Optimising carbon storage by land-management

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Geoderma 152 (2009) 74–84

Contents lists available at ScienceDirect

Geoderma

journal homepage: www.elsevier.com/locate/geoderma

Estimating a region's soil organic carbon baseline: The undervalued role of land-management

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A R T I C L E I N F O

Article history:
Received 6 March 2009
Received in revised form 20 May 2009
Accepted 22 May 2009
Available online 24 June 2009

Keywords:
Soil organic carbon
Soil organic carbon stock estimates
Soil series
Land-use
Land-management

A B S T R A C T

In light of recent concern over the extent of global warming and the role of soil carbon as a potential store of atmospheric carbon, there is increasing pressure and demand for regions to estimate their current soil organic carbon (SOC) stocks with the greatest possible accuracy. This study began by approaching the task in a similar way to previous studies where attempts at calculating SOC baselines at global, national or regional scale have used mean values for soil orders and multiplied these values by the mapped areas of the soils they represent. It also followed other methods that have approached the task from a land-cover point of view, making estimates using only land-use, or soil order/land-use combinations and others that have included variables such as altitude, climate and soil texture. The research assessed forms of stratification which could improve these baseline estimates by determining the major controls on SOC concentrations (%SOC) at the National Trust Wallington estate in Northumberland, NE England (area = 55 km^2) where an extensive soil sampling campaign was used to test what level of accuracy could be achieved in modelling the %SOC values on the Estate using a range of existing national and local data. Mapped %SOC values were compared to the values predicted from The National Soils Resources Institute (NSRI) representative soil profile data for major soil group, soil series and land-use corrected soil series values, as well as land-use/major soil group combinations from the Countryside Survey database.
The results of this study show that:

- When only soil series or land-use was used as a predictor only 48% and 44% of the variation in the dataset was explained.
- When soil series/land-use combinations were used explanatory power increased to 57%.
- Both altitude and soil pH proved to be significant controls on %SOC and including these variables gave an improvement to 59%.

A further improvement from 59% to 66% in the ability to predict %SOC levels at point locations when farm tenancy was included suggests that differences in land-management practices between farm tenancies could be responsible for more of the variation in %SOC than either soil series or land-use.

1. Introduction

Recent concerns over climate change and increasing levels of CO_2 in the atmosphere are strengthening the realisation that global warming can be alleviated through a reduction in carbon emissions and increased carbon sequestration. For a company, region or nation to assess how much they need to reduce their carbon emissions to become carbon neutral, they need an accurate assessment of their current carbon stocks.

Soils store twice as much carbon as vegetation and two thirds as much as the atmosphere (Smith, 2004), therefore contributing a significant quantity to any region's carbon stocks. Any action taken by countries or organisations to reduce their impact on climate change usually requires a % reduction of their current emissions in respect to their overall carbon stocks. It is therefore vitally important that any soil organic carbon (SOC) stock estimates are as accurate as possible in order to correctly quantify the emission reductions required. Accurate estimates of SOC stocks and their spatial distribution is also essential as it will highlight areas of high carbon storage which should be preserved and protected, and areas of low carbon storage with the potential for increase. The difficulty in estimating SOC stocks is revealed by the variation in global stock estimates, ranging from 1000 to 3000 Gt C (Schwartz and Namri, 2002). This is due to the large spatial variability in SOC (Zhi-Yao et al., 2006) and the use of different databases and scales, and therefore further investigation is needed to establish how best to calculate the most accurate SOC stocks (Meersmans et al., 2008).

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doi:10.1016/j.geoderma.2009.05.020

Krishnan et al. (2007) recognise that several variables are responsible for differences in SOC concentrations (%SOC); however they state that many countries and regions do not consider these variables in their SOC stock estimates, and instead base their estimation purely on soil type, using the average %SOC value for a soil unit. Davidson and Lefebvre (1993) raise the issue of how best to calculate SOC stocks, questioning the use of mean values for soil series versus mean values for major soil group, the implications of using different scale maps, and the advantages/disadvantages of making estimates using land-use rather than soil type values.

China's SOC stocks have been estimated using the soil survey approach. This involved using mean SOC stocks for a soil type and multiplying by its area. The stock estimates arrived at varied greatly from 50 to 180 pgC (Yu et al., 2007). Davidson and Lefebvre (1993) also used the soil survey approach but found issues relating to the scale of map used, with a 13% difference in SOC stock estimates accompanying a change in scale from a 1:250 000 to a 1:20 000 map. Kern (1994, cited in: Guo et al., 2006) used three methods: average value for soil group, average value for soil series and average value for ecosystem. These provided a range of estimates from 621 to 845×10^8 Mg for the USA's SC stock. Liebens and VanMolle (2003) used the average value for soil type, and secondly the average value for soil type/land-use combinations and found differences of up to 7% in SOC stock estimates depending on the methods used. Coomes et al. (2002) also used mean values for soil/land-use combinations and applied these to the areas of those combinations. Stratification of an area into categories such as soil type followed by multiplication of point measurements from the stratified areas by the land area of the stratification can result in major inaccuracies. The point measurements may have been taken from a small soil inclusion which has not been mapped due to scale (Tompson and Kolka, 2005) and these soil inclusions could have significantly different carbon contents to the soil series/group which they are then taken to represent.

A better method of predicting a region or nations SOC stock needs to be established as it is widely recognised that there are often large coefficients of variation (CVs) in %SOC within a soil order (Wilding et al., 2001; Davis et al., 2004). If the relationships between %SOC and controlling factors can be better established it will provide a more accurate guide to the reliability and accuracy of current SOC bank estimates. The more accurate models that can be made, the less time and money will need to be spent on extensive sampling and analysis to establish SOC baselines.

Krishnan et al. (2007) have identified a range of variables controlling %SOC, including pH, vegetation type, land-cover, temperature, rainfall and soil texture. Tompson and Kolka (2005) are among many authors that have expressed the need to identify the spatial controls on %SOC in order to be able to better estimate SOC stock. They found terrain attributes to be a major control and including this variation in the estimation produced a value 2 times greater than using soil survey data alone. Campbell et al. (2008) found large differences in an estimate produced by the soil survey approach and one produced by including temperature, precipitation and land-use history. Factors found in other studies to control the spatial distribution of %SOC include soil moisture, temperature and texture (Yang et al., 2008), elevation (Powers and Schlesinger, 2002), historical land-use (Schulp and Veldkamp, 2008), precipitation (Dai and Huang, 2006) texture, drainage and slope (Tan et al., 2004), forest management practices and land-use age (Schulp et al., 2008), slope aspect, elevation and terrain attributes (Mueller and Pierce, 2003). Although other research has found management practices to control %SOC levels due to different levels of organic matter input, grazing intensity and soil disturbance (Venteris et al., 2004; Huang et al., 2007; Frazluebbers and Stuedemann, 2009), it has not been common practice to include this variable in estimating an area or regions SOC baseline.

As the largest non-government landowner in the UK (owning more than 250 000 ha), The National Trust wants to do as much as it can to reduce its carbon emissions and increase its carbon stores. It has therefore set up a pilot project to assess its carbon stocks within its estate and as such it has chosen its largest single and most diverse estate (The Wallington Estate) in order to develop methods and understanding. The aim of this study is to compare the various options available for calculating the National Trust's Wallington Estate SOC baseline, and to compare the results of soil samples taken from the field with estimates that would be produced if only secondary data were available. The results of this should suggest the important factors needed to estimate %SOC levels, and identify the information needed in order to accurately calculate SOC baselines for other National Trust estates across the UK, as well as suggest important variables which need to be considered in any researcher's attempt to estimate %SOC values and SOC stocks.

2. Materials and methods

2.1. Study site

The Wallington estate is the largest area of contiguous land owned by the National Trust in the UK, covering an area of 55 km^2. It is located 35 km North of Newcastle Upon Tyne (Fig. 1). The extent and variation in land-use, altitude and soil type across the one estate (Fig. 2) make it the perfect location to attempt to identify controls on %SOC typical of at least England. The majority of land is leased to agricultural tenancies undertaking livestock and arable farming, and a further large component is currently leased to the Forestry Commission, operating as a commercial coniferous plantation. Small areas of the estate are under natural woodland as field margins. Altitude ranges from 100 m in the Southern end of the estate to over 350 m above sea level in the Northern areas under Harwood Forest. The estate is covered by a range of soil types, including mineral soils, organo-mineral soils (seasonally waterlogged with 15–40 cm thick black surface organic horizons) and organic soils (deep peats with >40 cm thick organic horizons). The data in this study only refers to the results collected from mineral and organo-mineral soils, as it is realised that organic soils behave differently and may not be controlled by the same variables.

2.2. Estimate of %SOC values using soil samples

As spatial variation in %SOC can be very large (Saby et al., 2008), a high sampling density was required. A total of 618 mineral/organo-mineral soil samples were collected during the period September 2007 to May 2008.

For each sample taken in the field a GPS location was recorded and notes of the altitude, aspect and land-use were made. Any relevant notes on landscape position (e.g. topographic decline) were also taken as this is recognised to control %SOC (Dick and Gregorich, 2004). The land-use at each sample point was classified into the following categories: arable, improved temporary pasture, improved permanent pasture, rough pasture, lowland woodland and forestry plantation. Classification was made using the National Trusts Biological survey (Hewins et al., 2001) as a guide, combined with subjective observation in the field and information provided by tenant farmers. It was recognised that any soil samples taken would need to be accurate representations of the area in order to provide reliable results (Cook and Ellis, 1987). Before entering the field initial references to ordnance survey, soil maps and National Trust Biological survey maps were made to get an idea of the distribution of potential influencing factors within each field and any areas of particular interest. In fields that appeared highly homogenous (uniform aspect, land-cover, altitude, drainage etc.) a simple random sampling technique was adopted. In fields with a heterogeneous character a more intense sampling rate was used. In large fields a stratified random sampling technique was adopted to break down each field into a number of subpopulations and then a random sample taken from each. Stratification was based

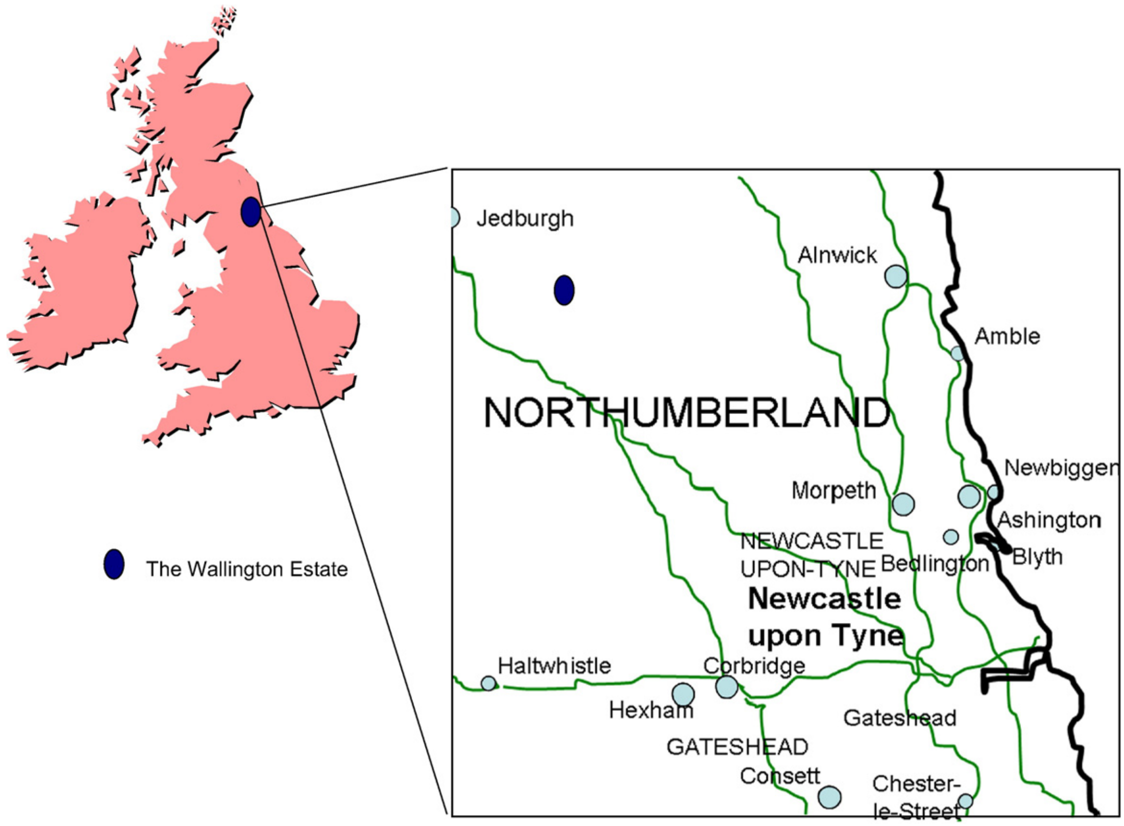

Fig. 1. Wallington location in North East England.

on topography, slope aspect and vegetation cover. Samples from areas close to field boundaries were avoided due to the possibilities of compaction from machinery resulting in an unrepresentative sample, as were the corners of fields (which may have been sites for crop and fertiliser storage), gate entrances and other unrepresentative areas. Attempts have been made to take samples from every field belonging to each tenant farm; however time limitations have meant that some fields remain un-sampled. As a quality control check and to ensure sufficient sampling of the major soil/land-use combinations, it was ensured that each combination covering >1% of the estate was sampled.

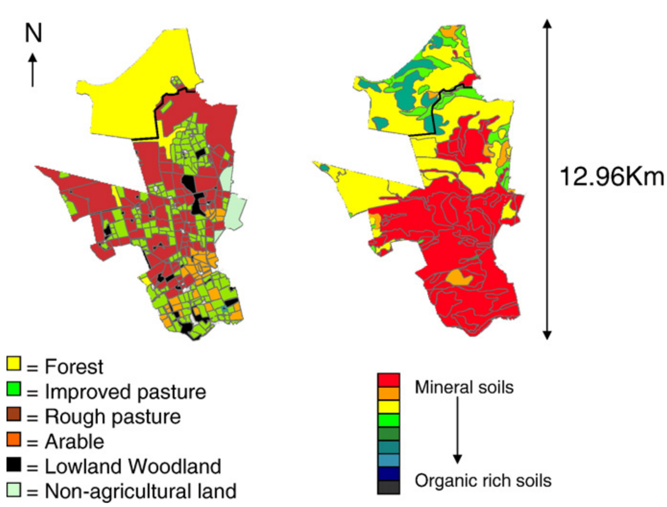

Fig. 2. Land-use and soil series distribution at Wallington.

Measurements of %SOC were made by collecting a sample using either an auger or by digging to a depth of 22 cm. A soil sample was then taken from the 18–22 cm layer, giving a value for %SOC at a depth of 20 cm across the estate: 20 cm was chosen as it is the depth to which SOC in mineral soils is most likely to be affected by land-use change, (Woomer et al., 2001; Cheng and Kimble, 2001; Kimble et al., 2001) and is the depth used in several similar studies (e.g. Nyssen et al., 2008).

The Wallington estate boundary was entered into ARC GIS and the National Soils Resources Institute (NSRI) map was used to create feature classes for soil series, major soil group, land-use and farm tenancy respectively. The mean %SOC values from the 618 soil samples were then calculated for each soil series, major soil group, land-use category and farm tenancy respectively. This value was applied to the area of each feature class to which it represented.

2.2.1. Analysis of %SOC

All samples were dried overnight at 105 °C and stored. Loss On Ignition (LOI) and the Walkley–Black wet oxidation method (De Vos et al., 2007) were used to establish %SOC in each sample. In the first method the samples were placed in a furnace overnight at 500 °C to burn off the organic matter. % organic matter (OM) was then calculated by subtracting the final weight from the weight of the air-dried sample. In the second method organic matter within the soil was oxidised with acidified Potassium Dichromate to CO_2. Any unused Potassium Dichromate was back titrated with Ammonium Ferrous sulphate and %SOC calculated. Triplicate or duplicate measurements were made on each individual sample.

Although the carbon content for the large majority of samples was estimated using both methods, time limitations meant that some samples were only analysed by LOI. Accurate estimates of the %SOC of these samples were however made using a regression equation from previous calibration of the methods. This method of applying a regression equation was also used by Garnett et al. (2001).

2.2.2. Clay content and pH

Several studies have found a significant relationship between %SOC and clay content due to chemical protection of microbial decay (Grigal and Berguson, 1998; Paul et al., 2002; Leifeld et al., 2005; Axel Don et al., 2007). As well as providing physical protection, Jones et al. (2005) state that soils with higher clay contents generally have higher %SOC due to greater moisture levels and lower aeration inhibiting oxidation. To establish if clay content is controlling %SOC, particle size distribution was measured using the centrifuge method (Tan, 1996). Although a large majority of studies use the Pipette method, time limitations meant the centrifuge method was chosen as it produces results just as accurate as other methods (Tan, 1996). Again due to time limitations all 618 samples could not be analysed for clay content. All samples were entered into a General Linear Model (GLM) and those under the Soil/land-use combinations covering the largest areas of the estate, with particularly high or low %SOC values for their soil/land-use category were chosen for analysis: in total 160 samples were analysed for clay content.

Higher pH results in greater microbial activity (Jones et al., 2005), meaning greater organic matter mineralisation is expected. Measurement was undertaken to establish if a relationship exists between soil pH and %SOC on all 618 samples. pH was measured using a glass electrode and pH meter following the method of Rowell (1994) and Tan (1996). Although this method of determining soil pH in water will never give an absolute value, comparisons between soil types can be made with confidence (Rowell, 1994).

2.2.3. Land-use history (years in current land-use)

A detailed land-use history was required to assess which soil carbon pools are in equilibrium and which are adjusting to previous land-use change (Stevens and Van Wesemael, 2008). This was done by interviewing the tenant farmers regarding their land-use from 1980–2008, following the approach used by Nyssen et al. (2008). Limitations at this stage included the fact that some of the tenants are relatively new to the estate and had to make a best guess of land-use during the earlier period.

2.2.4. Water content

Although the water content of soil could be a significant factor affecting SOC levels it has not been measured in this study. This was due to the widespread sampling interval spanning September to May, and the realisation that water content would be to some extent influenced by the time of year the sample was taken (Hamer et al., 2008).

2.3. Estimate of soil carbon using published soil survey data and maps

2.3.1. NSRI data

The NSRI soil map of the region (1:50 000 scale — Payton and Palmer, 1989) was digitized and the Wallington estate boundary overlain with each individual soil series given a feature class. The %SOC contained within the top 20 cm of a representative profile for each soil series was obtained from soil survey publications: this involved referring to soil surveys from across the country to find representative profile descriptions for all soil series present at Wallington. The %SOC contained within the top 20 cm of a major soil group was found by calculating the mean value of the soil series within that soil group. Major soil groups were classified by reference to Payton and Palmer (1989). The representative soil profiles did include a classification of what land-use each soil profile was under at the time of sampling. For a large number of profiles this was permanent grassland, although some profiles were taken under arable, rough grassland and woodland. The land-use information was then used to estimate %SOC values for land-uses under which soil series at Wallington occurred, but which were not represented in the NSRI representative profiles. This was done by calculating conversion factors for the limited soil series under which a variety of land-uses were represented in the NSRI database, and applying these conversion factors to all soil series present at Wallington. This was done to investigate if soil series/land-use combination values would improve estimates of %SOC. The %SOC maps of the estate were then produced by assigning the mean value for that soil series or major soil group to the area of the soil series/major soil group.

2.3.2. (CSS) Countryside Survey data

The Countryside Survey database is funded by the Department for Environment, Food and Rural affairs and the Natural Environment Research Council (Countryside Survey data © NERC — Centre for Ecology & Hydrology. All rights reserved). It details information relating to land-use, habitat types and soil data from a random sample of 1 km grid squares across Great Britain and provided 760 point measurements of SOC values from mineral and organo-mineral soils analysed in 1998 and 2000. Major soil group and land-use data was provided for each %SOC measurement, allowing mean values to be calculated for each major soil group, land-use and major soil group/land-use combination present at Wallington. The data from the 2000 Countryside Survey data was split into separate land-uses and classified into one of the five land-uses identified at Wallington. The land-use in italics refers to the Countryside Survey classification and that in brackets to the new classification: *Crops/weeds* (arable); *Fertile grassland* (improved pasture); *Infertile grassland/heath/bog/moorland grass/mosaic/tall grassland/herb* (rough pasture); *Lowland wooded* (woodland); *and Upland wooded* (forestry plantation). Mean values were then assigned to each soil polygon (from the NSRI map), each land-use area (from fieldwork observation and local knowledge) and each soil type/land-use combination.

2.3.3. Statistical analysis

The sampling design conducted within this study could be considered as a three factor experiment with multiple covariates. The three factors are: soil series (and or main soil group); land-use and farm tenancy. All three factors were entered into a General Linear Model (GLM) as categorical variables using Minitab statistical software. The covariates considered are: altitude, pH, clay content, slope angle and years in current land-use (all continuous variables). This means that the data can be analysed by analysis of covariance (ANCOVA). Results were considered statistically significant if $p<0.05$ (95% confidence interval). The results of ANCOVA were post-hoc tested using the Tukey test and proportion of the original variance explained by factor and covariate was calculated using the ω^2 method of Howell (2002). To meet the requirement of ANCOVA that all data are normally distributed all %SOC at 20 cm depth data were log transformed. Descriptive statistics were used to compare the variability within the different levels of soil or land-use classification.

3. Results and discussion

When comparing coefficients of variation (CV) for individual soil series/land-use combinations the combinations covering either less than 1% of the estate or with less than 5 samples were eliminated. During creation of the %SOC maps any combinations of soil/land-use/tenancy which were un-sampled were left blank.

3.1. SOC estimate using field samples

3.1.1. Stratification into major soil group

Large CVs ranging from 16.14% to 48.18% show that there is an extensive amount of variation in %SOC within some major soil groups (Table 1), indicating that there is not a strong relationship between major soil group and %SOC and that other factors are important. The large sample number of 368 for Surface-Water Gley Soils (Avery, 1980) confirms that it is not small sample numbers that are responsible for high CVs. Although there are statistically significant differences ($p<0.05$) between some major soil groups, the fact that only 16.18% of

Table 1
%SOC variation within different soil groups, soil series and soil series/land-use categories: decreasing variation when both soil series and land-use class are known.

S group[a](*N*[b])	Mean	CV[c]	S series[d](*N*)	Mean	CV	Land-use(*N*)	Mean	CV	Land-use(*N*)	Mean	CV
Disturbed(8)	5.19	16.14	92(8)	5.19	16.14	IP[e](1)	4.68		Arable(94)	2.73	24.9
						IT[f](3)	4.56	24.36	Forest[g](61)	15.67	28.4
						RP[h](4)	5.87	10.27	IP(128)	3.70	23.9
Brown[i](188)	3.32	24.84	Heapey(13)	4.51	37.35	Arable(29)	2.54	17.32	IT(81)	3.10	28.1
			Nercwys(137)	3.23	21.51	IP(47)	3.44	22.49	IP(241)	5.15	39.8
			Waltham(30)	3.14	24.28	IT(32)	3.06	22.38	Wood[j](8)	4.55	37.19
						RP(80)	3.70	22.84			
GWG[k](26)	3.84	34.16	Belmont(3)	20.28	12.60	Arable(4)	3.26	30.40			
			Enborne(19)	3.92	29.42	IT(4)	2.26	49.05			
						RP(18)	4.49	26.79			
Lith[l](4)	8.63	42.04				IP(1)	3.88				
						RP(3)	11.27	37.07			
Pod[m](20)	14.54	26.25	Cartington(9)	18.70	13.30	Forest(15)	15.41	23.69			
						IP(2)	10.94	29.24			
						RP(2)	9.64	65.40			
SWG[n](368)	5.05	48.18	Brickfield(125)	3.45	27.36	Arable(61)	2.80	26.30			
			Dunkeswick(33)	3.16	38.88	Forest(46)	15.77	30.09			
			Greyland(53)	3.44	20.69	IP(77)	3.74	20.86			
			Kielder(22)	8.20	35.51	IT(42)	3.14	29.13			
			Ticknall (13)	3.16	23.95	RP(134)	6.19	40.51			
			Wilcocks(122)	9.62	39.06	Wood(8)	4.55	37.19			

[a] Major soil group.
[b] Number of samples.
[c] Coefficient of variation (%).
[d] Soil series.
[e] Improved permanent pasture.
[f] Improved temporary pasture.
[g] Forestry plantation.
[h] Rough pasture.
[i] Brown soils.
[j] Woodland.
[k] Ground-water-gley soils.
[l] Lithomorphic soils.
[m] Podzols.
[n] Surface-water-gley soils.

the %SOC values from samples collected in the field can be predicted from the mean values for major soil group (Table 2) indicates that major soil group is not sufficient information to correctly predict any SOC baseline. Table 3 shows that this can be expected due to the large range in altitude and land-use beneath the one major soil group. The %SOC map produced by this method is shown in Fig. 3a.

Table 2
The predictive value of SOC baseline estimates using different data sources and classification methods.

SOC[a] mean value data from										
NSRI[b] MSG[c]	NSRI SS[d]	CS[e] MSG	CS LU[f]	Wall[g] MSG	Wall SS	Wall LU	Altitude	pH	Farm[h]	%SOC[i]
✓										16.85
	✓									48.35
	✓					✓				58
		✓								15.97
			✓							44.75
		✓	✓							51.53
				✓						16.18
					✓					48.69
						✓				45.25
				✓		✓				48.96
					✓	✓				57.72
					✓	✓			✓	64.58
					✓	✓	✓	✓	✓	66.65
					✓	✓	✓	✓		59.27

[a] Soil organic carbon.
[b] National Soils Resources Institute.
[c] Major soil group.
[d] Soil series.
[e] Countryside Survey.
[f] Land-use.
[g] Wallington.
[h] Farm tenancy.
[i] Soil organic carbon concentration correctly predicted.

3.1.2. Stratification into soil series

Smaller CVs ranging from 12.60% to 39.06% indicate less %SOC variability within soil series (see Clayden and Hollis, 1984 for classification) than major soil group (Table 1) and that soil series is a better predictor of %SOC. Two out of the three soil series within the Brown Soils (Avery, 1980) group have a lower CV than for the category Brown Soils, indicating that stratification into soil series is a more accurate method for estimating SOC stock. This is supported by the fact that both soil series within the Ground-Water Gley Soil (Avery, 1980) category have lower CVs than the major soil group (12.6% and 29.24% compared to 34.16%). Within the Surface-Water Gley major soil group all soil series have lower CVs compared to the CV for major soil group (48.18%).

Table 3
Different levels of stratification, their areal coverage and ranges in other controls on %SOC.

Stratification	%SOC predicted	Area (km^2)	Altitude range (m)	No. of soil series	No. of land-uses	No. of farms
Major soil group	16.18	34.86	188	7	4	17
Land-use	45.25	11.92	167	22	1	16
Soil series	48.69	8.88	122	1	4	12
Farm	55.46	2.47	35	9	3	1
Soil series/land-use	57.27	4.25	124	1	1	10
Soil series/land-use/altitude	59.27	1.41	15	1	1	7
Soil series/land-use/altitude/farm	66.65	0.42	15	1	1	1

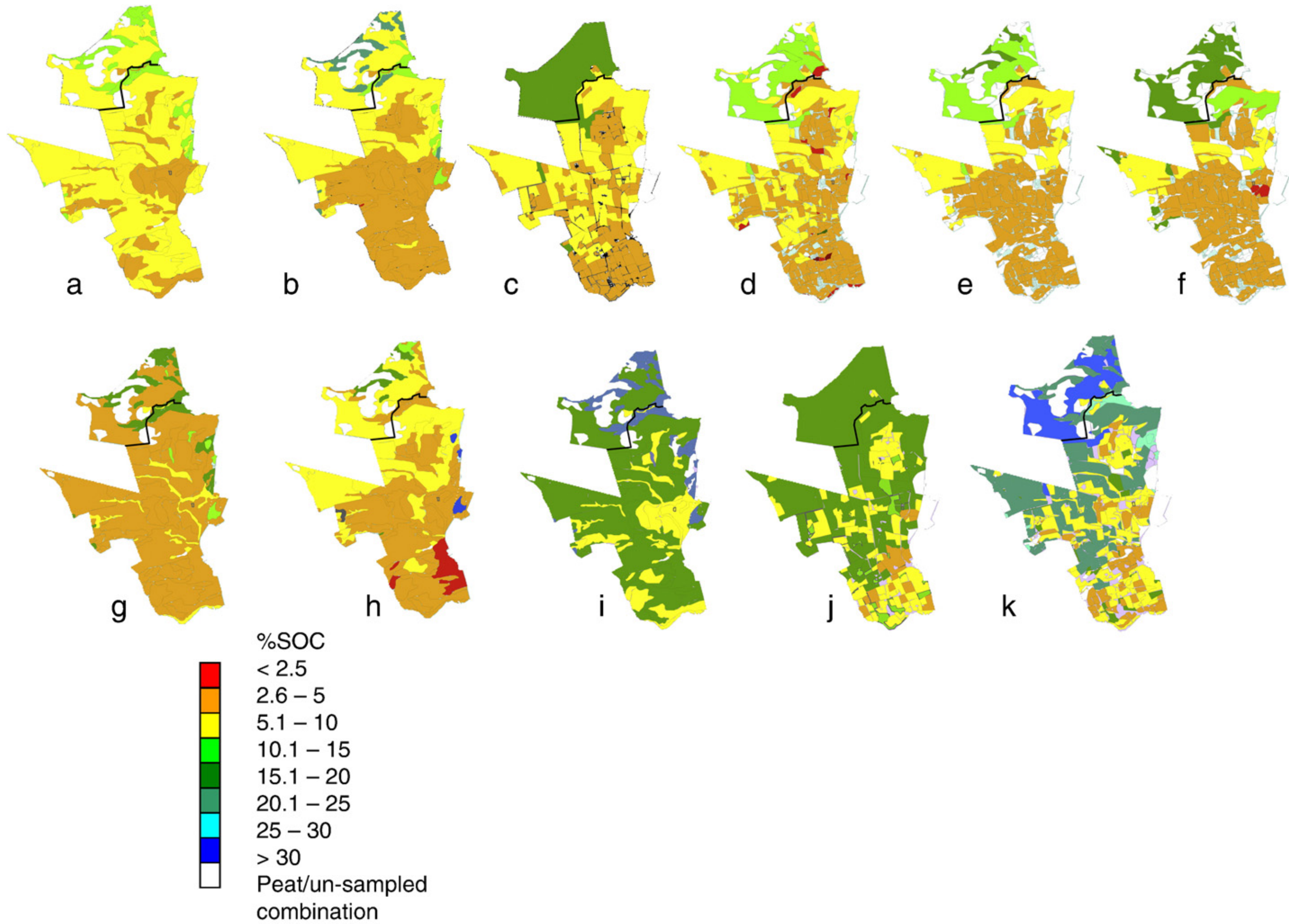

Fig. 3. %SOC distribution estimated using mean values from: a) Fieldwork major soil group; b) Fieldwork soil series; c) Fieldwork land-use; d) Fieldwork major soil group/land-use; e) Fieldwork soil series/land-use; f) Fieldwork soil series/land-use/farm tenancy; g) NSRI major soil group; h) NSRI soil series; i) Countryside Survey major soil group j) Countryside Survey land-use; k) Countryside Survey major soil group/land-use. %SOC = soil organic carbon concentrations.

There is a significant improvement from 16.18% to 48.69% in the ability to predict %SOC values correctly from the mean value for soil series rather than major soil group (Table 2). Statistically significant differences between several soil series further indicate that soil series is having some degree of control on %SOC levels. The %SOC map produced by this method is shown in Fig. 3b. Reference to Table 3 again indicates how this can be expected due to a smaller range in altitude beneath the one soil series than the one major soil group.

3.1.3. Stratification into land-use

CVs ranging from 23.97% to 39.89% indicate less variability within land-use categories than within major soil groups (Table 1, columns 10–12 compared to 1–3), however the lowest CV of 23.97% compared to the lowest CV for soil series of 12.06% suggests that some soil series have less variation than some land-use classes. This indicates that generally soil series is a better predictor of %SOC than land-use, if this is the only information available. This is confirmed by the lower r^2 value of 45.25% indicating less chance of correctly predicting %SOC at a specific location if the estimate is based purely on land-use as opposed to soil series. There are however statistically significant differences between arable and forestry, rough permanent pasture and improved permanent pasture; forestry and all land-uses; improved permanent pasture and rough permanent pasture; improved temporary pasture and rough permanent pasture, suggesting that land-use is having some influence on %SOC. The %SOC map produced by this method is shown in Fig. 3c. Reference to Table 3 shows how the area of the estate covered by an individual land-use is large, therefore covering a large range in altitude and soil series, which will again be responsible for the variation in %SOC beneath a particular land-use.

3.1.4. Stratification into farm tenancy

The range in CVs from 15.28% to 40.91% indicate that some farm tenancies have much less variation in %SOC than others, most likely due to some having various land-uses and soil types, compared to others with one dominant land-use and soil type. An r^2 value of 55.46% suggests that farm tenancy is a better predictor of %SOC than soil series or land-use if this is the only information available on which to estimate %SOC. The majority of tenancies show no significant differences, however there are 3 farms with significantly higher %SOC values, therefore, although estimation of SOC stocks based on stratification into farm tenancy will produce an estimate more accurate than soil group, soil series and land-use stratifications respectively, this is most likely the result of inconsistencies in the other variables affecting %SOC between farms. Single variant analysis cannot establish whether farm management practices are responsible for %SOC variation due to differences in soil series, land-use, altitude and other variables between farms.

3.1.5. Stratification into major soil group/land-use

The CVs for all land-uses within the major soil group Brown Soils are lower than the CV for just Brown Soils (Table 1, columns 7–9 compared to 1–3). Within the major soil group Ground-Water Gley soils, the land-use categories arable and rough pasture have lower CVs than for the Ground-Water Gley Soil category. Rough pasture within the Lithomorphic Soil (Avery, 1980) category has a lower CV than the category Lithomorphic Soils, and all land-use categories within the major soil group Surface-Water Gley have lower CVs than the CV for Surface-Water Gley. This confirms that stratification into major soil group/land-use category would achieve a more accurate estimate of %SOC compared to stratification using major soil group alone. This is also confirmed by the large increase in r^2 from 16.18% to 48.96%. Stratification of the area into major soil group/land-use categories would also provide a more accurate estimate than stratification into land-use (r^2=45.25%) and soil series (r^2=48.69%). The %SOC map produced by this method is shown in Fig. 3d.

3.1.6. Stratification into soil series/land-use

As mentioned earlier, access difficulties and remote areas of small soil series inclusions meant that a mean value for each soil series/land-use combination at Wallington has not been measured. The result of this is that the predictive value of using the mean values to estimate %SOC values for these soil/land-use combinations cannot be assessed. These areas however tend to cover less than 1% of the estate and therefore inaccuracies in calculating total %SOC levels as a result of this are small.

Within the soil series Breamish, 4 out of 5 of the land-use categories have lower CVs than Breamish; all land-uses within Dunkeswick have lower CVs than Dunkeswick, as is the case with land-uses within Greyland, Nercwys and Wilcocks soil series. The large increase in r^2 to 57.72% indicates that soil series/land-use stratification is the most accurate method of predicting SOC stocks if you only have information relating to soil type and land-use. The %SOC map produced by this method is shown in Fig. 3e.

3.1.7. Stratification into soil series/land-use/farm tenancy combinations

If however you also know which farm tenancy the land-use and soil series is located under, the probability of correctly predicting %SOC will be improved from 57.72% to 64.58%. The CVs for all tenancies within the category Brickfield/arable are lower than the CVs for soil series stratification into Brickfield and land-use stratification into arable. The CVs for both Newbiggen and Prior Hall within the category Brickfield/arable are lower than the CVs for stratification based purely on tenancy. The same is true of many other soil series/land-use/tenancy stratifications. The %SOC map produced by this method is shown in Fig. 3f.

Although there is a statistically significant difference between many of the farm tenancies under the same soil series and land-use, the possibility that this could be the result of other potential %SOC controlling factors including altitude, pH and clay content must be investigated.

Regression analysis of %SOC against altitude reveals that 41.5% of the variance in %SOC can be explained by altitude. Again however, single variance analysis at such a complex site is insufficient to establish the factors controlling %SOC. Soil series and land-use as well as tenancy are all governed to some extent by altitude. The r^2 value of 41.5% does however reveal that having information only relating to altitude would produce a SOC estimate of greater accuracy than stratification into major soil group alone. Regression analysis of %SOC against pH reveals that 32.8% of the variance in %SOC can be explained by pH: the same issues relating to single variance analysis again however exist. Although it is unlikely that you would have information relating to soil pH and not altitude, land-use, soil series or farm tenancy, if this was the case, you would be able to achieve a more accurate estimate of SOC using pH as a predictor rather than major soil group alone.

Other factors which were also thought to be possible controls on %SOC including land-use history (years in current land-use), slope aspect, slope angle and clay content were also included in the model but did not have a statistically significant affect on %SOC (p>0.05).

3.1.8. Stratification into soil series/land-use/farm tenancy/altitude/pH

Inclusion of altitude and pH in the model increased the r^2 value from 64.58% to 66.65% and both factors were identified as having a statistically significant affect on %SOC (Table 2).

To assess the impact of classification into farm tenancy on %SOC estimates, farm tenancy was removed from the model (leaving soil series, land-use, altitude and pH), and the statistically significant differences between land-uses were compared to the statistically significant differences between land-uses in the model stratified by farm tenancy (soil series, land-use, farm tenancy, altitude and pH). At a specific altitude, land-use, soil series and pH, when tenancy is kept constant there is no longer a difference between arable and improved permanent pasture. This suggests that without the inclusion of tenancy there was a larger spread in the %SOC values found under these categories. With tenancy included there is now a difference between arable and improved temporary pasture suggesting that there was previously a larger spread in the values for these categories and these have been reduced with stratification into farm tenancy. There is no longer a difference between forestry and rough pasture suggesting that the spread of %SOC values for rough pasture are greater across the entire Wallington estate than they are within tenancies, indicating that different levels of management practice within rough pasture are causing differences in %SOC. There is now a difference between improved permanent pasture and rough pasture suggesting that the CVs for these categories have become more constrained. This again suggests that farm management practices within these categories are controlling %SOC levels. There is no longer a difference between improved temporary pasture and rough pasture. This again suggests a reduction in variation within land-use classes when stratified by farm tenancy.

The role of farm management practices on %SOC is emphasised when the magnitude of the effect of each variable is analysed. When altitude, soil series, land-use, farm tenancy and pH are constant, a change in any of these variables has a statistically significant affect on %SOC. The magnitude of the effect of each variable is shown in Table 4. These results indicate that farm tenancy has a greater influence on %SOC than both land-use and soil series. The generally good model fit is shown in Fig. 4; however the prediction of 66.65% of %SOC values with these variables included means that 33.35% of the variation is still unexplained.

3.2. SOC estimate using published soil survey data

3.2.1. NSRI data

Regression analysis of the 618 samples versus the mean values for major soil group from the NSRI map series indicates that only 16.8% of the %SOC values could be correctly predicted from the mean values for these soil groups. The %SOC map produced by this method is shown in Fig. 3g. Using mean values for soil series from the NSRI map series would produce a significantly better estimate, correctly predicting 48.35% of the %SOC values. The %SOC map produced by this method is shown in Fig. 3h. However, the r^2 value of 48.35% shows that more than 50% of the observed variation is unexplained, and that other variables must be included. Using mean values for soil series/land-use

Table 4
Controls on %SOC: the greater impact of farm tenancy compared to land-use and soil series: an indication of land-management effects.

Variable	Magnitude of effect (%)
pH	5.14
Altitude	13.47
Soil series	9.17
Land-use	19.67
Farm tenancy	35.29

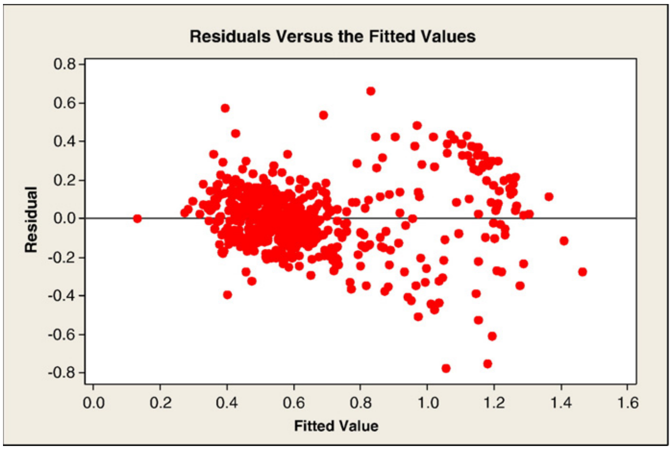

Fig. 4. Modelled values of SOC versus residuals: using soil series, land-use, altitude, pH and farm tenancy as inputs.

combinations calculated from a limited NSRI database increased the estimate further still to 58%, indicating the major importance of land-use on %SOC values.

3.2.2. Countryside Survey data

Regression analysis of the 618 samples versus the mean values for major soil group from the Countryside Survey database indicates that only 15.97% of the %SOC values could be correctly predicted from the mean values for these major soil groups. The %SOC map produced by this method is shown in Fig. 3i. Using mean values for land-use would produce a significantly better estimate, correctly predicting 44.75% of the %SOC values, however the predictive value is increased further still when mean values for major soil group/land-use combinations are applied. Applying these values correctly predicts 51.53% of the variation in the measured %SOC data. The %SOC maps produced by these methods are shown in Fig. 3j and k.

These results suggest that the Countryside Survey database is the more accurate of the two methods for calculating SOC baselines if no local soil sampling and fieldwork is available, and only raw data provided by the two sources is used, however the highest r^2 value of 51.53% implies that other variables are controlling %SOC levels and should be included to achieve greater accuracy. Although the CSS is predicting 51.5% of the %SOC values correctly, the green and blue colours in Fig. 3i, j and k show that the CSS is predicting values that are systematically too high for the more organic rich soils and areas of rough pasture. This is very important when calculating SOC stocks and although the majority of this study refers only to %SOC values rather than SOC stocks, a comparison of SOC stocks at this point emphasises this point. NSRI data for soil series would predict a carbon stock for the top 20 cm of soil on the estate of 556.13Kt C, CSS data for major soil group/land-use combinations would produce a carbon stock value of 1188.43Kt C and fieldwork values for soil series/land-use combinations a carbon stock value of 785.24Kt C.

The accuracy of predicting %SOC values can be increased using published data if NSRI data is manipulated and soil series %SOC values are converted to take account of land-use.

3.3. Discussion

This study highlights the issues of scale involved in calculating SOC baseline inventories. Examination of Table 3 indicates why applying the mean %SOC value for a particular major soil group gathered from an area as large as 55 km^2 will limit the accuracy of the prediction, due to the large range in other possible controls on %SOC beneath that one land-use. The same is true when applying mean values taken from a particular land-use or soil series covering such a large scale. Applying mean %SOC values taken from beneath one particular farm tenancy could possibly increase the accuracy of the estimate due to the farm covering a much smaller scale than a particular land-use, major soil group or soil series (Table 3), therefore decreasing the variation in altitude beneath that feature class, however the range in land-uses undertaken by that one farm tenant are likely to be just as great, and therefore even at this small scale %SOC variation can be large. The application of mean values collected from national databases such as the CSS or NSRI will result in even less accurate %SOC estimates as a result of the values being taken from an area of a much greater scale (national level), increasing the likelihood of an even greater range in altitude and other possible controlling factors of %SOC beneath that one land-use or soil group/series etc. This study reveals that for the Wallington Estate in North East England the most accurate estimates of %SOC for particular locations are made when mean values taken from the same particular land-use/soil series/altitude/farm tenancy combination as that of the area in question are applied. Table 3 emphasises how the application of these mean values may be responsible for the increase in predictive accuracy due to the much smaller scale of the estate covered by a land-use/soil series/altitude/farm combination compared to the scale of the estate covered by individual factors such as major soil group.

Although it was earlier suggested that soil series is a better predictor of %SOC than land-use, this was based on single variance analysis and is likely the result of soil series having a smaller variation in altitude and pH than land-use (Table 3). When altitude and pH are constant, land-use has been identified as a better predictor of %SOC than soil series, but more importantly farm tenancy is also a better predictor than soil series. This is confirmed by the greater magnitude of the effect of farm tenancy (35.29%) compared to that of soil series (9.17%) and land-use (19.67%) when all other variables are constant. This research suggests that different farm management practices within a land-use category are causing differences in %SOC, and therefore that land-use stratification into the categories arable, improved temporary pasture, improved permanent pasture, forestry and woodland is not sufficient on which to base SOC baseline estimates.

Table 2 shows the predictive value of %SOC estimates produced using different combinations of the variables discussed here. Comparison of the bottom 4 rows indicates that farm tenancy is an important variable to include and emphasises the suggestion that farm management practices are controlling %SOC. Examination of Table 3 also reinforces this suggestion. Although the scale of the land area from which the mean %SOC is calculated has declined when stratification of soil series/land-use/altitude classes is increased into soil series/land-use/altitude/farm tenancy classes, there is no decline in the number of other possible controls on %SOC. It must therefore be either land-management differences between farms, or some other unidentified factor which also varies under different farms that is responsible for the observed variation in %SOC.

Although this research highlights the importance of including farm management practices in any SOC predictions, it has not identified what precise farm management practices are responsible for increasing SOC levels. It has been suggested that fertiliser use can cause a loss of CO_2 to the atmosphere (Zhang and McGrath, 2004), however this is not taken into account when predicting SOC baselines and is an area needing further research. Although many attempts at predicting SOC baselines have stratified the areas into land-use, recognising a difference between improved and unimproved agricultural grassland, this study suggests that this stratification does not go far enough, and that factors such as fertiliser type and application rates as well as grazing intensity and type may be other factors playing a major role (Soussana et al., 2004). Sonneveld et al. (2002) also recognise the need for further research into this area, quote: "Distinguishing between mowing and grazing regimes or specific silage maize cultivation practices might further explain the variability observed."

Much recent literature has attempted to establish the role of fertiliser input on SOC stocks (Triberti et al., 2008; Purakayastha et al., 2008), however these factors are rarely considered when establishing SOC baselines. Dedonker et al. (2004) reveal that organic amendments increase soil carbon levels. A lack of disturbance reduces outputs. Previous studies have found animal manure incorporation to increase carbon accumulation, as well as sewage sludge incorporation, straw incorporation and no-till management. These previous findings combined with the results of this study go towards further confirming that SOC is affected by agricultural management (Frazluebbers and Stuedemann, 2009) due to changes in the levels of organic matter input and soil disturbance. Crop type, crop rotation, tillage type, fertiliser use and organic amendments all influence the amount and distribution of the organic matter within the soil. Management practices also influence how organic matter is lost as a result of soil erosion, plant harvest and microbial decomposition. Differences in %SOC between farms located at similar altitudes and on similar soil types at Wallington help to emphasise that land-management practices such as these have a large impact on SOC levels. Despite this realisation, farm management is often ignored when predicting SOC levels for un-sampled regions. Franzluebbers et al. (2001, cited in: Frazluebbers and Stuedemann, 2009) found greater SOC accumulation in pastures that were grazed by cattle in summer compared to those that were not grazed. In other studies however, no differences have been found between lightly grazed and unharvested grasslands — but differences have been found between those that are heavily grazed and unharvested. The results are very mixed but there is clearly a difference resulting from management practices, supporting the results of this research, confirming that SOC baselines and estimations without consideration of these factors will be inaccurate.

The use of secondary data to estimate a SOC bank has many limitations. Although the %SOC values estimated for the estate using NSRI mean values for soil group or soil series can correctly predict approximately the same % of %SOC values as using the mean values collected in the field (16.85% using NSRI major soil group, 16.18% using fieldwork major soil group, 48.35% using NSRI soil series and 48.69% using fieldwork soil series), examination of maps produced by these approaches (Fig. 3) reveal many spatial differences in the %SOC values across the estate depending on the source of data. This method of estimation relies on soil survey data measured in the 1980s to calculate the soil carbon stock and could be inaccurate due to land-use change and climate change since the period of survey (Gao et al., 2008). The same inaccuracies are therefore likely in any attempt to calculate a region or organisations carbon stock in Britain using the NSRI database, and could be responsible for the range in estimates of SOC stocks and maps produced in this study. The majority of NSRI surveying was undertaken in the 1970s/1980s and climate/land-management change could have resulted in a change in soil carbon values for the same soil types under present day conditions (Bellamy et al., 2005; Smith et al., 2007). This could help to explain the differences in %SOC calculated in this field study and those that would be predicted for the Wallington site using NSRI data from earlier decades.

This study shows that predicting a SOC bank based entirely on %SOC values for soil type is insufficient. This can be expected as SOC is known to vary greatly as a result of land-use, and therefore to predict a region's carbon stock using just soil type mean %SOC values is ignoring this major influence on SOC levels. Prediction at a large scale may be accurate in terms of a figure for total C stock, due to the mean value averaging out over all land-uses; however this method is unlikely to correctly predict the SOC stock values for particular locations. The assumption that agricultural soils, for example, will have the same SOC values as forestry soils if they belong to the same soil series should not be made (Heath et al., 2002). A large amount of the variability in SOM is unexplained by soil classification (Schulp and Veldkamp, 2008) and this research highlights that soil classification can miss the variation within soil classes.

Although it is suggested that it is land-management practices within a land-use that are responsible for the statistically significant differences in %SOC between farm tenancies located on the same soil type, at the same altitude and under the same land-use class, the possibility that these differences are the result of issues associated with scale must also be considered. In this study all estimates using soil type as a SOC predictor, whether it be the use of field data %SOC values, CSS %SOC values or NSRI %SOC values is that they are all estimated using the NSRI soil map. Major errors can occur in extrapolating point data if small inclusions of organic soils occur within a mapped soil unit and these are then either not accounted for (if the sample was not taken from the inclusion), therefore the carbon stock is under-predicted, or the carbon stock may be greatly over-predicted if the representative profile for the soil unit was taken from the inclusion, and this value is then applied to the whole soil type. The larger the scale of the soil map, the more errors in carbon inventories (Arnold, 1995), however these limitations are very difficult to overcome as these maps provide the most accurate identification of soil type if extensive sampling is not to be carried out. It is possible therefore that some of the difference that appears to result from farm tenancy could in-fact be the result of inaccurate soil series allocation due to the use of a 1: 50 000 scale soil map.

Other possible explanations for the apparent role of land-management in this study are related to aggregation issues. In this study the low predictive value of using land-use data alone could in part be explained by the subjective nature of classifying particular land-uses. This again however emphasises the role of farm management and stresses the fact that levels of management within a land-use category are an important control of SOC levels. It is very possible that the SOC predictions would be different had a different land-use map been used (Meersmans et al., 2008). The apparent differences between farm tenancies located on the same soil series at the same altitude and under the same land-use could therefore possibly be the result of a particular land-use under one farm tenancy being allocated a different/same land-use to the same/different land-use under a different farm tenancy due to the subjective nature of classification.

Although the application of mean values from local sampling rather than mean values from National databases appears the more appropriate method for SOC baseline estimation, the time and effort involved in such an intense soil sampling campaign must be considered. As the results from this study are presently only valid for the Wallington Estate the mean %SOC values for particular land-use/soil series/altitude locations cannot yet be applied to other areas of the country, however ongoing validation studies in these areas will reveal if this can be the case in the future. In order for an organisation such as The National Trust to estimate their entire SOC stocks it would therefore be most beneficial to use national databases, provided that the soil data is adjusted to take account of land-use and altitude using similar correction factors as found in this study. The previous suggestion however, that %SOC values from national databases may now be inaccurate due to the passing of several decades since data collection means that if values from this current study can be found to correctly predict the %SOC in other National Trust estates then referral to this database should be the method employed in the future. The implication from this study that farm management practices are responsible for differences in %SOC also suggests that in the future the mean %SOC values from national databases could be increased or decreased to take account of practices such as fertiliser application rates and grazing levels, however to date these adjustments cannot be made until the exact effects of land-management on %SOC are clarified.

It must also be realised that this study has only assessed the accuracy of SOC baseline estimates made by aggregating %SOC values from a variety of soil types and land-uses from national databases and local soil sampling into different classes to produce mean %SOC values which are then applied to the area of that classification. The study has not assessed the accuracy of SOC baselines produced using process models and geostatistical methods.

4. Conclusion

Calculating a SOC baseline based on major soil group stratification is the least accurate method and is significantly improved by stratification into soil series. Land-use stratification is a less accurate method than soil series; however this can be improved by stratification into soil series/land-use combinations.

Intensive soil sampling at Wallington, NE England has shown that other variables must be included to increase this accuracy further, and that the use of secondary data is insufficient if the most accurate soil organic carbon bank estimates are required. The results of this study can be summarised as follows:

- An increase in predictive value from 16.85% to 48.35% when using soil series rather than major soil group NSRI data indicates that if NSRI data is the only data available then this form of stratification should be used. The predictive value can be improved on slightly without any additional fieldwork if the Countryside Survey database is used instead, and applied to major soil group/land-use combinations.
- Additional information including altitude and soil pH is required to produce more accurate estimates, and these can be improved further still if the areas are also stratified by farm tenancy. This is shown by an increase in predictive value from 57.72% for soil series/land-use combinations, to 59.27% for soil series/land-use/pH/altitude combinations and 66.65% for soil series/land-use/pH/altitude/farm tenancy combinations.
- With all of these variables included in an estimate of SOC levels at Wallington, 33.5% of the variation in SOC still remains unexplained.
- This study suggests that stratification into a greater number of land-use categories is needed in order to take account of different land-use management practices within a land-use category, as well as emphasising the large spatial variability in %SOC.

Acknowledgements

Research was funded by a grant from The National Trust. Thanks to the tenant farmers and Forestry Commission for access to their land and the provision of land-use and land-use history information. Thanks to the National Trust for access to their Biological Survey information and Wallington estate boundary maps. Thanks also to Newcastle University for provision of soil sampling equipment.

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