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Controls on soil organic matter content within a northern hardwood forest

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ABSTRACT

Forest soils can act as both sinks and sources for atmospheric CO_2 and therefore have an important role in the global carbon cycle. Yet the controls on forest soil organic matter content (SOM) distribution at the scale of operational land management scales within forest types are rarely quantified in detail. To identify factors that influence the spatial distribution and accumulation of SOM in forests, soils and stand composition data from 42 even-aged northern hardwood forest plots were analyzed using multiple linear regression and non-parametric statistical approaches. The analysis included three layers of SOM pools (forest floor, 0–20 cm mineral soil, and 20+ cm mineral soil) over three spatial scales (point, plot and regional). The largest amounts of total SOM (mean = 289, std dev = 70 Mg ha^{-1}) occurred in deep and well drained soils located on gently grading slopes. When soil layers were analyzed separately, the following relationships were observed: 1) highest forest floor SOM occurred under mixed species composition as opposed to stands dominated by sugar maple, 2) highest 0–20 cm mineral SOM occurred at high elevations (greater than 450 m) in moderately well drained soils, and 3) highest 20+ cm mineral SOM also occurred at high elevations and when soils were deeper. Further analysis of 0–20 cm mineral layer revealed that lower rock volume and finer soil texture resulted in higher SOM at a single point. When SOM that was predicted from models based on plot-specific attributes (soils series, slope and aspect) were compared to soil survey SOM estimates, the mean SOM values for both approaches were similar (253 and 269 Mg ha^{-1} respectively). Easily identifiable characteristics such as mixed stand composition, the presence of forest floor and E horizon thickness may be used as field indicators of SOM storage. The variety of controls identified in this study should be considered when assessing soil carbon response to management options and future changes in climate.

1. Introduction

Soils contain twice as much carbon as the atmosphere and about 75% of the total terrestrial organic carbon pool (Prentice, 2001). Over 40% of this soil carbon is found beneath forests. The carbon stored in these soils can be directly managed to absorb or release atmospheric carbon to a degree that may have global implications (Johnson and Curtis, 2001; Paul et al., 2002; Lal, 2005). However, forest soils are under-sampled and under-studied compared to aboveground carbon pools (Lal, 2005; Peltoniemi et al., 2007). The large spatial variability in forest soil organic matter (SOM) has also limited our ability to predict its spatial distribution (Johnson et al., 1991; Yanai et al., 2000; Fahey et al., 2005). Nevertheless, being able to quantitatively describe the spatial distribution of SOM is essential to assessing the impacts of land use change and designing carbon mitigations programs.

Regional and spatially explicit estimates of forest SOM contents have been made using widely available NRCS soil series data (e.g. Guo et al., 2006). At these regional and national scales between 50 and 90% of the spatial variation in SOM content can be explained when major vegetation types or environmental gradients are considered (Arrouays et al., 1995; Homan et al., 1995; Arrouays et al., 1998; Powers and Schlesinger, 2002; Wang et al., 2002; Perruchoud et al., 2000). Within regions of similar climate and land cover, site-specific edaphic and topographic information can also yield correlations to SOM content and include soil series, soil depth, soil drainage, parent material (Davis et al., 2004), litter depth (Martin and Timmer, 2006) and topographic position (Kulmatisky et al., 2004; Thompson and Kolka, 2005; Martin and Timmer, 2006). Yet, the coefficients of variation in SOM within soil types, watersheds, or regions can be as high as 50%. Each county has its own SOM average for a particular soil series and differences in averages for the same soil series can be as high as two-fold. (Johnson et al., 1991; Kern, 1994; Galbraith et al., 2003; Davis et al., 2004 and others). Forest floor SOM can range from being a substantial portion of the total solum SOM to not being present at all (Huntington et al., 1988; Yanai et al., 2003; Kulmatisky et al., 2004; Fahey et al., 2005).

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There are relatively few studies that describe or quantify variations in forest SOM where forest type and climate are relatively constant. Furthermore, the specific controls on different SOM pools are rarely modeled in detail (Jobbagy and Jackson, 2000). This is partly due to the challenges of collecting and modeling highly variable, non-normally distributed SOM data. This study approached this challenge by investigating controls on SOM accumulation with SOM estimations from a relatively high sample density of SOM per plot, non-parametric statistical techniques, and multiple linear regressions. Three soil pools (forest floor, 0–20 cm mineral, 20+ cm mineral) over three spatial scales (point, plot, regional) were analyzed in the northern hardwoods of the Green Mountains of Vermont. Because these soils occur under similar forests, climate, and geology the analysis allowed us to identify landscape and landform scale variables that influence SOM accumulation that are often overlooked in larger scale spatial distribution studies. Once these relationships were determined, GIS-derived surfaces and modeled climatic data were used to develop empirically based models that predict the spatial distribution of SOM across this landscape.

2. Methods and data

2.1. Study area

The Green Mountains are characterized by short cool summers and long cold winters. Average monthly temperatures range from −18 °C in January to 17 °C in July. Estimated mean annual temperature for the plots in this study ranged from 4.3 to 7.5 °C. Their mean annual precipitation ranges from 113 to 147 cm per year and is distributed evenly throughout the year. All plots of the study were located between 244 and 762 masl (median elevation 550 masl) and were dominated by sugar maple (*Acer sachharum*), american beech (*Fagus americana*), yellow birch (*Betula alleghaniensis*) and paper birch (*Betula papyrifera*). White ash (*Fraxinus americana*), red maple (*Acer rubrum*) and other species were also present. The northern hardwood forest type was one of the most exploited for agriculture during the colonization of New England (Foster et al., 1998; Cronon, 2003). Northern hardwoods currently contribute about 11% of the total C held in U.S. forest soils (Johnson and Kern, 2003).

The geology of the Green Mountains is dominated by complex folds of metamorphic schists and to a lesser extent gneiss, quartzite, phyllite and granite (Post and Curtis, 1970). Pleistocene glaciations transported calcium rich material from mid ordovician limestone and dolomite deposits into the area from the west (Stanley and Ratcliffe, 1985; Lyons and Bothner, 1989). Glacial retreat since about 10,000 years before present has resulted in a surface veneer of till and excessively drained glacial outwash deposits. Organic matter concentrations in the mineral soil (%LOI) range from a mean of 12% (std dev = 4%) in the 0–10 cm and a mean of 6% (std dev = 2%) in the 20+ cm layer. Boulders and other material >2 mm make up a significant portion of the bulk soil material and Spodosols and Inceptisols derived from glacial till are the region's most common soils (Post and Curtis, 1970; Siccama, 1974). Due to the poorly sorted nature of the till, the spatial distribution of boulders is highly variable. Drainage classes range from excessively-drained to somewhat poorly drained (Post and Curtis, 1970). The majority of the soils found in the study plots are well-drained or moderately well-drained glacial till soils.

Both natural and human induced disturbances are common in the study area. Extreme weather (e.g. ice storms, wind storms and hurricanes) and fires can affect stand composition and structure (Cook and Johnson, 1989; Irland, 2000). Logging and prior land-uses (woodlot, pasture, cropping) were the main human disturbance in these plots. Logging has been documented to influence the vertical distribution SOM in these soils but has little effect on the total SOM content (Johnson et al., 1995).

2.2. Data

This study used biomass and soils data from plots that were originally established by Post and Curtis (1970) between 1957 and 1959. The plots extend throughout much of the total length of the Green Mountains in the state of Vermont (Fig. 1) and were originally established to develop timber site indices for even-aged northern hardwood stands growing on acid-till soils. Between 1990 and 1992, 33 years after the original plots were established; the University of Pennsylvania relocated and resampled the majority of the plots (41 of 78). During the intervening period, 19 of the plots had been logged. This study analyzed soils data collected from both the 1957–59 and 1990–92 plot surveys and in some cases data were pooled (see explanation below). For the current analysis, “SOM content” refers to soil organic matter contents of a soil layer (e.g. Mg ha^{-1}) and “total solum SOM” refers to the mineral plus forest floor pools. Additionally, though all the plots were at some time disturbed, “logged” plots refer to plots that were selectively logged or clear-cut between 1960 and 1990 while “undisturbed” plots refer to those unaffected by logging activities during that period.

In both the 1957–60 and 1990–92 samplings, “pit”, “mound”, and “predominant” locations were sampled (hereafter referred to as ‘horizon pits’). The first two locations refer to the characteristic “pit

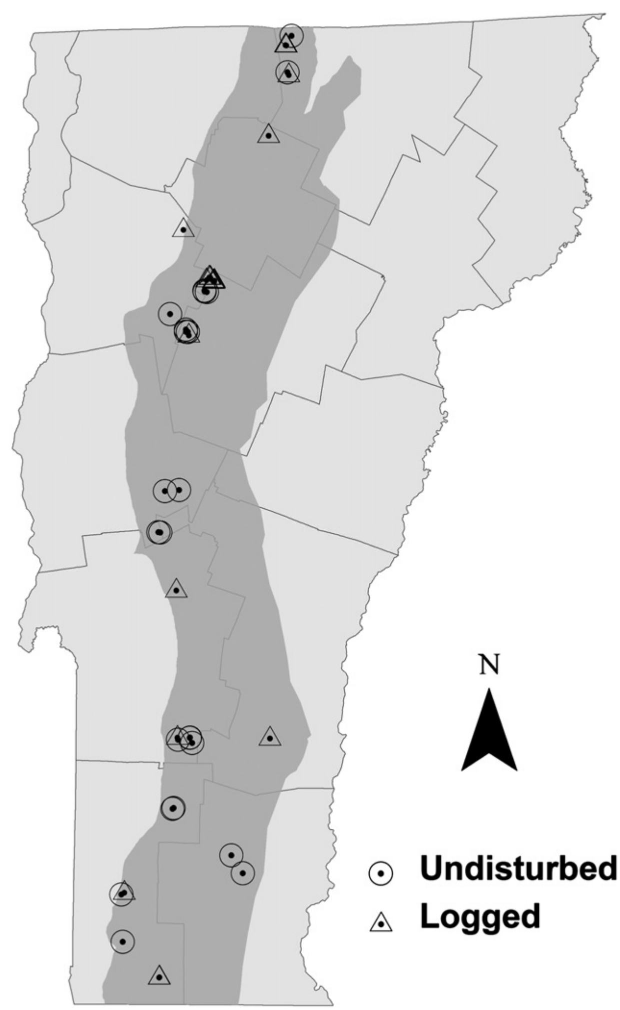

Fig. 1. Reference map of the 41 study plots re-located by the University of Pennsylvania. Twenty-two of the plots were undisturbed and 19 had been logged between 1957 and 1990. Darker area is the Green Mountain physiographic region of Vermont where most soils are acid-till and covered with northern hardwood forest.

and mound topography" of the Green Mountains. Overall, six spatially explicit samples were collected from 0.081 or 0.041 ha plots (1/5 or 1/10 acre). In each sampling the horizons were exposed and sampled in the same way. However, the 1957–60 study samples were composited on site and then analyzed. In the 1990–92 study, each sample was analyzed separately. Both studies measured soil organic matter content by percent loss on ignition (%LOI). Bulk density was estimated using a bulk density and %LOI relationship (Federer et al., 1993). The percent volume of coarse rock fragments (>2 mm) was obtained from ocular estimates of the Post and Curtis (1970) study and was also applied to the measurements of the University of Pennsylvania study.

In addition to the method used above, the 1990–92 study sampled each plot using the quantitative pit method at the "predominant" location (Huntington et al., 1988; Johnson et al., 1991). This method, although more labor intensive, directly measures soil weights and rock fractions for an accurate measurement of bulk density. From a 50×50 cm area, the forest floor is weighed and sampled independently of the mineral soil. The mineral soil is then excavated, weighed, and sampled at three depths: 0–10 cm, 10–20 cm, and 20 cm to top of the C horizon. At each sampled depth the roots, <2 mm fraction, and >2 mm fraction were separated to obtained coarse fragment and root measurements.

2.2.1. Response variables

Three soil pools (forest floor, 0–20 cm mineral, 20+ cm mineral) over three spatial scales (point, plot, regional) were analyzed separately (Table 1). At the point scale, only SOM estimates from the quantitative pit method were used. At all other scales, the mineral soil SOM estimates of both studies (i.e. a total of six spatially explicit samples) were pooled together to achieve a spatial average of each plot. The logged plots had to be corrected for changes in the bulk density of the soils in the 0–20 cm due to logging activity. Note that after this correction, there was no significant change in SOM content over the 33 year period.

Only the forest floor estimates from the original 1957–60 study were analyzed because of the uncertainty introduced by time, compaction and removal of biomass due to logging between the two studies. All samples with an LOI of 40% or greater were considered forest floor, otherwise samples were considered mineral soil. Additionally, for the 0–20 cm mineral soil analysis, the SOM estimates of the six independent profile locations were adjusted to 20 cm depth from the top of the mineral soil (e.g. Minasny et al., 2006). One plot, Plot 5704, had an unusually high organic matter concentration in the 20+ cm layer; a value of 3.5 times higher than the mean. This sample was removed from the analysis because it was likely an error, perhaps due to sampling procedure or instrument error.

2.2.2. Predictor variables

Predictor variables were chosen so that factors known to be important to SOM formation were represented (e.g. Jenny, 1941; Brady and Weil, 1996). Variables which were explored for their relations to SOM can be summarized as follows: 1) soil depth, slope and topographic position (i.e. topography), 2) photosynthetic active radiation (PAR), aspect, mean annual temperature (MAT), yearly precipitation, latitude, elevation, and total N deposition (i.e. climate), 3) tree biomass, percent biomass by species, vegetation group and stand age (vegetation), 4) percent sand, soil series, and rock volume (edaphic or parent material) (Table 2).

2.3. Statistical methods and tools

In all, 9 response variables and 28 predictor variables were analyzed (Tables 1 and 2) using multiple linear regression (MLR) and non-parametric approaches. The decision about which approach to use was based on how well a statistical tool was able to utilize available data and give interpretable results. For example, forest floor and vegetation data were difficult to analyze with MLR because either the forest floor or a particular species were not present in some plots and yet were very high in other plots. Such data distributions were better suited for non-parametric approaches.

MLR analysis was initiated by exploring pair-wise correlations between response and predictor variables and then using forward step-wise regression (JMP IN 5.1 software) to identify factors potentially important to SOM storage. The residuals of the initial one or two parameter model were then explored for additional correlations with remaining predictor variables. All MLR parameters are significant at the $p=0.05$ level and all correlations were compared to known principles of soil organic matter formation before they were accepted (Jenny, 1941; Brady and Weil, 1996, pg. 25).

To determine association among tree species non-metric multidimensional scaling (NMS) ordinations was used (PC-ORD version 4.0, McCune and Grace, 2002). In this analysis the abundances of all species in each plot are compared to other species in all other plots by calculating dissimilarity coefficients (e.g. Sorensen distance). The ranks of the Euclidean distances between plots in ordination space are then compared to the ranks of the dissimilarity coefficients. Where they do not match, a new distance is assigned so that monoticity is achieved (i.e. ranks are adjusted so that they increase linearly). The total departure from monoticity, or 'stress', is then calculated. These

Table 1
Response variables

Pool	Pit description	*N* per plot	*N* plots	Mean SOM Mg/ha (std dev)	Notes
Forest Floor	Horizon pits Undisturbed plots	6	19	21 (48)	Surface organic material>40% LOI; includes plots with no Oa; the average of both studies; only undisturbed plots
	Horizon pits All plots	6	38	24 (37)	Surface organic material>40% LOI; includes plots with no Oa; the average of both studies
	Horizon pits All plots	3	39	26 (46)	Surface organic material >40% LOI; includes plots with no Oa; from the 1957–1960 study (before recent disturbance)
Surface mineral 0–20 cm	Quantitative pits Undisturbed plots	1	22	148 (33)	Quantitative pit estimate
	Horizon pits All plots	6	39	124 (34)	Calculated with %LOI on bulk density relation; adjusted to 20 cm; logged plots adjusted for bulk density; the average of both studies
Deep mineral 20+ cm	Quantitative pits Undisturbed plots	1	22	150 (79)	Quantitative pit estimate
Total mineral	Quantitative pits Undisturbed plots	1	22	295 (103)	Quantitative pit estimate
	Horizon pits All plots	6	38	254 (50)	Calculated with %LOI on bulk density relation; logged plots adjusted for bulk density; the average of both studies
Total solum	Horizon pits All plots	6	38	272 (61)	Forest floor plus 'Total Mineral SOM'; logged plots adjusted for bulk density; the average of both studies

Table 2
Predictor variables

Predictor	*N*	Mean (Range)	Description	Source
Topography				
Soil depth–Quantitative pit	22	55 (34–86)	Soil depth measured from the surface of the mineral horizon to the top of the C horizon (cm)	2
Soil depth—Average of Other other pits	37	55 (27–106)	The average of both the 1957–1960 and 1990–1992 studies (cm)	1, 2
Soil depth–Plot average	40	63 (31–122)	The average of 12–17 independent measures of soil depth by probe (cm)	1
Slope—30 m	40	25 (4–56)	Slope as determined from 30 m×30 m DEM	5
Slope—90 m	40	31 (2–61)	Slope as determined from 90 m×90 m DEM	5
Topographic Position	40	−3 (−64 to 51)	Measure of slope position; i.e. topographic high vs. topographic low	5
Climate				
Mean Annual Temperature (MAT)	40	5.0 (3.9–7.5)	Modeled 25 year average (C), 1 km resolution	3
Photosynthetic Active Radiation (PAR)	40	588 (557–617)	Modeled yearly average, averaged for 25 years (MJ/m2/day), 1 km resolution	3
May PAR	40	796 (772–820)	Modeled yearly average for month of May (MJ/m2/day), 1 km resolution	3
Yearly precipitation	40	135 (113–149)	Modeled 25 year average (cm/year), 1 km resolution	3
Latitude	42	44.3 (42.8–45.0)	Degrees	5
Elevation	42	1717 (1026–2479)	Elevation from 30 m×30 m DEM	5
Aspect—30 m	40	Categorical	Aspect Class (N,E,S,W) from 30 m×30 m DEM	5
Aspect—90 m	40	Categorical	Aspect Class (N,E,S,W) from 90 m×90 m DEM	5
N Deposition	37	1.0 (0.7–1.2)	Modeled yearly wet and dry NO3 and NH4+; 20 year average (gN/m2/yr)	4
NH4+ wet Deposition	37	1.9 (1.6–2.2)	Modeled interpolated wet NH4+ deposition (gN/m2)	4
Vegetation				
Stand age	37	68 (47–99)	Time since abandonment or logging in 1957–60 (years) from tree core analysis	1
Percent biomass of species	42	–	The percent biomass of a particular species during 1957–1960	1
Total plot biomass	42	271 (98–401)	Biomass at 1957–60 and 1990–92 (Mg/ha)	1, 2
Vegetation group	40	Categorical	NMS results (see text); sugar maple+white ash, white birch+red maple, other	5
Composite site index	41	70 (51–91)	Site productivity measure developed from the 1957–60 study	1
Edaphic				
E horizon thickness	41	2.4 (0–16)	The average of 12–17 independent measures of E horizon thickness by probe (cm)	1
Soil pH	42	4.5 (3.8–5.8)	Soil pH in the top 8 in. of soil as measured by the 1957–60 study	1
Percent sand	42	62 (46–82)	The percent sand as determined by the settling column method	1
Rock volume 0–20	39	1E4 (8E2–3E4)	The volume of rock in the quantitative pit layer as determined in the field (cm3)	2
Soil series	40	Categorical	Woodbridge, Sutton, Marlow, Berkshire, Colton, Hartland, Paxton, Charlton, Ridgebury	1

1—Post and Curtis (1970).
2—Johnson et al.
3—Thornton et al. (1997); from DAYMET website.
4—Grimm and Lynch (2004).
5—This study.

steps are iterated many times as the plots are configured differently between iterations so that stress is minimized. The same procedure is then applied to randomized data and compared to real data to obtain a p-value as a measure of significance (McCune and Grace, 2002).

The forest floor was modeled using non-parametric multiplicative regression (NPMR), a regression tool which is useful for exploratory and modeling purposes of presence/absence data or datasets that contain many zeros (McCune, 2006). Values are predicted based on kernel estimation where observed values closest to the target point in predictor space are given more weight in the estimation. The multiplicative nature of the model allows for interactions and the possibility that the response will not occur when certain conditions

Table 3
Non-parametric models

a. Non-parametric Multiplicative Regression (NPMR)

Number	SOM pool	Term	Tolerance	XR2	*N*
1	Forest Floor[a]	Veg group (Red maple>Other)	0.000	0.65	37
	All plots; Plot Scale	May-PAR	7.09		

b. Multivariate Regression Tree (MRT)

Number	SOM pool	Term	[b]% SS	Total R^2	*N*
2	Forest floor+	Veg group (Red maple>Other)	45	0.57	37
	All plots; Plot scale	May-PAR	4		
		Elevation (m)	8		
4	0–20 cm Mineral	Drainage (MWD>WD)	21	0.53	38
	All plots; Plot scale	Slope—90 m (%)	15		
		Aspect—90 m (N,W,E>S)	13		
		Elevation (m)	4		
8	Total mineral	Aspect—90 m (N,W>S, E)	34	0.51	38
	detrended for depth	Elevation (m)	9		
	All plots; Plot scale	Slope—90 m (%)	5		
		Sand (%)	3		
9	Total solum	Soil series (Deep_WD>Shallow_MWD)	37	0.60	38
	All plots; Regional scale	Aspect—90 m (N,W,E>S)	12		
		Slope—90 m (%)	11		

[a] Data from 1957–60 study only (forest floor unaffected by logging).
[b] The percent sum of squares explained by each variable.

Table 4
Multiple Linear Regression (MLR) Models

Number	SOM pool	Term	Coefficient	Std Error	*p*-value	Cont R^2	Adj. R^2	Obs.
3	0–20 cm mineral	Intercept	370.7900	45.9400	<0.0001		0.62	22
	Undisturbed; Point scale	Rock volume 0–20 (cm3)	−0.0042	0.0010	0.0004	0.32		
		Sand (%)	−2.0751	0.7147	0.0095	0.17		
		Slope—30 m (%)	−1.1770	0.4371	0.0149	0.13		
5	20+ cm mineral	Intercept	−232.4664	53.0155	0.0003		0.74	22
	Undisturbed; Point scale	Soil depth—Q. pit (cm)	3.9630	0.5766	<0.0001	0.54		
		Elevation (m)	0.3097	0.0759	0.0006	0.20		
6	Total mineral	Intercept	162.0658	126.5619	0.2186		0.65	21
	Undisturbed; Point scale	Soil depth—Q. pit (cm)	3.5403	0.9353	0.0016	0.35		
		Elevation (m)	0.4216	0.1210	0.0031	0.13		
		Sand (%)	−3.3786	1.6330	0.0551	0.10		
		Rock volume 0–20 (cm3)	−0.0049	0.0023	0.0513	0.07		
7	Total mineral	Intercept	144.0340	34.1833	0.0002		0.52	38
	All plots; Plot scale	Soil depth—Avg. all pits (cm)	0.1585	0.0404	0.0004	0.27		
		Aspect 90 m (N,W>E,S)	−16.8318	5.9463	0.0079	0.08		
		Elevation (m)	0.1315	0.0481	0.0101	0.09		
		Slope—30 m (%)	−1.3354	0.4943	0.0108	0.08		

(represented by predictor variables) are not met. A parsimonious model can be found with computer software such as HyperNiche (version 1.23, McCune and Mefford, 2004). Model fitting is evaluated by the XR^2 ('cross R^2') statistic. This statistic compares the residual sum of squares to the total sum of squares in the same way as the traditional R^2, except that cross-validation data set is introduced by leaving out one data point.

Multivariate regression trees (MRT) can handle all types of numerical and categorical data (De'ath and Fabricius, 2000) and were used in this study to group plots by various predictor variables. This technique splits the data based on the predictor variable and predictor value (or identifier if categorical) which achieves the greatest reduction in the sum of squares. The splits produce a tree and have the effect of creating homogenized subgroups. MRT techniques can be used for predictive modeling; however in this paper we use it primarily as an exploratory tool to identify the relative importance of predictor variables (De'ath and Fabricius, 2000). MRT analysis has previously been applied successfully to predict SOM distribution in a Connecticut forest (Kulmatisky et al., 2004).

2.4. Regional SOM model approach

To demonstrate the MRT estimation approach to total SOM content (forest floor plus total mineral SOM) estimation at the county level, a spatially weighted average was calculated from Model 9 of the following analysis. Then, for comparison, four different estimations of total SOM content were calculated for northern hardwood forests over

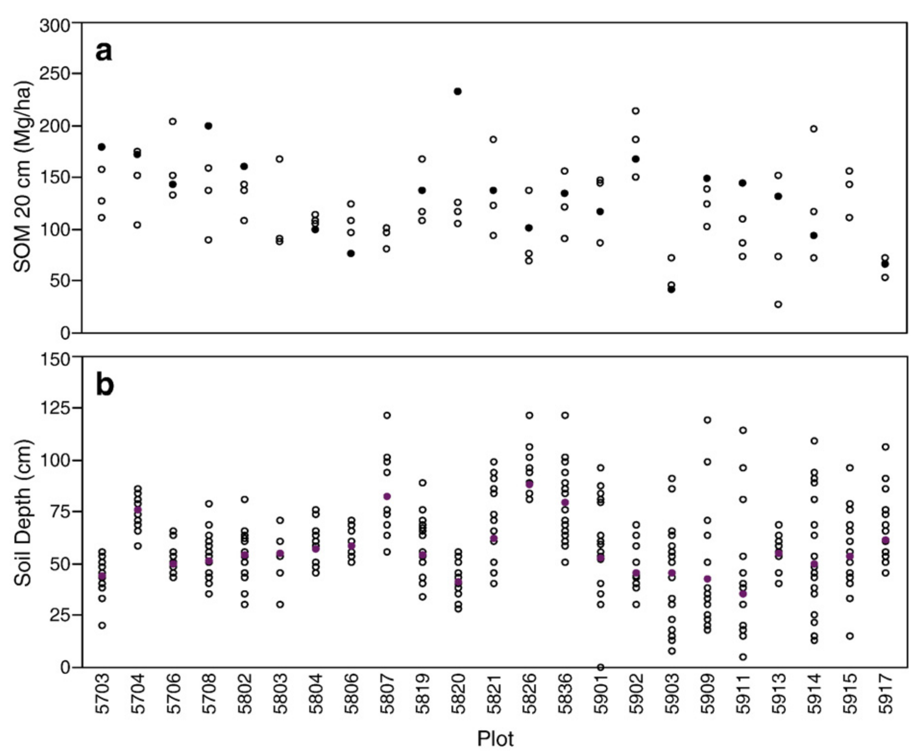

Fig. 2. Variability charts of undisturbed plots: a) the 0–20 cm of mineral soil by plot. Open circles are the University of Pennsylvania estimates. Closed circles are the mean of all the Post and Curtis (1970) estimates. b) the soil depths measured along transects in each plot by Post and Curtis (1970). Open circle are independent measurements and closed circles are plot means.

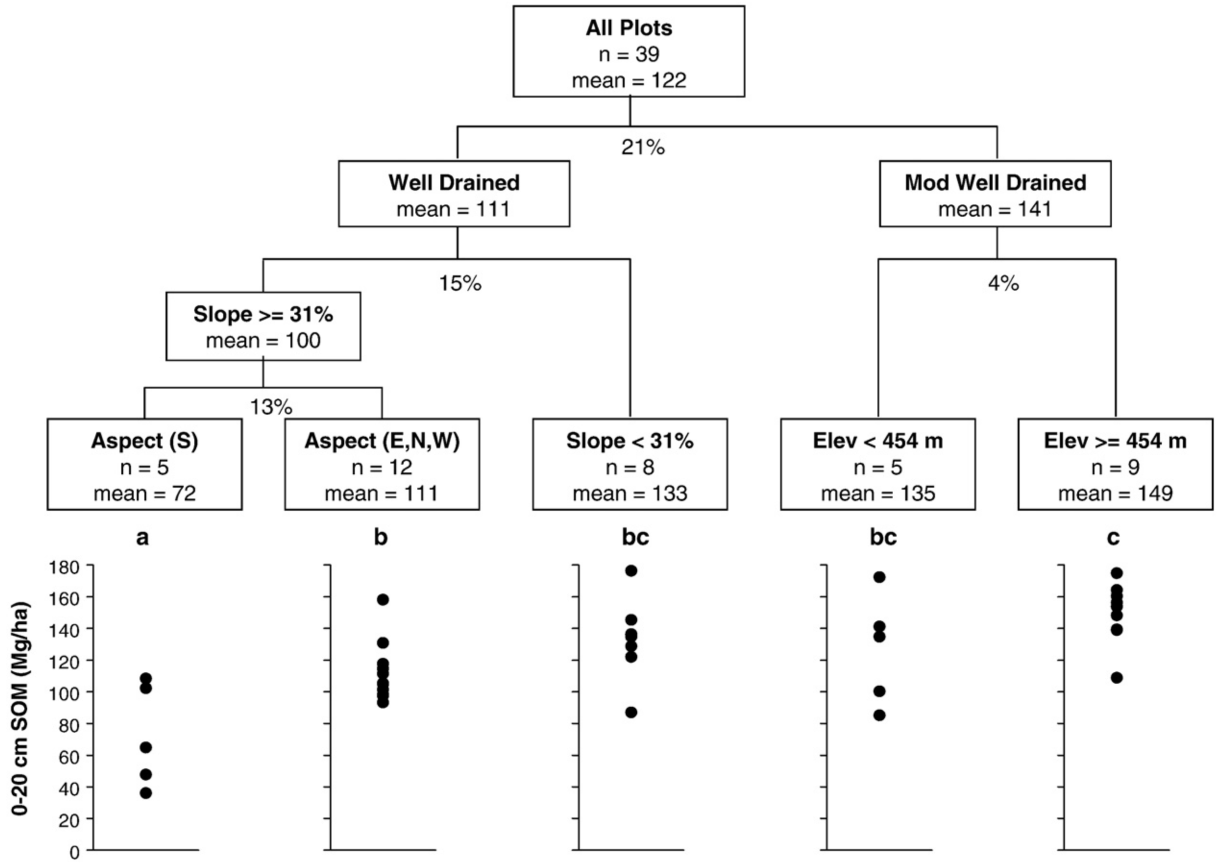

Fig. 3. Graphical representation of Model 5 in Table 3; the multivariate regression tree (MRT) of SOM content in the 0–20 cm mineral soil (Mg/ha). Percentages under the nodes refer to the percent sum of squares explained by the split. Letters of individual leaves not connected by the same letter are significantly different ($p<0.05$).

acid-till soils for a single county in Vermont. These estimations included: 1) the mean of the quantitative pits of this study (Table 1), 2) the mean of the horizon pits of this study (Table 1), 3) the mean of a comparable forest in Hubbard Brook, NH (Watershed 5; Fahey et al., 2005), and 4) the spatially weighted mean values calculated from downloadable soil series data, STATSGO (Soil Survey Staff; available at http://soildatamart.nrcs.usda.gov). Excluded from the analysis were poorly drained soils, soils under conifer forest and other non-forest land-uses that were not represented in the original dataset.

3. Results

3.1. Forest floor SOM

Forest floor SOM had the highest spatial variability of all the soil pools studied (c.v. of 1.57) but was strongly related to stand composition and PAR. The NMS analysis revealed three distinct groups of plots: 1) plots abundant in sugar maple and white ash, 2) plots abundant in red maple and white birch, and 3) plots which could not be distinguished by a dominating species. Plots relatively abundant in red maple or white birch had significantly higher forest floor than plots where these species were not abundant (p-value <0.05; student's t-test). NPMR also indicated that vegetation group and average May-PAR were significant predictors of Forest Floor SOM (Table 3a; Model 1). When May-PAR in this model was replaced by mean annual PAR, latitude or elevation, similar results were demonstrated but had somewhat lower XR^2 (0.61, 0.52 and 0.57 respectively). The addition of elevation to Model 1 resulted in a somewhat higher XR^2 of 0.67, and reflects the linkages of elevation and climatic gradients in the Green Mountains (not shown). MRT results indicate the same relationships where vegetation group, May-PAR and elevation explained 57% of the sum of squares (Table 3b; Model 2). The first split was between red maple/white birch abundant plots and all other plots. Model 2 also indicates that no forest floor accumulated in plots that were abundant in sugar maple and received greater than 800 MJ/m2/day radiation.

3.2. 0–20 cm SOM

For a single point, an MLR model of quantitative pit estimates of the 0–20 cm mineral layer of the undisturbed plots showed that the combination of rock volume, percent sand, and slope explained 62% of the variation in 0–20 SOM content (Table 4; Model 3). All of these relationships were negative and significant. The spatial variability of

Table 5
Comparisons of mean SOM pools and selected parameters

Mean pool or parameter	Significance	Mod well drained	Well drained
Plots		15	27
Forest floor#	*	5	38
0–20 cm Mineral SOM	**	145	112
20+ cm Mineral SOM	***	81	154
Total Mineral SOM	**	226	267
Total solum SOM#	*	246	309
Soil depth—Plot Average average (cm)	**	51.5	61.8
Sand (%)	**	57.8	64.6
Surface soil pH	***	4.89	4.24
Average E horizon thickness (cm)	**	0.2	3.6
Proportion sugar maple (%)	**	53	29
Proportion yellow birch (%)	**	3	20.0

*$p<0.05$.
**$p<0.01$.
***$p<0.001$.
#data from 1957–60 study only (forest floor unaffected by logging).

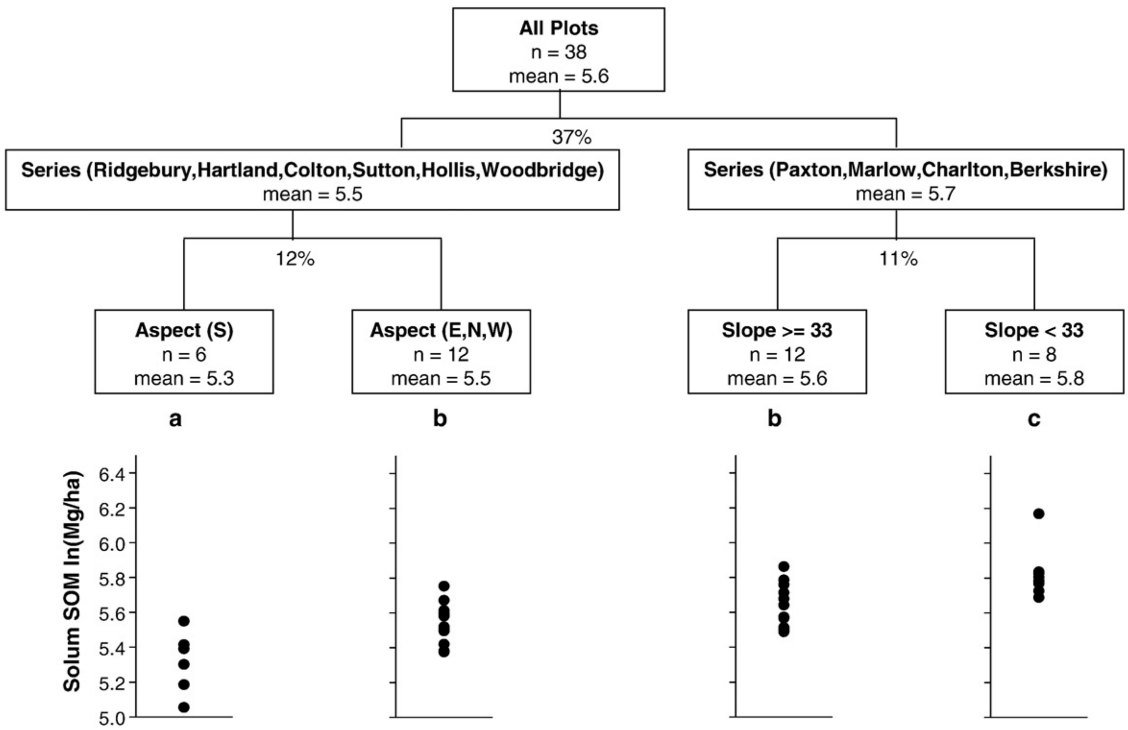

Fig. 4. Graphical representation of Model 9 in Table 3; the multivariate regression tree (MRT) of the logged transformed total solum SOM content (Mg/ha) used in Fig. 5. Percentages under the nodes refer to the percent sum of squares explained by the split Letters of individual leaves not connected by the same letter are significantly different ($p<0.05$).

SOM contents in the 0–20 cm mineral layer of the undisturbed plots is represented in Fig. 2a. The mean c.v. for all the plots (logged and undisturbed) was 0.22. Two of the logged plots, 5828 and 5835, had very high c.v. at 0.95 and 0.86 respectively (not shown).

At the plot scale, MRT analysis revealed that drainage class, slope, aspect, and elevation were strongly related to 0–20 SOM (Fig. 3) (Table 3b; Model 4). Soil drainage class alone explained 21% of the variation in the original dataset. Under well drained conditions, slope (15%) and aspect (13%) were important variables, but in moderately well drained plots, elevation (4%) was more important. The final model explained 53% of the sum of squares in the original dataset. The final five-leaf tree showed low 0–20 cm SOM contents on well-drained steep south-facing slopes and higher SOM on moderately well-drained higher elevation soils. Well drained soils on gentle slopes had similar SOM contents to moderately well drained soils at lower elevations.

3.3. 20+ cm and total mineral SOM

For a single point in the plot over half of the variation (54%) in SOM content of the 20+ mineral soil layer was explained by the depth of the C horizon (Table 4; Model 5). Elevation was also positively correlated and explained an additional 20% of the variation. All together, 74% of the variation in the deep mineral layer was explained by Model 5. The variation of the total mineral SOM for a single point (i.e. the combined 0–20 cm and 20+ cm mineral soils) was best explained by soil depth, elevation, percent sand, and rock volume (Table 3; Model 6). The average soil depths of the plots were also highly variable (Fig. 2b), and were significantly positively correlated with total SOM content.

At the scale of the whole plot the total mineral SOM variation was best explained by soil depth, aspect (where north and west slopes were greater than east and south slopes), slope, and elevation in the MLR analysis (Table 4; Model 7). The residuals of the regression of total mineral SOM on soil depth were also modeled using MRT (Table 3a; Model 8). The resulting “detrended” values in the MRT were explained by aspect (34%), elevation (9%), slope (5%) and percent sand (3.4%). The full model explained 51% of the sum of squares of the original dataset. This analysis indicates that the largest amounts of total mineral SOM were found on gently grading north and west facing slopes. The environments with the least amount of SOM were on sandy, low elevation sites, on south and east facing slopes.

3.4. Total solum SOM and regional scale models

When all soil layers were combined, total solum SOM was significantly higher in well drained plots than moderately well drained plots ($p<0.05$; student's *t*-test). Generally, soils in well drained plots were deeper, sandier, had thicker E horizons, and were more acidic than moderately well drained soils (Table 5). The two drainage classes were also different in species composition in that moderately well drained plots had more sugar maple and white ash.

MRT analysis resulted in a four-leaf model with the variables soil series, aspect, and slope accounting for 37%, 12% and 11%, respectively, of the sum of squares in the total SOM dataset (Table 3b; Model 9) (Fig. 4). Total SOM was lowest in soil series that were moderately well-drained and shallow (Ridgebury, Sutton, Hollis and Woodbridge;

Table 6
Five approaches to estimate total SOM stocks in Lamoille County and SOM density

Method	Mean MgSOM/ha (std error)	Total petagrams SOM[a]
Measured averages for a northern hardwood forest		
Quantitative pit average	344 (27)	0.017
Horizon pit average	274 (9)	0.014
Hubbard Brook—Watershed 5	315 (18)	0.016
Spatially weighted averages for Lamoille County, VT		
MRT 4 Leaf Model (soil series, slope, aspect)	264	0.013
MRT 2 Leaf Model (soil series)	253	0.010
Soil survey data only	269	0.014

Only WD and MWD soils under northern hardwood canopy included.
Note: Poorly drained soils of Lamoille County have a mean of 687 Mg/ha and make up 5% of total land area and 12% of SOM stock in Lamoille County, VT (from STATSGO).
[a] The extrapolated estimate of SOM for Lamoille County, VT.

n=16) or deep and fluvial (Hartland and Colton; n=2) and occurred on south facing slopes. In contrast, the highest SOM occurred on gently grading slopes and in soil series that were well-drained and deep (Paxton, Marlow, Charlton and Berkshire; n=20). Because of the structure of the MRT, two models were obtainable: 1) a simplified two-leaf model accounting for differences in soil series, and 2) the full four-leaf model accounting for differences in aspect and slope in addition to soil series (Table 6). The total area that represented each of the two or four leaves (from digital layers of soil series, aspect and slope) were used as weights for the estimation of mean total SOM (Fig. 5 and Table 6). The spatially averaged results of the full four-leaf model were lower than the quantitative pit estimates of this study and at Hubbard Brook (Table 6). When only soil series was considered (i.e. the two-leaf version of Model 9) total SOM estimates are still lower. In contrast, the pits estimated by the %LOI and bulk density approach were similar to the three spatially weighted averages.

3.5. Additional correlations

The average E horizon thickness of the plot was strongly correlated with forest floor and total solum SOM content (p<0.01, n=41 and p<0.05, n=38 respectively; Spearman's ρ; 1957–60 dataset only). The total modeled atmospheric N deposition (Grimm and Lynch, 2004) was also strongly and positively correlated with forest floor SOM content in both the 1957–60 and 1990–92 studies when plots with no forest floor occurrence were ignored (p-value<0.01; n=11 and 16 respectively). Total N deposition was also positively correlated with the concentration of OM (%LOI) in the 0–20 cm mineral layer (p-value<0.05; n=34).

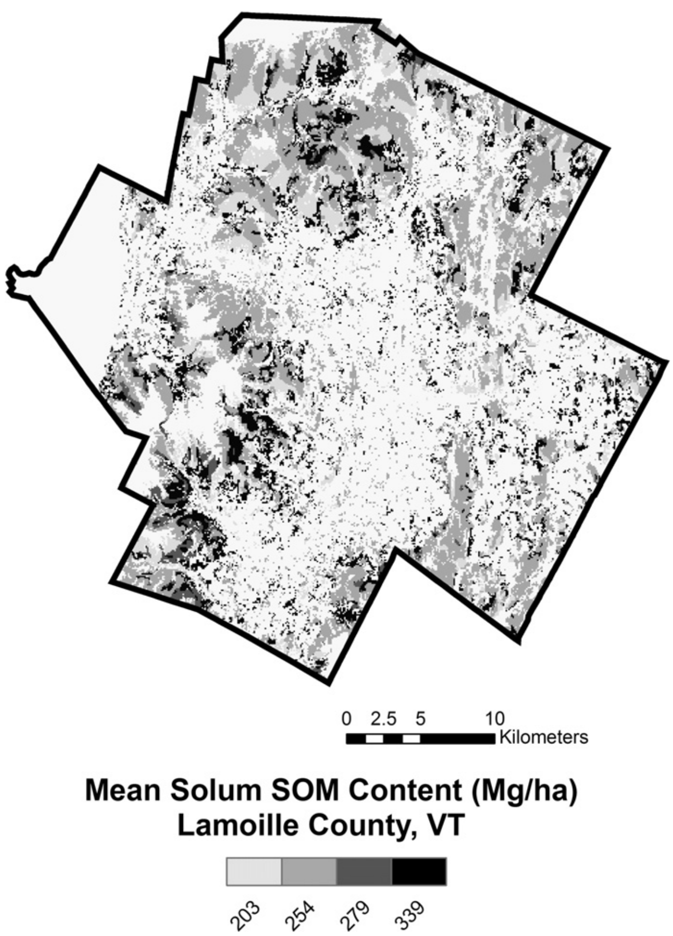

Fig. 5. Total solum SOM content for Lamoille County, VT based on the multivariate regression tree (MRT) (Model 9) in Fig. 4. Land cover and land use areas that are not northern hardwood forest over acid-till soil (mostly spruce/fir and developed areas) are in white.

4. Discussion

4.1. Forest floor SOM

Forest floor SOM was higher in plots with high abundances of red maple and white birch, whereas plots with abundant sugar maple tended to have lower forest floor SOM. Soil pH was also higher in the moderately well drained plots. Higher pH is known to allow greater microbial activity than acid conditions and therefore results in lower organic matter content in the forest floor (Vesterdal et al., 1995; Finzi et al., 1998). Indeed, the A horizon organic matter concentrations (%LOI) of this study were strongly negatively correlated with pH (p-value<0.01; n=38). Further, it has been shown that higher rates of Ca mineralization in the forest floor SOM occur under sugar maple and white ash stands than under red maple, beech, red oak and hemlock (Dijkstra, 2003). Since higher Ca results in higher pH and decomposition rates of SOM, this suggests a species control on forest floor SOM.

After considering species composition, climate is an important control on forest floor SOM, even in this area of relatively uniform climate. MRT results reveal that forest floor tends to build up in areas which receive less solar radiation per unit area (PAR). PAR is largely dependent on latitude and aspect (Thornton et al., 1997) and lower PAR is often associated with colder conditions. Apparently, lower PAR areas are colder, have decreased microbial decomposition and thus allow more forest floor to accumulate. The NPMR results confirm this observation by indicating that PAR was the most important predictor variable after species composition.

4.2. 0–20 cm mineral SOM

The quantitative pit MLR model of the 0–20 cm mineral soil layer reveals that parent material and topography are key controlling factors for this layer. Rock volume is clearly an important component of the soil matrix in these glacial till soils as it is the most strongly correlated variable of SOM content. It is generally understood that sandy soil texture affects SOM content by providing less protection of organic material against microbial decomposition (e.g. van Veen and Kuikman, 1990). Therefore, the negative correlation with rock volume and sand was expected. That steeper slopes, which sometimes exceeded 60%, had lower SOM content likely reflects a combination of soil erosion, less litter input due to lateral transport of aboveground material and perhaps lower overall litter inputs.

MLR was less successful in explaining the variation in SOM content of the 0–20 cm for the whole plot. This was in part due to a lack of accurate rock volume data for the entire plot. MRT, however, indicated that in addition to slope, soil drainage was an important control at the plot scale. The first split of the MRT in Fig. 4 showed that moderately well drained soils were higher in SOM than well drained soils. Note that well drained plots also had much thicker E horizons reflecting the downward movement of organic material. This will result in lower overall SOM content in the 0–20 cm mineral layer (Lundstrom et al., 2000). Since moderately well drained plots were typically shallower and had finer texture, there was less opportunity for downward movement of dissolved organic matter. That SOM was lowest on south facing slopes may be tentatively explained by higher microbial activity stimulated by more sunlight and warmer temperatures at the soil surface. For moderately well drained soils, elevation provided the best information for a split and reflects slower decomposition at colder and wetter conditions.

4.3. 20+ cm SOM

Higher SOM was observed in deeper soils simply because the more soil that could be excavated resulted in more SOM. Soil depth in the

Green Mountains, even at the plot scale, is highly variable (Fig. 2b). Soils were excavated until the fragipan, bedrock or bottom of the rooting zone—which in most cases was the top of the C horizon. Soil depth proved to be a first order variable, showing stronger correlation with deep and total mineral SOM pools than other variables. As noted previously, deeper soils tended to be well drained and have a greater mix of tree species. Sugar maple favor moderately well drained soils which tend to be shallower (Table 4) (Post and Curtis, 1970).

After accounting for soil depth in the quantitative pits, SOM content in the 20+ cm layer was also influenced by elevation, suggesting a stronger effect of temperature than in the other soil pools. Further, there was a negative relation between maximum July temperature and 20+ cm SOM content (adj. $R^2=0.28$; p-value<0.05), that was not observed in the 0-20 cm layer. There are several possible reasons for this. For example, deeper mineral SOM may be affected by fewer processes than surface mineral SOM (e.g. eluviation and tree uprooting). Therefore SOM changes over temperature gradients may be more easily observed lower in the soil profile. Alternatively, the positive relation between SOM and elevation could be due to increased precipitation at higher elevations resulting greater eluviation surface SOM and higher SOM levels in the 20+ cm layer.

4.4. Total mineral SOM

Results from quantitative pit data (i.e. at a single point) and data for the whole plot showed that aspect had a greater influence on SOM contents than elevation (Models 6, 7 and 8, Tables 3 and 4). North facing slopes receive less radiation from the sun and are more likely to be cooler (and perhaps wetter) than south facing slopes (Kang et al., 2003). Also, in the Green Mountains, moisture is brought from the west and precipitated in greater amounts on the windward, or west facing, slopes. That north and west facing slopes had higher amounts of SOM suggests orographic effects may be influencing SOM content, but this relationship is unclear.

Unlike the MLR model of a single point via the quantitative pit measurements (Table 4; Model 6), slope was a significant factor of the total mineral SOM layer for the whole plot (Table 4; Model 7). This slope variable was calculated from a digital elevation model with grid cells of 90 m by 90 m, which is much larger than the plot sizes (20 m by 20 m). Therefore, this slope variable is only capturing larger scale influences of soil transport and not those occurring at a specific point (i.e. the quantitative pit). In the MRT model (Table 3b; Model 8), percent sand occurs as a factor but probably plays a minor role in SOM storage compared to the effect of topography.

4.5. Indicator variables for SOM contents

Above and belowground predictors which relate to soil drainage are the most useful as indicators of high SOM storage in any given area. For example, high sugar maple abundance on moderately well drained soils and the absence of forest floor and E horizons are indicative of high SOM content in the 0–20 cm mineral SOM layer. On the other hand, a mixed species stand on deep well drained soils had high amounts of forest floor and thick E horizons and contain more total solum SOM at a site. Recent studies suggest that SOM stabilization is enhanced under mixed forests (Jandl et al., 2007). Further, note that deeper E horizons at the plot level are indicative of microclimatic conditions such as colder temperatures and higher precipitation that are needed for forest floor development (Lundstrom et al., 2000). These variables are more easily observed in the field than other variables which require sampling and laboratory analysis (e.g. sand and pH).

The mechanisms responsible for the positive correlation of forest floor SOM content and N deposition cannot be determined from the present dataset. Yearly precipitation was also positively correlated with N deposition and forest floor SOM (p-value<0.01). The autocorrelation between the two predictors (and others such as elevation, latitude and aspect) makes it difficult to separate their effects on SOM without additional research. It is possible that more N deposition allows for fertilization of plants and therefore the higher organic inputs into the soil or that SOM decomposition is retarded (Nadelhoffer et al., 1999; Hagedorn et al., 2003; Dijkstra et al., 2004; Knorr et al., 2005).

4.6. Regional analysis and future research

Results for the different approaches that estimate SOM content in Lamoille County reflect the inherent uncertainty with this calculation. The measured averages that did not account for the spatial distribution of soil conditions specific to the county (i.e. they are estimates of the Green Mountains in general) vary widely due to differences in sampling methods (Table 6). The discrepancy between the horizon pit SOM average and quantitative pit SOM average is likely due to the difference in spatial coverage of each approach. Recall that the quantitative pit was located at "predominant" microtopographical site conditions and therefore was less affected by tree uprooting. Watershed 5 at Hubbard Brook was densely sampled by the quantitative pit method. That this SOM estimate is within the range of the two previous estimates suggests that it may be an adequate general measure of SOM storage in a northern hardwood forest at various localities, but this is difficult to determine.

It is possible that the proportion of conditions represented in the dataset do not correlate with the proportion of conditions that prevail in Lamoille County. This is confirmed by the lower SOM estimates of the spatially weighted approaches compared those of the current dataset (Table 6). The calculations of total SOM density for this county, whether from soil series data alone or from MRT determined groups (i.e. from soil series and topographical data), were within the range of 253 to 269 Mg/ha. The estimates derived from the various approaches provides a range of northern hardwood forest SOM content for this region (about 270 to 340 Mg/ha or 0.01 to 0.02 Pg).

Differences in the estimates of SOM content in Lamoille County reflect the inherent uncertainty with this calculation and the amount of variation that results from different sampling and scaling approaches (Table 6). The estimates of northern hardwood forest SOM derived from the various approaches range between 270 and 340 Mg/ha (0.01 to 0.02 Pg). The calculations of total SOM density for Lamoille County, whether from soil series data alone or from MRT determined groups (i.e. from soil series and topographical data), were within the range of 253 to 269 Mg/ha. The spatially weighted approaches were approximately 16% lower than averages that did not account for the spatial distribution of soil conditions.

5. Conclusions

The current analysis demonstrates that differences in carbon levels of the forest floor, shallow mineral and deep mineral soil pools are controlled mostly by a variety of topographic and edaphic conditions imposed on them. Slope was a significant control on the 0–20 cm mineral SOM pool; therefore the risk of carbon lost by soil removal due to logging activities or development should be considered. Practical management of SOM content may be enhanced by using certain site-specific indicator variables that identify relative differences in SOM contents such as the abundance of sugar maple (or the opposite measure of mixed species abundance), forest floor presence, and E horizon thickness.

Simple models based only on elevation and other GIS-derived variables are not adequate for the modeling of SOM content in the three dimensions of this heterogeneous landscape. This is mainly due to the high spatial variation in soil depths and forest floor SOM, which influence total solum SOM content at the landscape scale. However, GIS-based variables of slope and aspect can be combined with landform-scale information collected from forest plots, such as soil drainage and soil series, to yield meaningful models of SOM distribution (e.g. Fig. 4).

Of future interest are the questions of whether these pools at landscape scales will respond differently to climate changes, and if so, where will carbon losses be greatest? For example if the north facing, well drained, and steep 0–20 cm soils in this study achieved the same conditions that occur on similar soils on south facing slopes (i.e. soil warming), then a loss of approximately 17.5 MgC ha^{-1} may result in this pool alone. Yet, if the same soil pool but at high elevations and under moderately well drained conditions were to experience soil temperatures of lower elevations, there apparently is no difference. Though the current dataset is excellent in terms of sample design and density (compared to many forest soil datasets) still more data would allow greater predictive power of the approaches used in this study. Future research of soils response to climate changes should consider sample designs that include the main components that drive soil heterogeneity in landscapes so that soil carbon losses can be assessed more thoroughly.

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