spatial autocorrelations have been documented for SOC or TC, but studies do not explain the spatial behavior and cross-relationships with other ecological landscape variables.

Along with the given examples, the majority of investigations of the spatial dependence of soil C were conducted at the field scale. However, some investigations have identified the spatial dependence of soil C at larger extents, including van Meirvenne et al. (1996) (3,164 km^2) in Belgium, McGrath and Zhang (2003) (41,462 km^2), and Zhang and McGrath (2004) (15,460 km^2) in Ireland, Hengl et al. (2004) (2,500 km^2) in Croatia, and Vasques et al. (2010a, b) (3,585 km^2) in the USA. These studies identified spatial autocorrelation ranges for SOC or soil organic matter (SOM) in the order of 3–100 km. This large span in spatial autocorrelation ranges may be explained by differences in geology, soils, ecosystem types, and topographic and climatic gradients within these large systems. At these regional to continental scales, the spatial dependence of soil C is not sufficiently characterized, and still subject to investigation.

Investigations relating soil C (or SOM) to ecological landscape variables have been conducted in different regions and environments throughout the world. For example, Pei et al. (2010) used a topographic wetness index as a covariate to map SOM across a 52-km^2 agricultural area (soybean and wheat) in northeastern China. Hancock et al. (2010) observed TC patterns in a 50-ha mixed area (forest and grassland) in northern

Australia to be linked to vegetative biomass, which was in turn controlled by topography. Several studies have quantified soil C stock and change as a function of land use and management (e.g., Post and Kwon 2000; Guo and Gifford 2002; Murty et al. 2002; Ostle et al. 2009).

Examples over larger extents include: Phachomphon et al. (2010), who modeled SOC across Laos (230,566 km^2, mostly forested) as a function of elevation, precipitation, and soil clay content, obtaining a R^2 of 0.36; and Zhou et al. (2008), who mapped SOC across China ($\sim$9.60 million km^2) based on a process-based model that used remotely sensed normalized difference vegetation index (NDVI), and other soil, and climatic variables.

Specifically in Florida, USA, three studies have recently related soil and ecological patterns in a vast wetland area—the Everglades. Corstanje et al. (2006), and Bruland et al. (2006) observed main TC patterns at 0–10, and 10–20-cm depths to be associated with predominant hydrologic patterns in Water Conservation Areas 1 (559 km^2), and 3 (2,330 km^2), respectively. In Water Conservation Area 2A (433 km^2), Rivero et al. (2007) characterized the spatial variation of TC (0–10 cm), relating the observed patterns to vegetation and organic matter dynamics and hydrologic patterns at the fine scale, and to the slough-ridge topography at a coarser scale.

In a 3,585-km^2 watershed with mixed land uses and natural environments in Florida, Vasques et al. (2010a) demonstrated that TC was significantly higher in Histosols (organic soils) in wetlands than in other land uses or better drained areas. Although their study suggested that soil hydrology, and land use controlled soil C sequestration and decomposition, there are other ecological variables, such as topography and vegetation, which may confound C dynamics. However, it is still unknown how strongly these ecological variables control C dynamics in Florida or if they do at all. Furthermore, our knowledge on the spatial behavior of soil C as influenced by ecological landscape variables in this type of environment (flat topography, widespread presence of wetlands, and predominantly sandy soils) is still limited.

Our objectives were to (i) identify the appropriate spatial scale to observe TC in a subtropical landscape with pronounced hydrologic and biotic variation, and (ii) investigate the spatial behavior and relationships between TC and ecological landscape variables which aggregate various hydrologic and biotic processes.

Materials and methods

Study area

The study was conducted in Florida, which spans about 150,000 km^2 between latitudes 24.55 and 31.00° N, and longitudes 80.03 and 87.63° W (Fig. 1). Mean annual precipitation is 1,373 mm, and mean annual temperature is 22.3°C (National Climatic Data Center 2008). Florida soils are mainly Spodosols (32%), Entisols (22%), Ultisols (19%), Alfisols (13%), and Histosols (11%) (Natural Resources Conservation Service 2006), and land uses/land covers are predominantly wetlands (28%), pinelands (18%), croplands (9%), rangelands (9%), improved pasture (8%), and urban or barren lands (15%) (Florida Fish and Wildlife Conservation Commission 2003).

Topography is flat, with elevations below 114 m, and 0–5% slopes in most of the state (United States Geological Survey 1984). Limestone bedrock originating from marine sediments is present throughout most of Florida. In the south, these materials are overlain by partially decomposed organic materials and/or secondary carbonates (marl), while in the north they received sandy and loamy materials of marine and continental origin.

Field sampling and laboratory analysis

Field sampling was conducted at three nested regions within Florida (Fig. 1). The broadest region encompassed the whole state ($\sim$150,000 km^2), the second region had an intermediate extent ($\sim$3,585 km^2), delimited by the Santa Fe River watershed, and the third and smallest region was the University of Florida Beef Cattle Station ($\sim$5.58 km^2), nested inside the Santa Fe River watershed. The dimensions of these three areas were orders of magnitude different, reflecting a progressively increasing variability of TC from the field to the state extent.

Soil samples were collected at multiple depths, obeying to either a horizon-based sampling to 2 m or more across the state (1,193 soil profiles) (Florida Soil Characterization Database 2009), or a stratified random sampling design using soil-land use strata across the watershed (141 profiles), and cattle station (152 profiles), respectively, with samples collected at fixed depth intervals (0–30, 30–60, 60–120, and 120–180 cm).

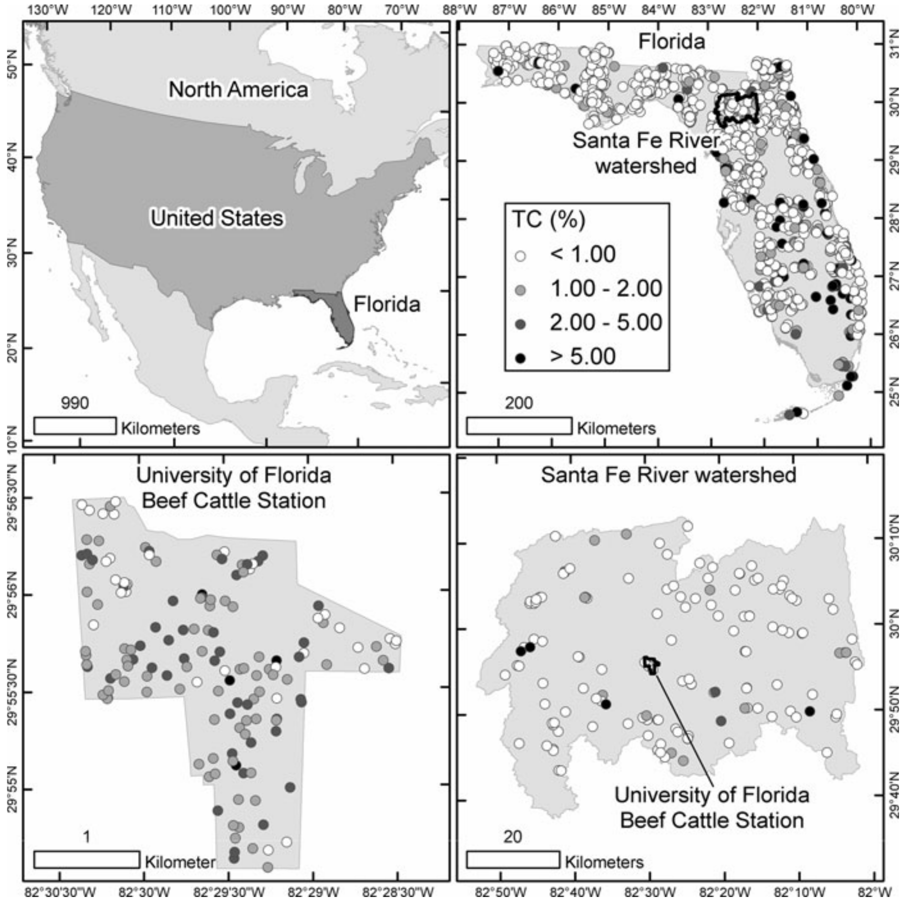

Fig. 1 Three nested regions in Florida, with their respective sample distributions of TC. Latitude/longitude coordinates correspond to each map individually

Laboratory analysis of TC was conducted using air-dried and sieved (2 mm) samples and involved three methods: (i) high temperature combustion (FlashEA 1112 Elemental Analyzer) (Thermo Electron Corp., Waltham, MA) for samples collected at the watershed; (ii) loss on ignition (Natural Resources Conservation Service 1996) for samples collected at the cattle station, and samples from organic horizons collected from the state; and (iii) Walkley–Black modified acid–dichromate oxidation (Walkley and Black 1934; Natural Resources Conservation Service 1996) for samples from mineral horizons from the state. For the latter two methods, which measure SOM, SOC was calculated by multiplying SOM by the van Bemmelen factor (0.58) (Natural Resources Conservation Service 1996).

Soil C measurements from the different methods were standardized to high temperature combustion units using linear conversion factors between loss on ignition and Walkley–Black SOC, respectively, and high temperature combustion TC. The conversion factors were derived based on 144 samples from the state dataset, and are shown in Eq. 2 ($R^2 = 0.97$) for loss on ignition, and Eq. 3 ($R^2 = 0.94$) for Walkley–Black measurements, respectively.

$$TC_{HTC} = 0.90 \times SOC_{LOI} \quad (2)$$

$$TC_{HTC} = 0.98 \times SOC_{WB} \quad (3)$$

where TC_{HTC} is TC measured by high temperature combustion, in %; SOC_{LOI} SOC measured by loss on ignition, in %; and SOC_{WB} SOC measured by Walkley–Black, in %.

Soil total C concentration (in %) was calculated for the first 1 m as the depth-weighted average TC across all depth or horizon intervals to 1 m, and then transformed using natural logarithm (ln) to approximate a normal distribution. After standardizing the unit and depth (support), samples from the cattle station, watershed, and state were grouped together to form a pooled dataset comprising 1,486 samples.

Variogram analysis of soil total carbon and ecological variables

We used variogram analysis to characterize the spatial dependence of ln-transformed soil total carbon (LnTC) within 1 m using the pooled dataset, and of 19 selected ecological variables that could potentially generate or explain the spatial patterns of TC. The 19 ecological variables included six soil, three topographic, and 10 Landsat Enhanced Thematic Mapper Plus (ETM+) reflectance and derived variables (Table 1). For LnTC and each ecological variable, respectively, two empirical variograms were derived: one using 30 lags (bins) of 210 m, spanning a total of 6.3 km; and another using 24 lags of 15.5 km, spanning 372 km. The objective was to characterize their individual spatial dependence structures over the short and long ranges (distances). In addition, we derived cross-variograms (Eq. 4) (Chilès and Delfiner 1999; Grunwald 2006) for all ecological variables with LnTC, also over the short and long ranges. Finally, we modeled the empirical variograms/cross-variograms using either exponential (Eq. 5) or Gaussian (Eq. 6) models (Chilès and Delfiner 1999) to obtain variogram parameters, i.e., the nugget variance, sill variance, and range of spatial autocorrelation, for all variables.

$$\gamma_{ij}(h) = \frac{1}{2m(h)}\sum_{i=1}^{m(h)}[z_u(x) - z_u(x+h)][z_v(x) - z_v(x+h)] \tag{4}$$

$$\hat{\gamma}(h) = c_0 + c\left[1 - e^{-3(h/r)}\right] \tag{5}$$

$$\hat{\gamma}(h) = c_0 + c\left[1 - e^{-3(h/a)^2}\right] \tag{6}$$

where $\gamma_{ij}(h)$ is the observed cross-semivariance at lag distance h; $m(h)$ the number of paired data at lag distance h; $z_u(x)$, $z_u(x + h)$ the measurements of variable u separated by a lag distance h; $z_v(x)$, $z_v(x + h)$ the measurements of variable v separated by a lag distance h; $\hat{\gamma}(h)$ the estimated semivariance at lag distance h; c_0 the nugget variance; c the partial sill variance; e the natural exponential base; h the lag distance; r the effective range, where $\gamma(h)$ achieves 95% of the total sill variance ($c_0 + c$), at about $3a$; and a the range.

Variograms for the 19 ecological variables were derived using data extracted from raster maps (30-m resolution) co-located spatially with the 1,486 TC samples that comprised the pooled dataset. This ensured that the comparisons of spatial structures between ecological variables and LnTC were based on the same sampling design, and thus, were consistent across all ecological variables.

Landscape structure analysis of ecological variables

We also calculated two metrics of landscape structure based on three other categorical ecological variables: land use, soil drainage class, and soil hydrologic group. The two landscape metrics used were the area-weighted mean radius of gyration of patches of the same class (GYRATE_AM; Eq. 7), and the mean Euclidean distance between nearest neighboring patches of the same class (ENN_MN; Eq. 8) (McGarigal et al. 2002).

$$GYRATE\_AM = \sum_{j=1}^{n}\left[\sum_{r=1}^{z}\left(\frac{h_{ijr}}{z}\right)\left(\frac{a_{ij}}{\sum_{j=1}^{n} a_{ij}}\right)\right] \tag{7}$$

$$ENN\_MN = \sum_{j=1}^{n} h_{ij}/n \tag{8}$$

where h_{ijr} is the distance between cell ijr (located within patch ij) and the centroid of patch ij; z the number of cells in patch ij, where $r = 1, \ldots, z$; a_{ij} the area of patch ij; n the number of patches of the same class, where $j = 1, \ldots, n$; and h_{ij} the distance from patch ij to nearest neighboring patch of the same class.

As a measure of landscape connectivity, the GYRATE_AM can be interpreted as the average traversable distance within a patch, i.e., the average distance between a random position inside a patch and a patch edge. Thus, it corresponds to a *correlation length* (Keitt et al. 1997) analogous to the range of spatial autocorrelation given by the variogram. The ENN_MN complements the GYRATE_AM by giving the expected distance between patches of the same class that are disconnected on the landscape.

Results

Descriptive statistics and correlation of soil total carbon with ecological variables

Soil total C varied from 0.03 to 54.59%, with a mean of 1.87%, and showed a positively skewed distribution, which approached a normal distribution after natural

Table 1 Descriptive statistics of TC and ecological landscape variables at the 1,486 sampling sites

Variable	Data source	Mean	SD	Min	Max	Skewness	Correlation with LnTC[a]
TC (%)	Field sampling	1.87	5.92	0.03	54.59	5.81	
LnTC (ln%)	Field sampling	−0.50	1.14	−3.56	4.00	1.41	
Soil clay content (%)	NRCS (2009)	8.22	9.61	0.23	69.90	2.42	0.21*
Soil silt content (%)	NRCS (2009)	5.71	8.33	0.15	82.82	5.16	0.25*
Soil sand content (%)	NRCS (2009)	86.05	15.80	1.92	99.27	−2.50	−0.26*
Soil pH	NRCS (2009)	5.59	0.83	4.35	8.50	1.20	0.12*
Soil AWC (cm cm^{-1})	NRCS (2009)	0.08	0.05	0.02	0.42	2.46	0.58*
Soil KSAT (μm s^{-1})	NRCS (2009)	82.88	50.17	0.41	383.28	1.72	−0.30*
Elevation (m)	USGS (1999)	22.26	18.25	0.00	104.00	1.02	−0.15*
Slope (%)	USGS (1999)	1.46	2.07	0.00	13.87	2.18	−0.02
CTI	USGS (1999)	13.41	5.52	5.39	28.24	0.14	0.14*
ETM+ band 1 (DN)	FWC (2003)	55.47	8.92	0.00	118.00	−0.80	−0.12*
ETM+ band 2 (DN)	FWC (2003)	42.41	8.94	0.00	113.00	2.52	−0.15*
ETM+ band 3 (DN)	FWC (2003)	40.65	14.58	0.00	142.00	1.79	−0.19*
ETM+ band 4 (DN)	FWC (2003)	68.64	12.90	14.00	131.00	0.14	0.02
ETM+ band 5 (DN)	FWC (2003)	61.42	24.71	10.00	152.00	0.71	−0.12*
ETM+ band 7 (DN)	FWC (2003)	37.48	17.97	9.00	120.00	1.27	−0.15*
NDVI	FWC (2003)	0.27	0.16	−0.47	1.00	−0.74	0.16*
Tasseled cap 1 (DN)	FWC (2003)	128.58	27.18	42.77	269.45	0.89	−0.13*
Tasseled cap 2 (DN)	FWC (2003)	0.42	14.15	−68.79	55.72	−0.75	0.17*
Tasseled cap 3 (DN)	FWC (2003)	−4.91	16.07	−73.79	54.10	−0.84	0.11*

AWC available water capacity; *CTI* compound topographic index; *DN* digital number; *ETM+* Landsat Enhanced Thematic Mapper Plus; *FWC* Florida Fish and Wildlife Conservation Commission; *KSAT* saturated hydraulic conductivity; *LnTC* ln-transformed soil total carbon; *Max* maximum; *Min* minimum; *NDVI* normalized difference vegetation index; *NRCS* Natural Resources Conservation Service; *SD* standard deviation; *TC* soil total carbon; *USGS* United States Geological Survey

* Significant correlation at the 0.05 significance level

[a] Pearson's product-moment correlation coefficient

logarithm transformation (Table 1). The ecological variable most strongly correlated with LnTC was soil available water capacity (AWC), with a Pearson's product-moment correlation coefficient of 0.58 (Table 1). The second highest correlation with LnTC was observed for soil saturated hydraulic conductivity (KSAT) (−0.30), another soil hydrologic variable. Among the 19 ecological variables selected for this study, only slope, and Landsat ETM+ band 4 were not significantly correlated with LnTC at the 0.05 significance level.

Variogram analysis of soil total carbon

Over the short range (30 lags × 210 m), LnTC exhibited Gaussian spatial dependence structure (Fig. 2a), with nugget, sill, and range of 0.24 ln%^{2}, 0.94 ln%^{2}, and 5.56 km, respectively. Over the long range (24 lags × 15.5 km), LnTC exhibited exponential spatial dependence (Fig. 2b), with nugget, sill, and range of 0.42 ln%^{2}, 1.29 ln%^{2}, and 119.42 km, respectively (Table 2).

The modeled LnTC variograms had good agreement with the empirical variograms over both the short and long ranges (Fig. 2). The spatial autocorrelation of LnTC was stronger (smaller nugget-to-sill ratio) over the short range, which also captured the short-range Gaussian-like variation of LnTC not observed in the long-range variogram, thus decreasing the nugget variance. This suggests nested scales of variation for TC, which is not surprising given the multi-scale nature of soil–ecological relationships.

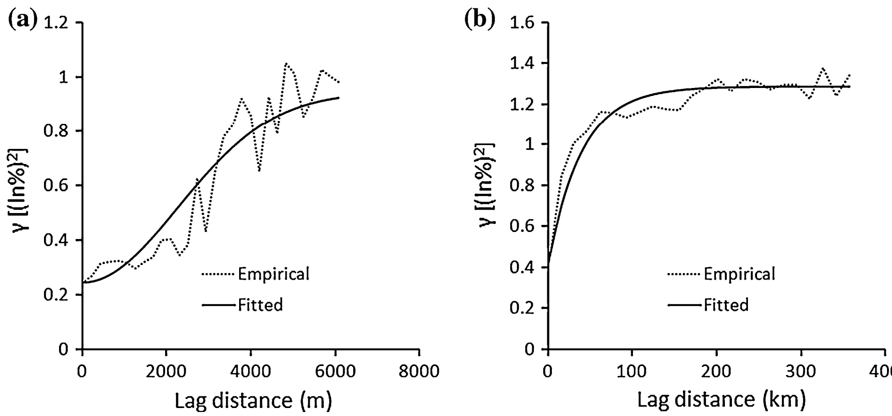

Fig. 2 Empirical and modeled variograms of LnTC over the **a** short and **b** long range, respectively

Variogram analysis of ecological variables

Over the short range, only 10 out of the 19 ecological variables had well-defined positive spatial autocorrelation that could be modeled by an exponential or Gaussian function. Over the long range, 16 ecological variables had well-defined positive spatial autocorrelation (Table 2).

The empirical variograms of LnTC and ecological variables showed some similarities in the shape and position of semivariogram structures (Fig. 3). Over both the short and long ranges, the general shapes of LnTC's empirical variograms were reproduced by the variograms of soil KSAT, and soil pH (Fig. 3a, c), and had some agreement with those from Landsat ETM+ band 3, and NDVI (Fig. 3b, d). For example, similarities between LnTC's and Landsat ETM+ band 3 and NDVI's variograms included, in the short range, a relatively leveled variogram at distances up to about 3,500 m, and the position of positive peaks (e.g., around 4,000, and 5,000 m) (Fig. 3b). In the long range, similarities included a steep raise over short distances, and the presence of positive peaks around 250, and 350 km, respectively (Fig. 3d).

In the short range alone, empirical variograms of Landsat ETM+ bands 1 and 2 also had similarities with LnTC's, including the position of two peaks around 3.5 and 4.5 km, respectively (not shown). In the long range alone, LnTC's variogram showed similar structures to those from elevation, and compound topographic index (CTI) (Fig. 3e), both associated with the distribution of Florida's wetlands and uplands.

In the empirical variograms, one position of interest is where the maximum semivariance is achieved. For LnTC, this position was close to 4.8 km in the short range (Fig. 2a), and 326 km in the long range (Fig. 2b). Variables with maximum semivariance close to these positions included: (i) in the short range, soil AWC, soil KSAT, and Landsat ETM+ bands 1, 2, 3 and 7, NDVI, and tasseled cap 1; and (ii) in the long range, soil pH, CTI, and elevation.

Remarkably, the variograms of soil AWC showed very similar shapes to the variograms of LnTC (Fig. 4a, b), especially over the long range. In the short range, soil AWC's variogram approached a Gaussian model, exhibiting a range of autocorrelation (6.2 km; Table 2) close to LnTC's (5.6 km). In the long range, soil AWC's variogram approached an exponential model, also having a similar range of autocorrelation (124 km; Table 2) to LnTC's (119 km). This indicates that the spatial dependence structures of LnTC and soil AWC are closely related at these two scales.

Cross-variogram analysis of soil total carbon and ecological variables

Over the short range, among the 10 ecological landscape variables that exhibited well-defined positive spatial autocorrelation, only three had positive and well-defined spatial cross-correlation with LnTC (Table 3). Ecological variables that exhibited negative spatial cross-correlation with LnTC over the short range included CTI, and Landsat ETM+ bands 5 and 7, and tasseled cap 1.

Over the long range, only seven ecological variables had positive spatial cross-correlation with LnTC (Table 3). Variables that exhibited negative spatial cross-correlation with LnTC over the long range included soil sand content, soil KSAT, elevation, and

Table 2 Modeled variogram parameters of LnTC and select ecological variables over short and long ranges

Variable[a]	Model	Nugget	Sill	Range (km)
Short range				
LnTC	Gaussian	0.24	0.94	5.56
Soil pH	Gaussian	0.05	0.32	5.26
Soil AWC	Gaussian	~0.00	~0.00	6.19
Elevation	Exponential	0.50	109.85	2.98
CTI	Exponential	4.45	25.98	2.39
ETM+ band 5	Exponential	83.02	494.34	1.05
ETM+ band 7	Exponential	45.92	239.33	0.99
NDVI	Gaussian	~0.00	0.03	5.22
Tasseled cap 1	Exponential	121.25	559.73	1.83
Tasseled cap 2	Exponential	45.37	201.10	1.24
Tasseled cap 3	Exponential	31.11	217.70	0.97
Long range				
LnTC	Exponential	0.42	1.29	119.42
Soil clay content	Exponential	77.43	92.53	109.59
Soil silt content	Gaussian	17.18	47.78	255.56
Soil sand content	Gaussian	152.48	230.87	283.26
Soil pH	Exponential	0.16	0.65	171.32
Soil AWC	Exponential	~0.00	~0.00	124.34
Soil KSAT	Exponential	1,058.35	2,604.48	201.32
Elevation	Exponential	73.76	293.37	125.15
CTI	Exponential	21.45	29.84	158.74
ETM+ band 2	Exponential	41.49	79.55	50.14
ETM+ band 3	Exponential	135.06	209.36	57.99
ETM+ band 5	Exponential	510.23	609.94	57.06
ETM+ band 7	Exponential	230.41	321.30	55.91
NDVI	Exponential	0.02	0.03	130.48
Tasseled cap 1	Exponential	507.07	731.69	57.06
Tasseled cap 2	Exponential	185.72	199.98	122.85
Tasseled cap 3	Exponential	229.63	257.02	145.93

AWC available water capacity; *CTI* compound topographic index; *ETM+* Landsat Enhanced Thematic Mapper Plus; *KSAT* saturated hydraulic conductivity; *LnTC* ln-transformed soil total carbon; *NDVI* normalized difference vegetation index

[a] Only those ecological variables that had positive spatial autocorrelation and a well-defined empirical variogram were modeled

Landsat ETM+ bands 2, 3, 5 and 7, and tasseled cap 1; slope exhibited negative spatial autocorrelation. Over the long range, spatial patterns of LnTC and ecological variables are in better agreement than at the short range, indicating that overall spatial patterns of TC across Florida are governed more strongly by long-range soil-landscape patterns correlated as far as 170 km apart.

Not surprisingly, soil AWC exhibited the most well-structured spatial dependence with LnTC among all ecological variables, both at the short and long ranges (Fig. 4c, d; Table 3), indicating the presence of a coupled soil C-soil hydrology landscape pattern.

Landscape structure analysis of ecological variables

Among land use classes, the GYRATE_AM varied from 3,177 to 7,916 m (Table 4), placing the edges between different land uses in the region where LnTC's semivariance raises and reaches its maximum (sill) in the short range (~4–6 km). Overall, soil drainage classes and hydrologic groups had GYRATE_AM values beyond 2.5 km, indicating that these water-related variables can also contribute to the observed raise of LnTC variation at this range. Noticeably, very high GYRATE_AM values were

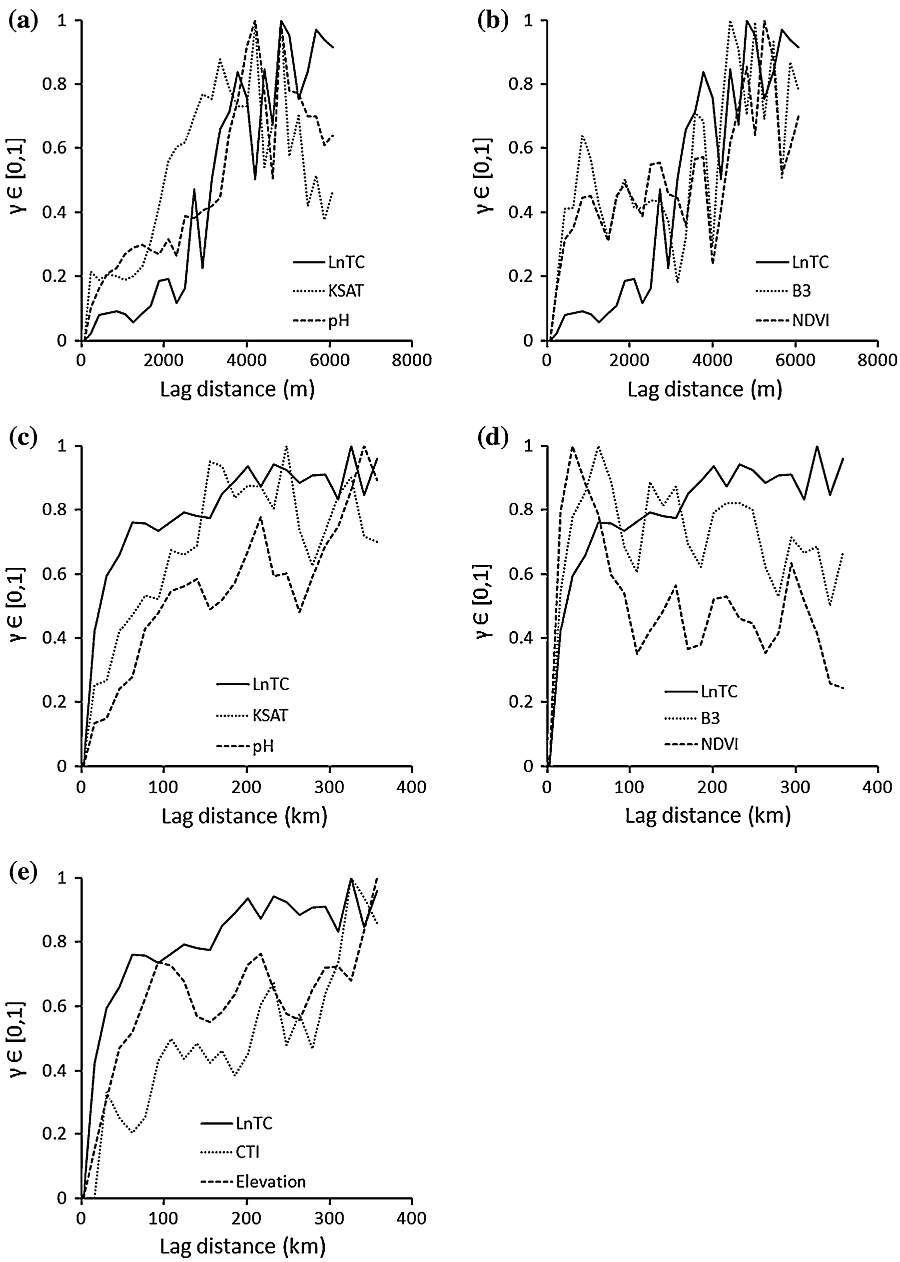

Fig. 3 Empirical variograms of select ecological variables in comparison with LnTC: **a** soil KSAT, and soil pH over the short range; **b** Landsat ETM+ band 3 (B3), and NDVI over the short range; **c** soil KSAT, and soil pH over the long range; **d** B3, and NDVI over the long range; and **e** CTI, and elevation over the long range. All variograms were transformed ([γ − minimum]/range) to fit within a 0–1 interval

observed for poorly drained soils, and soil hydrologic groups A, and B, which have high, and moderate infiltration rates, respectively. These high GYRATE_AM values reflect in both cases the relatively large patches of poorly drained soils, and soil hydrologic groups A, and B, respectively.

The ENN_MN did not provide information to explain TC's spatial patterns, but did confirm the findings above that areas with similar LnTC values (i.e., of the same class) would occur less than 2.5 km apart from each other. Had ENN_MN values gone beyond the 2.5-km threshold, one would probably see smaller LnTC semivariance values beyond 3 km in the short-range variogram.

Discussion

Variogram analysis coupled with landscape metrics offered a framework to understand and connect

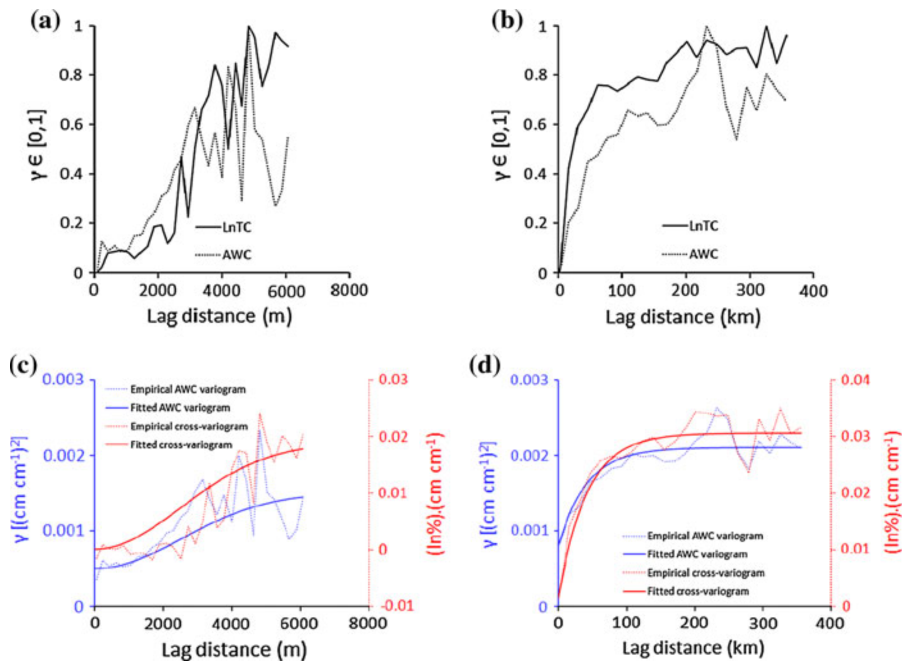

Fig. 4 Empirical variograms of soil AWC in comparison with LnTC over the **a** short and **b** long range, respectively, and empirical and modeled variograms of soil AWC (*left axis*) in comparison with cross-variograms of soil AWC and LnTC (*right axis*) over the **c** short and **d** long range, respectively. The soil AWC and LnTC variograms (**a**, **b**) were transformed ([γ − minimum]/range) to fit within a 0–1 interval. (Color figure online)

Table 3 Modeled cross-variogram parameters of LnTC with select ecological variables over short and long ranges

Variable[a]	Covariance with LnTC	Model	Nugget	Sill	Range (km)
Short range					
Soil pH	0.12	Gaussian	~0.00	0.07	5.26
Soil AWC	0.03	Gaussian	~0.00	0.02	6.19
NDVI	0.03	Gaussian	~0.00	0.06	5.22
Long range					
Soil clay content	2.28	Exponential	0.34	2.36	109.59
Soil pH	0.12	Exponential	~0.00	0.06	171.32
Soil AWC	0.03	Exponential	~0.00	0.03	124.34
CTI	0.91	Exponential	0.01	0.93	158.74
NDVI	0.03	Exponential	0.02	0.03	130.48
Tasseled cap 2	2.81	Exponential	2.06	2.86	122.85
Tasseled cap 3	2.06	Exponential	1.44	2.31	145.93

AWC available water capacity; *CTI* compound topographic index; *NDVI* normalized difference vegetation index

[a] Only those ecological variables that had positive spatial cross-correlation and a well-defined empirical cross-variogram with LnTC were modeled

landscape patterns. They were confirmatory pointing to hydrologic and biotic processes controlling the spatial behavior of TC in Florida.

The similar variograms (Fig. 4a, b; Table 2) and well-structured cross-variograms (Fig. 4c, d; Table 3) of LnTC and soil AWC indicate that processes influenced by the amount of water which can be stored in the soil (as represented by the AWC) could explain the spatial patterns of LnTC across Florida. In a region with constantly high water supply through rainfall, it is likely that the AWC correlates with the amount of water present in the soil profile. Because Florida is a region of high rainfall, the AWC is more likely to be filled. This in turn reduces organic matter decomposition rates, and increases net primary productivity. Thus, the capacity of soils to store water is likely to control the amount of C. By extension, processes related to the accumulation of water in soils dictate TC dynamics. Albeit having similar spatial dependence structures does not necessarily guarantee that AWC solely controls the spatial patterns of TC, it offers evidence of a pattern–process linkage between them.

Table 4 Landscape metrics of three categorical ecological variables

Variable	Class	GYRATE_AM (m)	ENN_MN (m)
Land use	Wetland	7,916	312
	Pineland	5,189	311
	Upland vegetation	3,177	343
	Agriculture	4,999	468
	Urban and barren	5,773	328
	Grassland	7,787	317
Soil drainage class	Excessively drained	13,595	445
	Well drained	8,258	427
	Moderately well drained	3,291	392
	Somewhat poorly drained	1,531	373
	Poorly drained	79,314	315
Soil hydrologic group[a]	A	31,078	379
	B	56,928	318
	C	1,510	361
	D	7,650	319

GYRATE_AM area-weighted mean radius of gyration of patches of the same class; *ENN_MN* mean Euclidean distance between nearest neighboring patches of the same class

[a] The letters A, B, C, and D designate, respectively, soils with high, moderate, slow, and very slow infiltration rates when thoroughly wet

In effect, the amount of water and redox potential of the soil ultimately dictate whether plant and animal residues (organic matter) accumulate over time in the form of soil C, or degrade, returning to the atmosphere through soil respiration (e.g., Reddy and Patrick Jr 1975). Our results show that the spatial structure and process scale of water supply is similar to that of TC. The topography of Florida is overall leveled, generating a landscape of wetlands, formed in depressions, interspersed with upland areas. The depressions accumulate water, creating anaerobic environments that slow down the decomposition of organic matter, fostering soil C build-up. On the other hand, in well-aerated upland soils, the presence of oxygen promotes faster decomposition of organic matter, favoring soil C degradation (Reddy and Patrick Jr 1975; Freeman et al. 2001). The link between TC and hydrologic processes in Florida is also supported by the association of TC with other variables, including soil drainage class, hydrologic group, KSAT, elevation, and CTI, a surrogate for water supply.

Short-range associations as identified by the variograms and cross-variograms suggest that LnTC's spatial dependence is connected to hydrologic processes operating locally. The relatively small semivariance for LnTC until about 2.5 km (Fig. 2a) indicates that either repetitive patterns or uniform areas of high or low LnTC, respectively, occur within this distance. Beyond 2.5 km, the semivariance increases, indicating that contrasting (high vs. low) LnTC patterns start to occur. This suggests that one or more sources of soil-landscape variation have 'fragmented' TC generation processes, creating homogeneous patches of less than 2.5 km in size, or placed within a distance of less than 2.5 km from one another, so that beyond this point dissimilar soil-landscapes and dissimilar LnTC occur. Such fragmentation effects can be related to socioeconomic or political decisions that determine the fate (use) of the land, or to physical processes related to geology, topography/hydrology and vegetation (Vasques et al. 2010a, b). Each of these fragmentation effects interact with the biogeochemical dynamics of TC and soil C pools (Parton et al. 1987; Ahn et al. 2009).

As discussed previously, the NDVI, which captures vegetation patterns in a landscape, resembled the spatial behavior of TC in the short range (Fig. 3b). This suggests a vegetation or land use control of LnTC in the short range, corroborated by the two landscape metrics on land use (Table 4). In effect, differences in land use and management are similar to differences in TC content at this finer scale.

Over the long range, it is reasonable to accept that hydrologic gradients, which occur over hundreds of kilometers, are the sources of landscape variation most closely related to TC (Figs. 3c–e; 4b, d). Contrary to other regions, where the topography exerts a more direct control over soil forming processes (e.g., through transport and deposition), in Florida, the presence of high water tables and wetlands have created a patchy landscape, with areas of higher and drier land interspersed with areas of stagnant waters and saturated terrain with only minor elevation differences.

Our LnTC variogram results corroborate those found in the literature. Over the short range, similar TC autocorrelation ranges to that observed in this study (5.6 km) were found for SOC at 0–30 cm by Wang et al. (2002) in a forested region in northeastern Puerto Rico (110 km^2), and also for SOM in the topsoil by Hengl et al. (2004) in central Croatia (2,500 km^2), both with a range of about 3.1 km. Over the long range, McGrath and Zhang (2003), and van Meirvenne et al. (1996) observed autocorrelation ranges for SOC of about 40 km in southeastern Ireland (41,462 km^2, 0–10 cm), and northwestern Belgium (3,164 km^2, topsoil), respectively, whereas Zhang and McGrath (2004) observed ranges from 58 to 100 km for SOC at 0–10 cm in southeastern Ireland (15,460 km^2). These ranges were closer to that found in this study for TC (119 km) and more modest than the range of 632 km observed for SOC at 0–20 cm in a 3,435-km^2 region in northeastern China (Liu et al. 2006).

Conclusions

In Florida, the spatial dependence and patterns of soil C are closely associated with those of soil AWC at local and regional scales. In this environment, water-related soil forming processes, as represented by AWC, control organic matter decomposition, transformation, and accumulation in the soil, and, along with other ecological processes, are responsible for the observed soil C spatial behavior and patterns. This study provides further guidance to select and assess variables and processes which control C dynamics, pointing to the appropriate scale to observe them in regional C assessments.

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