

Magnitude and sources of uncertainties in soil organic carbon (SOC) stock assessments at various scales

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Summary

Uncertainties in soil organic carbon (SOC) stock assessments are rarely quantified even though they are critical in determining the significance of the results. Previous studies on this topic generally focused on a single variable involved in the SOC stock calculation (SOC concentration, sampling depth, bulk density and rock fragment content) or on a single scale, rather than using an integrated approach (i.e. taking into account interactions between variables). This study aims to apply such an approach to identify and quantify the uncertainties in SOC stock assessments for different scales and spatial landscape units (LSU) under agriculture. The error propagation method (δ method) was used to quantify the relative contribution of each variable and interaction involved to the final SOC stock variability. Monte Carlo simulations were used to cross-check the results. Both methods converged ($r^2=0.78$). As expected, the coefficient of variation of the SOC stock increased across scales (from 5 to 35%), and was higher for grassland than for cropland. Although the main source of uncertainty in the SOC stock varied according to the scale and the LSU considered, the variability of SOC concentration (due to errors from the laboratory and to the high SOC spatial variability) and of the rock fragment content were predominant. When assessing SOC stock at the landscape scale, one should focus on the precision of SOC analyses from the laboratory, the reduction of SOC spatial variability (using bulk samples, accurate re-sampling, high sampling density or stratified sampling), and the use of equivalent masses for SOC stock comparison. The regional SOC stock monitoring of agricultural soils in southern Belgium allows the detection of an average SOC stock change of 20% within 11 years if very high rates of SOC stock changes occur ($1 \text{ t C ha}^{-1} \text{ year}^{-1}$).

Amplitude et sources des incertitudes liées aux estimations des stocks de carbone organique dans le sol (COS) à différentes échelles

Résumé

Les erreurs associées aux estimations du stock de carbone organique dans le sol (COS) sont rarement quantifiées bien qu'elles puissent empêcher l'obtention de résultats significatifs. Les quelques études qui le font focalisent en général sur une seule variable nécessaire au calcul du stock de COS (concentration en COS, profondeur échantillonnée, densité apparente et contenu en fragments rocheux) ou sur une échelle spatiale particulière, sans utiliser d'approche intégrée (prenant en compte les interactions entre les variables). Cette étude a pour objectif d'utiliser une telle approche pour identifier et quantifier les incertitudes liées aux estimations de stock de COS à différentes échelles spatiales et pour diverses unités spatiales de paysages (USP) agricoles. La loi de propagation des erreurs (méthode δ) permet de quantifier la contribution relative de chaque variable et interaction à la variabilité finale du stock de COS. Les simulations de Monte Carlo sont utilisées pour la vérification croisée des résultats. Les deux méthodes ont convergé ($r^2 = 0.78$). Comme prévu, le coefficient de variation du stock de COS a proportionnellement augmenté avec l'échelle spatiale considérée (de 5 à 35%), et était plus élevé pour les cultures que pour les prairies. Bien que la principale source d'erreur sur le stock de COS soit fonction de l'échelle spatiale et du type d'USP considérés, la variabilité du contenu en COS (du fait des erreurs de laboratoire et de sa grande variabilité spatiale) et du

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contenu en fragments rocheux étaient prédominants. Lors de l'estimation des stocks de COS à l'échelle du paysage, l'attention devrait prioritairement porter sur la précision des analyses en COS du laboratoire, la réduction de la variabilité spatiale du COS (en utilisant des échantillons composites, un ré-échantillonnage précis, une densité d'échantillonnage élevée ou un échantillonnage stratifié), et sur l'utilisation de masses équivalentes pour comparer les stocks de COS. Le réseau régional de suivi des stocks de COS des sols agricoles dans le sud de la Belgique permet la détection d'un changement de stock de COS moyen de 20% en 11 ans pour un taux très élevé de changement en stock de COS ($1 \text{ t C ha}^{-1} \text{ year}^{-1}$).

Introduction

Soil organic carbon (SOC) stock is an important issue in the context of climate change (soils being potential sinks or sources of CO_2) and of soil degradation (EC, 2006). The Kyoto Protocol, the EU soil thematic strategy and the European Common Agricultural Policy rely on SOC stock assessment as part of the greenhouse gas emission budget, the verification of changes in soil organic matter, or for the implementation of agri-environmental measurements (SOC management). However, SOC stock assessments are associated with large uncertainties that may impair the detection of temporal SOC stock changes and the identification of the main driving forces involved (Falloon & Smith, 2003; Ogle *et al.*, 2006).

Uncertainties are difficult to quantify and to identify because they stem from complex interactions between the variables involved in SOC stocks (i.e. SOC concentration, bulk density, sampling depth and rock fragment content). Uncertainties arise from manipulation, instrumental limitations and environmental variability in each variable. Different types of errors can be distinguished: systematic and random. Mathematical expressions of uncertainties may refer to the level of accuracy (usually represented by the mean error–ME) or precision (commonly represented by the standard deviation) (see Note 1, p 15). Although uncertainties need to be reduced, knowledge of uncertainty can also be used to optimise the design of a SOC stock monitoring scheme, as illustrated by the concept of the minimum detectable difference (MDD) in SOC stock: given the estimated variance in the SOC stock of a population and the MDD to achieve, the number of samples to collect can be adapted for a fixed level of confidence (Sokal & Rohlf, 1995; Zar, 1999). Besides, given a rate of SOC stock change, the time needed to detect the MDD can also be estimated (Smith, 2004). It is therefore essential to quantify and identify uncertainties in order not only to improve the design of SOC stock monitoring schemes, but also to use the results of SOC stock assessments properly for political and societal decisions (Saby *et al.*, 2008).

Some studies have focused on particular aspects of uncertainties in SOC stocks, such as the impact of using different analytical methods for SOC concentration determination. It has been shown that the precision (CV) of such analytical methods could range from 1.2 to 15.8% for the loss-on-ignition method (LOI), from 1.6 to 4.2% for the Walkley & Black method (WB), and

from 1.3 to 7.1% for dry combustion (Lowther *et al.*, 1990; Soon & Abboud, 1991; Sutherland, 1998; Bowman *et al.*, 2002), and that the relationships between the results from these different methods depended on the type of soil considered. Furthermore, the general underestimation of the total organic carbon concentration (TOC) by the WB method requires a correction factor that may vary from 1 to 1.6 according to land use, soil type (especially soil texture), SOM quality, sampling depth, or climate (Wang *et al.*, 1996; Jolivet *et al.*, 1998; Díaz-Zorita, 1999; Brye & Slaton, 2003; Lettens *et al.*, 2007). Therefore, the choice of a method to determine the SOC concentration already has an impact on the quality of the results and the use of empirical relationships or correction factors should preferably be related to the situation studied. Other studies on uncertainties in SOC stocks assessment have highlighted the importance of directly measuring the soil bulk density (BD), as indirect BD estimates based on pedotransfer functions can lead to errors from 9% up to 36% of the SOC stock (Boucneau *et al.*, 1998; De Vos *et al.*, 2005). The use of random errors in the SOC concentration either in geostatistics for spatial issues or in the MDD approach for monitoring design purposes has also been widely illustrated. While geostatistical models provided SOC maps at various scales based on the spatial variability of SOC, they still gave large variability at short distances (i.e. nuggets) resulting in inherent errors of prediction (Robertson *et al.*, 1993; Delcourt *et al.*, 1996; Geypens *et al.*, 2000; Zhang & McGrath, 2004). The application of the MDD for SOC stock, usually at the micro-site scale (Conant *et al.*, 2003), the field scale (Johnson *et al.*, 1990; Garten & Wullschleger, 1999; Kucharik *et al.*, 2003; Poussart *et al.*, 2004) or more recently the regional scale (Saby *et al.*, 2008), showed the high sampling density needed to detect differences in SOC stocks between two locations or surveys. While these studies provided insights into various sources of variability, they (i) do not consider uncertainties in the SOC stock in an integrated approach, i.e. resulting from the propagation of individual errors and their interaction and (ii) only focus on a single variable or a single scale. It is therefore difficult to compare the results from these different studies in order to identify the relative weights of the main errors involved in the total uncertainty in SOC stock assessment, and for different scales of interest.

However, the concept of error propagation can be directly applied to the mathematical expression of SOC stock, since

the random error (i.e. the variance, σ^2) in the SOC stock comes from the propagation of the random errors in each variable used in the SOC stock equation. Given that these individual random errors and interaction are first estimated, their propagation can be assessed by different methods: i) the Monte Carlo simulation method (MC), which generates numerous SOC stocks using random values for each individual variable (stochastic approach) (Hammersley & Handscomb, 1964; Rubinstein, 1981), or ii) the classical method of the law of covariances associated with the Taylor method (also called “the statistical differentials method” or the “ δ method”) (Goodman, 1960; Ku, 1966; Wells & Krakowsky, 1971; Mardia *et al.*, 1979), which gives a general equation for the error propagation in non-linear functions (deterministic approach). The advantage of the “ δ method” is to give an explicit equation for the final SOC stock variability (i.e. the solution comes in an analytical form), which allows one to quantify the relative contribution of the individual sources of uncertainties as well as their interaction (Heuvelink, 1998). However, when more complex functions than the SOC stock are considered, the MC method is easier to implement even if a large number of runs might be needed. Note that the MC simulations can also be used to cross-check the result (i.e. the SOC stock variability) given by the “ δ method”.

While integrated approaches have increasingly been applied to the uncertainty assessment of SOC stocks (Janik *et al.*, 2002; Ogle *et al.*, 2003; VandenBygaert *et al.*, 2004; Falloon *et al.*, 2006; Post *et al.*, 2008), they are mainly restricted to MC analyses and applied to predictive C models (either dynamic ones such as the RothC model, or empirical ones such as the IPCC method). To our knowledge, only two recent studies have applied the approach based on the “ δ method” to the SOC stock equation. Schwager & Mikhailova (2002) have illustrated the error propagation function for various sampling situations within one field, while Dileep *et al.* (2008) demonstrated the importance of taking covariances into account in the estimation of SOC stock variability.

Goidts & van Wesemael (2007) presented a methodology to assess SOC stocks and their evolution at a regional scale (southern Belgium) by re-sampling a reasonable number of locations belonging to spatial landscape units (LSU). Many questions still remain about the accuracy of a method based on stratified re-sampling, the sources of uncertainties and their importance across different scales. Given these questions, the main objective of this study was to identify and quantify the uncertainties in this particular SOC stock assessment using an integrated approach. The specific objectives were (1) to quantify the uncertainties in SOC stock occurring at different scales and for different types of LSU under agriculture, (2) to identify the main sources of these uncertainties, together with their relative importance, and (3) to provide guidelines to increase the potential of a regional SOC monitoring scheme to detect SOC changes.

Therefore, both the “ δ method” and the MC analysis were used at various scales (sample, microsite, field and landscape)

and for different types of LSU encountered in the study area. The results obtained were then used to assess the accuracy and precision of the SOC stock monitoring implemented in southern Belgium and to give guidance for setting up such a monitoring scheme.

Material and methods

Sampling scheme

Southern Belgium (Wallonia) had been stratified into spatial landscape units (LSU) for the previous assessment of the SOC stocks of agricultural soils and their evolution (Goidts & van Wesemael, 2007). The LSU are the result of the stratification of the study area according to three criteria: the agricultural land use (cropland or permanent grassland), the agricultural region (i.e. broad zones of similar geology, soil type, relief, climate and agricultural management), and the soil type (soil texture and drainage). Each LSU is characterised by a number of soil profiles that were originally sampled in the 1950s during the National Soil Survey (NSS) according to a directed sampling (in order to draw the Belgian soil map) (De Leenheer *et al.*, 1968). 15 LSU in total, covering about 54% of the agricultural area and each represented by 28 geo-referenced soil profiles on average, were re-sampled fifty years later in order to initiate a monitoring network (“CARBOSOL”). These soil profiles are under an agricultural land use, have not undergone any land use change since the 1950s, and were retrieved with a high level of confidence (agreement between the observations made in the field, and the geographical coordinates, the topography and the soil profile horization originally described in the NSS).

For each soil profile used in the regional SOC stock assessment, a composite soil sample (of 5 subsamples) was taken within a circle of 4 m radius (the microsite) centred on the soil profile (Figure 1). Subsamples were taken at a regularly increasing distance from the centre of the microsite (every 0.8 m) and along each cardinal direction. Sampling was done with an auger *by horizon* up to a depth of 30 cm (except for cropland when the plough depth was below 30 cm, then only one soil sample was taken up to the plough depth). These composite samples were further used to analyse the SOC and rock fragment content (RM) of each horizon. Three intact cores of 100 cm³ (diameter_{core} = 5.3 cm) were additionally taken within the microsite in order to measure the corresponding soil bulk density (BD) of each layer sampled (the BD was assumed to be constant within one soil horizon). When rock fragments prevented the insertion of the core in the soil, another position within the microsite was chosen nearby until three samples were obtained for the BD (this procedure can, however, lead to an underestimation of the effective rock fragment content).

Four LSU were selected for further investigation on uncertainties in the estimated SOC stocks. As there is a main gradient from the northwest to the southeast part of Wallonia in environment and land use characteristics (Note 2), the four LSU selected for

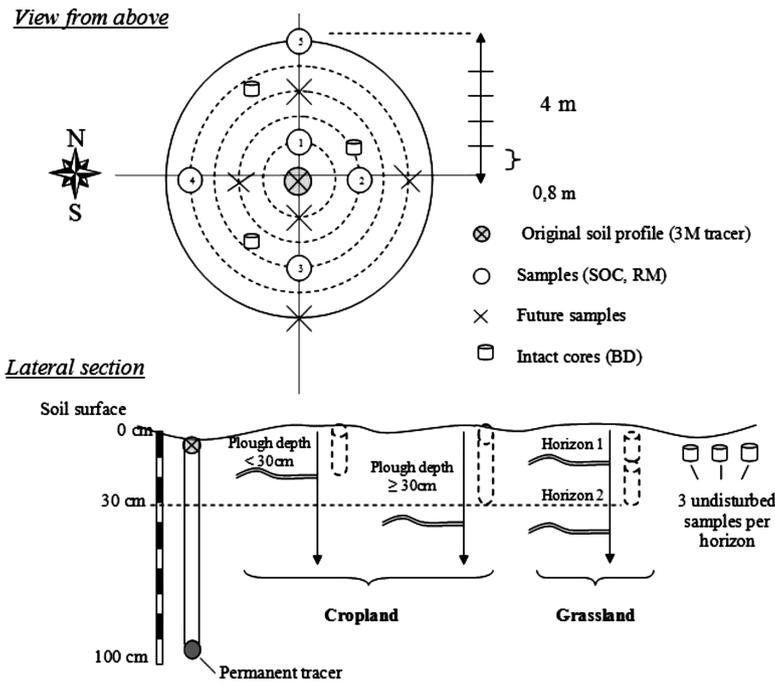


Figure 1 Sampling scheme of each soil profile sampled for the SOC monitoring network of southern Belgium (CARBOSOL).

this study are situated on each end of the gradient, i.e. two LSU in the North (the Loam region) and two LSU in the South (the Ardenne) with both types of land use represented (cropland and permanent grassland). Each of these LSU comprises between 23 and 47 geo-referenced soil profiles for which data needed to estimate the SOC stock are available, and these LSUs cover a discontinuous area ranging from 86 to 1407 km² (Table 1).

Different scales of interest can be found in the network implemented: from the sample scale (soil sample), to the microsite scale (3 to 5 samples within a circle of 4 m radius), the field scale (samples from the re-sampling within the same field), the landscape scale (samples from all soil profiles belonging to one LSU), and finally the most aggregated level, the regional scale (samples from all the soil profiles of the network). Uncertainties at each spatial level can therefore be studied using the same methodology and be compared.

Laboratory analyses and SOC stock calculation

Bulk soil samples were air-dried, sieved (2 mm), and analysed for SOC according to the Walkley & Black method (Walkley & Black, 1934) commonly used for soil routine analyses in the study area. As previously mentioned, this method requires a correction factor in order to correct for incomplete oxidation and estimate total OC concentration. The standard factor of 1.3 has been chosen as no specific study was available for our situation. However, this factor might be underestimated especially for grassland or soils with the highest reactive clay content. The BD was determined gravimetrically (includ-

ing drying of the undisturbed soil sample at 105°C) and corrected for rock fragments (Note 3) (using the rock fragment mass measured and the bulk density of the stones from CRC, 1996).

The SOC stock was calculated according to the following equation (equation 1):

$$\text{stock} = \frac{d \times C \times BD \times [1 - RM]}{100} \quad (1)$$

where *stock* is the SOC stock (t C ha⁻¹), *d* is the sampling depth considered (m), *C* is the soil organic carbon concentration (g C kg⁻¹), *BD* is the bulk density (kg m⁻³), and *RM* is the mass proportion of rock fragment content (dimensionless).

Propagation of errors

The “ δ method” is based on the law of covariances and on the linearization of non-linear functions through their Taylor series expansion (Goodman, 1960; Ku, 1966; Mardia *et al.*, 1979; Rice, 1995; Weisstein, 1999; Lindberg, 2000). The general equation was taken from Wells & Krakivsky (1971) (equation 2):

$$\Sigma_y = \mathbf{J} \Sigma_x \mathbf{J}^T \quad (2)$$

where Σ_y and Σ_x are the variance-covariance matrices of two random vectors of the variables *y* and *x*, respectively **y** and **x**, with **y** a non-linear function of **x** (**y** = **f**(**x**)). **J** is the Jacobian matrix of **f**(**x**) (with **J**^T the transposed **J**) and is defined as:

Table 1 Main characteristics of the topsoil (first horizon) of the landscape units (LSU) used to assess the uncertainties on the soil organic carbon stocks for the period 2005-2006 (SOC - Soil Organic Carbon; d - depth of the first horizon; BD - Bulk Density; RM - Rock fragment content by mass)

	unit	LSU 4	LSU 14	LSU 5	LSU 15
Land use		cropland	cropland	grassland	grassland
Agricultural region		Loam	Ardenne	Loam	Ardenne
Agricultural management		intensive	extensive	intensive	extensive
Area ^a	/km ²	1407	86	255	756
n		47	23	26	32
SOC ^b	/g C kg ⁻¹	10.8	29.0	25.3	34.9
d ^c	/m	0.25	0.29	0.21	0.21
BD ^b	/kg m ⁻³	1393	1027	1278	1095
RM ^b	/%	0	24	0	19
SOC stock ^b	/t C ha ⁻¹	36.6	64.0	71.9	64.6
Clay	/%	14.3	16.8	12.2	16.6
Silt	/%	79.3	60.3	77.3	59.8
Sand	/%	5.4	23.9	8.5	23.6
Soil texture	^d	A	G	A	G
	^e	Silt (loam)	Stony loam	Silt (loam)	Stony loam
Soil drainage	^f	1	1	1	1

^a Potential area if no land use change has occurred between 1955 and 2005

^b Variables normally distributed within each LSU (Kolmogorov-Smirnov test).

^c Variable not normally distributed for unit 14 and 15 (Kolmogorov-Smirnov test).

^d Symbol from the Belgian legend, Hanotiaux (1992).

^e According to the USDA textural triangle, Soil Survey Staff (1951); as the Belgian legend describes the soil texture in more details, parentheses are used to indicate the non-dominant soil texture.

^f Simplified from the Belgian legend; 1 = good to moderate drainage.

$$\mathbf{J} = \begin{pmatrix} \frac{\delta f_1}{\delta x_1} & \cdots & \frac{\delta f_1}{\delta x_n} \\ \vdots & \ddots & \vdots \\ \frac{\delta f_m}{\delta x_1} & \cdots & \frac{\delta f_m}{\delta x_n} \end{pmatrix} = \frac{d\mathbf{y}}{d\mathbf{x}} \quad (3)$$

Applied to the SOC stock equation (equation 1 where *stock* is the one dimensional vector \mathbf{y} function of \mathbf{x}), the Jacobian matrix becomes:

$$\mathbf{J} = \begin{pmatrix} \frac{\delta f_1}{\delta x_1} & \cdots & \frac{\delta f_1}{\delta x_n} \\ \vdots & \ddots & \vdots \\ \frac{\delta f_m}{\delta x_1} & \cdots & \frac{\delta f_m}{\delta x_n} \end{pmatrix} = \begin{pmatrix} \frac{CBD(1-RM)}{100} & \frac{dBD(1-RM)}{100} & \frac{dC(1-RM)}{100} & \frac{-dCBD}{100} \end{pmatrix} \quad (4)$$

The general error propagation equation (equation 2) can be re-written and solved:

$$\begin{aligned} \Sigma_y &= \sigma_{stock}^2 \\ &= \mathbf{J} \Sigma_x \mathbf{J}^T \\ &= (stock)^2 \times [X] \end{aligned} \quad (5)$$

with

$$\begin{aligned} X &= \frac{\sigma_d^2}{d^2} + \frac{\sigma_C^2}{C^2} + \frac{\sigma_{BD}^2}{BD^2} + \frac{\sigma_{RM}^2}{(1-RM)^2} + 2 \frac{\sigma_{dC}}{dC} + 2 \frac{\sigma_{dBD}}{dBD} \\ &+ 2 \frac{\sigma_{CBD}}{CBD} - 2 \frac{\sigma_{d(1-RM)}}{d(1-RM)} - 2 \frac{\sigma_{C(1-RM)}}{C(1-RM)} \\ &- 2 \frac{\sigma_{BD(1-RM)}}{BD(1-RM)} \end{aligned} \quad (6)$$

where σ_d , σ_C , σ_{BD} and σ_{RM} are the standard deviations of respectively d , C , BD and RM , and σ_{dC} , σ_{dBD} , σ_{CBD} , $\sigma_{d(1-RM)}$, $\sigma_{C(1-RM)}$ and $\sigma_{BD(1-RM)}$ are their covariances (Note 4).

Covariances are usually not taken into account due to the common use of simplified forms of equation 2. However, covariances may decrease or increase σ_{stock}^2 and should therefore be estimated (Dileep *et al.*, 2008). Covariances can directly be assessed for each LSU and scale when enough replicate samples are available, which is only the case for the landscape scale (~ 30 for each LSU, see previous subsection on the sampling scheme). The covariances for the finer scales of each LSU (the sample, the microsite and the field scale) have to be, therefore, indirectly estimated. A nested sampling would have been more judicious to separately compute covariances (Lark, 2005), but the choice of the sampling scheme was made prior to this uncertainty analysis. The indirect estimate of the covariances at finer scales was therefore based on the assumption of no scale-dependence of the correlations between the variables of equation 1 within a same LSU (equation 7). This means that the processes responsible for the data covariances were considered to be the same across the scales of one LSU, as the LSU definition explicitly excludes contrasting processes which may largely influence the data covariance (such as a change in land use or in soil type). While the assumption of the scale-dependence of correlation can be tested for continuous approaches (based on the co-dispersion coefficient or on the wavelet transform; Goovaerts & Webster, 1994; Lark *et al.*, 2004), it remains difficult to check this assumption in the case of our sampling scheme. However, other studies implicitly use this assumption of no scale-dependence, e.g. when applying the same pedotransfer function regardless of the scale considered. Therefore, while some caution is required in the results, the covariances at finer scales were calculated for each LSU based on the estimated covariances at the landscape scale and on individual variances estimated for each scale (equation 8):

$$\rho_{xy_i} = \rho_{xy \text{ landscape}} \quad (7)$$

$$\sigma_{xy_i} = \frac{\sigma_{x_i} \sigma_{y_i} \sigma_{xy \text{ landscape}}}{\sigma_{x \text{ landscape}} \sigma_{y \text{ landscape}}} \quad (8)$$

where x and y are the variables considered (d , C , BD or RM), σ_x and σ_y are their standard deviations, ρ_{xy} and σ_{xy} are respectively the correlation and the covariance between the variables x and y , and i is the finer scale considered (sample, microsite or field scale).

Based on the estimated variances and covariances of each variable for the different scales, the total random error on the SOC stock (σ_{stock}^2) can be assessed with both the δ method (equation 5) and the Monte Carlo simulations (MC) for each LSU considered. For the MC approach, 100,000 random numbers (normally distributed with a mean of zero and a variance of 1) of each variable were first generated (while this is in agreement with the variable distribution at the LSU scale, the normality of the variable distribution at finer scales was assumed). The vector obtained for each variable was constrained by multiplying it with a matrix characterised by previously estimated variances and covariances and finally inserted in equation 1 to simulate the corresponding number of SOC stocks. The standard deviation of each SOC stock population was therefore evaluated, and compared to that from the δ method to cross-check the deterministic and the stochastic propagation of errors. The δ method enables quantification of the contribution of each term of equation 5 thanks to the linear form of this equation. For clarity, a distinct notation for the standard deviation or covariance (σ) and their estimates (s) will be used from now on.

Quantification of uncertainties in the SOC stock at various scales

For each elementary unit of the scale considered (i.e. the soil sample, the microsite, the field or the landscape), the standard deviation of each variable and its corresponding coefficient of variation ($CV = 100 \times \sigma/\text{mean}$, %) were assessed as a measure for the extent of the uncertainty. The propagation of these estimated standard deviations (s) in equation 5 allowed calculation of the final variability of the SOC stock (s_{stock}) for the elementary unit considered. In addition, biases (mean error - ME , equation 9) and root mean square errors (RMSE, equation 10) were assessed for each variable and scale when possible by comparing the data from independent sampling campaigns. This results in an evaluation of the quality of the sampling schemes.

$$ME = \frac{1}{n} \sum_{i=1}^n (x_{i1} - x_{i2}) \quad (9)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (x_{i1} - x_{i2})^2} \quad (10)$$

where x_{i1} and x_{i2} are the value obtained from independent sampling for the variable x , and n is the total number of replicates (i) considered. The impact of taking or not into account equivalent masses when comparing SOC stock from two surveys on the same locations (using the equivalent mass of the second survey as the reference in our case) was also evaluated for the field and the landscape scale (Ellert *et al.*, 2002).

The sample scale. Forty-six soil samples were sent twice to the same laboratory for total OC analyses with the Walkley & Black (1934) methodology. Soil samples were chosen in order to cover the SOC range encountered in southern Belgium (from 0 to 85 g C kg⁻¹). Given the SOC concentration of the sample considered, the appropriate σ_C can be propagated in equation 5 to assess the error in the SOC stock at the sample scale. The replicate samples were used to assess the standard deviation of the SOC concentration (s_C). An estimated precision of 10⁻² m in the sampling depth was assumed (s_d). Estimated standard deviations of BD (s_{BD}) and RM (s_{RM}) were determined with equation 2 applied to the formula used to calculate BD and RM (based on estimated errors of 10⁻³ kg on weights and 10⁻⁶ m³ on volumes measured).

The microsite scale. Standard deviations were estimated using subsamples taken in the first soil horizon within the same microsite. For s_C , the five subsamples taken within the microsite to form the composite sample (see Figure 1) were individually available and therefore used to estimate the s_C . For s_{BD} and s_{RM} the three individual cores were used, except that for the s_{RM} calculation, instead of taking the mean of the three cores in the formula, the RM value from the composite sample was used (this composite sample having a larger volume than the core and being made of the 5 subsamples also taken within the same microsite) in order to avoid an underestimation of σ_{RM} . s_d was assumed to be equivalent to the precision at the sample scale (i.e. 10⁻² m).

The field scale. In our sampling scheme, the field scale corresponds to the area having a similar soil type and topography within a field. This area is only represented by two samples at a variable distance. These two samples were originally taken for LSU 4 and 5 in order to estimate the error when trying to re-sample the same location in a subsequent survey by another surveyor and according to the same methodology. However, in order to keep the error propagation approach coherent over the different scales involved in our sampling scheme, and despite the caution needed at that scale (as the standard deviations are estimated with only 2 samples), the error propagation assessment was also carried out. s_C and s_{BD} were determined using C and BD measurements from both re-sampling surveys. s_d was

assessed for cropland based on the plough depth recorded by the surveyor and the one assumed by the farmer (known from questionnaires), and for grassland based on the depth of the first horizon recorded by each surveyor.

The LSU scale. The landscape scale corresponds in our study to the discontinuous area covered by the LSU and is represented by all the soil profiles included in the LSU. The standard deviation of the soil profiles in the LSU was assessed for each variable (s_C , s_{BD} , s_{RM} , s_d) and also for the SOC stock (s_{stock}). In addition, the underlying assumption that any location belonging to a particular LSU will have the same SOC concentration was validated against the independent database ‘‘POLLUSOL’’ (Bock *et al.*, 2003). POLLUSOL focuses on the same area and contains SOC data collected during almost the same period as the one in our study (the potential SOC change between 2003 and 2005 should be negligible for such a short period). POLLUSOL was stratified into the same LSU (thanks to georeferenced data), and the soil profiles included in these LSU (from 1 to 13 soil profiles per LSU) were checked for their unchanged land use since the 1950s (to fulfil the same initial conditions

than our sampling scheme). SOC analyses of the first horizon from both databases were compared for the LSU available (13 out of 15 in total). The overall error of prediction of the SOC concentration with the LSU approach was evaluated using the soil profiles of the 13 LSU all together ($RMSEP$). The error of prediction of each individual LSU was also assessed ($RMSEP_{LSU}$). In addition, $RMSEP_{LSU}$ was compared to the initial estimated standard deviation in SOC concentration of the corresponding LSU ($s_{C\ LSU}$) to check for possible under- or over-estimation. The validated standard deviation of the SOC concentration of each LSU ($s_{C\ LSU\ val}$) was considered to be the maximum between $RMSEP_{LSU}$ and the corresponding $s_{C\ LSU}$.

Quantification of the uncertainties for the 4 LSU. The standard deviation of each variable previously estimated for each scale was averaged for each LSU considered (Table 2) (\bar{s}_C , \bar{s}_{BD} , \bar{s}_d , \bar{s}_{RM} , \bar{s}_{stock}), based on the number of elementary units (i.e. soil sample, microsite, field or landscape) available in each LSU. For \bar{s}_C at the sample scale, the SOC concentration range of the LSU was taken into account (as s_C increases with the SOC concentration). As \bar{s}_C at the microsite scale was only estimated

Table 2 Average estimated standard deviation (\bar{s}) and coefficient of variation (CV) on the soil organic carbon content (C), the bulk density (BD), the rock fragment content by mass (RM), the sampling depth (d) and the total soil organic carbon stock (stock) at various scales (sample, microsite, field and landscape) and for the landscape units (LSU) considered (see Table 1)

Scale	LSU	C		BD		RM		d		stock ^a			
		\bar{s}	CV	\bar{s}	CV	\bar{s}	CV	\bar{s}	CV	δ method		MC	
										\bar{s}	CV	\bar{s}	CV
		/g C kg ⁻¹	/%	/kg m ⁻³	/%	/%	/%	/m	/%	/t C ha ⁻¹	/%	/t C ha ⁻¹	/%
Sample	unit 4	1.3 ^b	12	20	1	/	/	0.01	4	4.3	12	4.2	12
	unit 14	1.1 ^b	4	20	2	1	3	0.01	3	3.7	6	2.5	4
	unit 5	1.1 ^b	4	19	1	/	/	0.01	5	3.7	5	2.9	4
	unit 15	1.4 ^b	4	20	2	1	4	0.01	5	5.2	8	3.1	5
Microsite	unit 4	0.9	8	48	3	/	/	0.01	4	3.4	9	3.2	8
	unit 14	(2.3) ^c	(8) ^c	55	5	5	22	0.01	3	6.2	10	4.9	8
	unit 5	3.7	15	54	4	/	/	0.01	5	8.5	12	7.8	11
	unit 15	(5.1) ^c	(15) ^c	73	7	11	62	0.01	5	10.5	16	11.0	17
Field ^d	unit 4	0.8	8	92	7	/	/	0.02	9	5.6	15	4.8	13
	unit 14	(2.3) ^c	(8) ^c	(68) ^c	(7) ^c	10	40	(0.03) ^c	(9) ^c	10.7	17	11.4	18
	unit 5	3.4	13	81	6	/	/	0.03	14	18.3	26	7.9	11
	unit 15	(4.7) ^c	(13) ^c	(69) ^c	(6) ^c	10	60	(0.03) ^c	(14) ^c	11.4	18	13.0	20
Landscape	unit 4	1.6	15	85	6	/	/	0.02	9	5.7	15	5.6	15
	unit 14	6.5	22	157	15	11	43	0.03	10	15.3	24	11.5	18
	unit 5	8.5	34	111	9	/	/	0.06	27	25.0	35	20.7	29
	unit 15	7.7	22	143	13	10	58	0.05	24	17.0	26	18.6	29

^aTwo methods are used to assess \bar{s}_{stock} : the δ method and the Monte Carlo simulation (MC) (see method section).

^bFunction of the C range of the LSU considered.

^cNo replicate sampling was done for this LSU, therefore the same CV than the LSU under a similar land use was applied.

^dSome caution at this scale: as the replicate sampling of the field was done once and was mostly driven by the re-sampling of a position according to similar soil and topography characteristics, the scale considered is more representative of the subfield scale than of the field scale.

for units 4 and 5 (in total, 30 microsites with individual subsamples were available in the Loam region—28 under cropland from units 4 and 2 under grassland from unit 5), \bar{s}_C of units 14 and 15 were estimated using the coefficient of variation (CV) of the unit in the Loam region having the same land use ($CV_{unit\ 4} = CV_{unit\ 14}$ and $CV_{unit\ 5} = CV_{unit\ 15}$). Similarly, \bar{s}_C and \bar{s}_{BD} of units 14 and 15 at the field scale were estimated from the CV of units 4 and 5, although the presence of rock fragments is likely to inflate the CV. \bar{s}_{RM} of units 14 and 15 at the field scale was assumed to reach a coefficient of variation (CV) of 40% for cropland (unit 14) and 60% for grassland (unit 15), based on the CV for *RM* measured at other scales.

Results

Uncertainties in the individual variables involved in SOC stock calculations

Extent of the variability across scales. The average precision of the prepared samples (i.e. dried and sieved) sent to the laboratory ranged from 1.1 to 1.4 g C kg⁻¹ for the four LSU (Table 2), with an overall precision of 2.0 g C kg⁻¹ for the 46 replicate samples (CV of 6.8%). Despite the slight increase of the value of s_C with the SOC concentration of the sample (results not shown), the highest CVs (up to 23% of the sample SOC concentration) were observed for soils having a low SOC concentration (< 13 g C kg⁻¹). Hardly any systematic error was found in the methodology used by the laboratory for SOC concentration analyses (ME = 0.7 g C kg⁻¹, Table 3). s_C at the microsite scale ranged between 0.9 and 2.3 g C kg⁻¹ for crop-

land (CV of 8%; units 4 and 14) and between 3.7 and 5.1 g C kg⁻¹ for grassland (CV of 15%; units 5 and 15) (Table 2). s_C at the field scale were similar to those at the microsite scale. The CV were the highest for the landscape scale, with CV ranging from 22 to 34% for grassland (units 5 and 15) and from 15 to 22% for cropland (units 4 and 14) (Table 2).

The BD variability was negligible at the sample scale with a CV of 1 to 2%. This CV stayed under the level of 10% at all the other scales, except for stony soils of units 14 and 15 at the landscape scale (average CV of 14%) (Table 2). While the RM variability was small at the sample scale (CV from 3 to 4%), it dramatically increased from the microsite scale upward (CV of 22% for cropland and of 62% for grassland) (Table 2). s_d , assumed to be 1 cm at the sample and the microsite scale, corresponded to quite small CVs (from 3 to 5%), but increased at the field (2 < s_d < 3 cm) and landscape scale (2 < s_d < 6 cm), especially for grassland (CV up to 27% - 6 cm) (Table 2).

Errors from an imprecise re-sampling of locations at the field and landscape scale. The error in distance arising from an imprecise re-sampling by different surveyors having similar information ranged from 1.5 to 68.6 m, with an average of 7.4 m for cropland (median of 4.5 m) and 10.7 m for grassland (median of 6.0 m). The increase in the absolute error in the variables measured with the distance was not highlighted (results not shown).

The methodology of re-sampling presented hardly any bias at the field scale for both the SOC concentration and the BD ($ME_C = 0.4$ g C kg⁻¹ and $ME_{BD} = -8$ kg m⁻³), while it was not

Table 3 Magnitude of the errors arising from the methodology used in the soil organic carbon (SOC) monitoring of non stony soils, for each variable involved in the SOC stock calculation. The mean error (ME) and the root mean square error (RMSE) are given in absolute and relative terms

Variable ^a	Unit	Source of the error	ME	%	RMSE ^b	%	(RMSE cropland; RMSE grassland)
C	/g C kg ⁻¹	Laboratory	0.7	2	4.4 ^c	12	
		Re-sampling (field)	0.4	2	4.4	28	(C: 1.5 - 14; G: 7.2 - 29)
		Re-sampling (landscape unit)	0.4	2	0.4	2	
		Landscape unit homogeneity ^d	-1.0	5	6.1	30	(C: 3.7 - 29; G: 10.4 - 33)
BD	/kg m ⁻³	Re-sampling (field)	-8	1	218	16	(C: 249 - 18; G: 149 - 12)
		Re-sampling (landscape unit)	-10	1	13	1	
d	/cm	Re-sampling (field)	1.7	7	6.5	25	(C: 5.0 - 20; G: 6.6 - 31)
		Re-sampling (landscape unit)	0.8	3	2.5	10	
stock	/t C ha ⁻¹	Re-sampling (field)	1.9	4	22.5	45	(C: 12.7 - 30; G: 33.7 - 54)
		Re-sampling (landscape unit)	0.04	≈ 0	6.7	13	

^aC - SOC content; BD - bulk density; d - sampling depth; stock - SOC stock.

^bDistinction between LSU under cropland (C) and grassland (G) is specified in the next column when relevant.

^cOr 2.5 for the RMSE of samples with a SOC content ranging from 5 to 50 g C kg⁻¹ which is the range of SOC content of the LSU monitored in this study.

^dAssumption that any location belonging to the same landscape unit will have the same characteristics (in SOC content in this case) (values are taken from Table 4).

the case for the sampling depth ($ME_d = 1.7$ cm) (Table 3). ME_d differed according to land use (3.4 cm for cropland and -1.5 cm for grassland). The re-sampling led to an overall RMSE at the field scale of 4.4 g C kg^{-1} for the SOC concentration, of 218 kg m^{-3} for the BD, and of 6.5 cm for the sampling depth (Table 3). Hardly any bias in the methodology of re-sampling was found for the variables at the landscape scale ($ME_C = 0.4 \text{ g C kg}^{-1}$, $ME_{BD} = -10 \text{ kg m}^{-3}$, and $ME_d = 0.8$ cm), while their RMSE amounted to 2% of the SOC concentration (0.4 g C kg^{-1}), 1% of the BD (13 kg m^{-3}), and 10% of the sampling depth (2.5 cm) (Table 3).

Spatial prediction power of the SOC monitoring implemented and SOC concentration heterogeneity within the landscape units. The ME per LSU amounted to -1.0 g C kg^{-1} (5%), reflecting a small bias between our database and POLLUSOL (Figure 2a, Table 4). The spatial prediction power of the SOC monitoring for individual locations (i.e. using the average

SOC concentration of the LSU monitored to predict the SOC concentration of any soil profile belonging to the same LSU) was less accurate as the ME amounted to -1.9 g C kg^{-1} (10%) (with -1.8 g C kg^{-1} for soil profiles under cropland and -2.4 g C kg^{-1} for those under grassland; Table 4 and figure 2b). The RMSEP of each LSU ($RMSEP_{LSU}$) was on average 5.1 g C kg^{-1} (or 24%), while the RMSEP of individual location was higher (5.9 g C kg^{-1} or 30%), with similar relative values for both land uses (Table 4).

The comparison of the $RMSEP_{LSU}$ of each LSU with their initially estimated standard deviations showed that the SOC concentration heterogeneity within each LSU was slightly underestimated on average (Table 4). The relative validated homogeneity of each LSU amounted to 30% on average and was similar for both land uses (29% for LSU under cropland and 33% for LSU under grassland; Tables 3 and 4).

Uncertainties in the SOC stocks

Magnitude. Both the δ and the Monte Carlo simulation (MC) methods used to quantify the uncertainties in SOC stock (s_{stock}) gave similar results ($r^2 = 0.78$) (Table 2, Figure 3), with a tendency of the δ method to overestimate s_{stock} of MC by about 17% (Figure 3a). s_{stock} ranged from 2.5 to 5.2 t C ha^{-1} at the sample scale (CV from 4 to 12%), from 3.2 to 11.0 t C ha^{-1} at the microsite scale (CV from 8 to 17%), from 4.8 to 18.3 t C ha^{-1} at the field scale (CV from 11 to 26%), and from 5.6 to 25.0 t C ha^{-1} at the landscape scale (CV from 15 to 35%) (Table 2). At the landscape scale, the δ method overestimated the observed s_{stock} by 6%, while the MC method underestimated s_{stock} by 4% (Figure 3b).

The re-sampling of locations by another surveyor led to a small bias in the SOC stock at the field scale (ME of 1.9 t C ha^{-1} , Table 3). However, the ME differed between each land use (6.7 t C ha^{-1} - 15% for cropland, and -6.7 t C ha^{-1} - 11% for grassland, results not shown), due to the corresponding bias on the sampling depth (positive for cropland and negative for grassland). At the landscape scale, no bias was found in the SOC stock (ME of 0.04 t C ha^{-1} , Table 3). Given the variability of the SOC stock within each LSU, the difference in SOC stock between both surveyors at the landscape scale was significant for unit 4 (cropland), while no significant difference was found for unit 5 (grassland) (results not shown). The RMSE of the re-sampling at the field scale was 22.5 t C ha^{-1} (45%) in total (with 12.7 t C ha^{-1} - 30% for cropland, and 33.7 t C ha^{-1} - 54% for grassland), while it amounted to 6.7 t C ha^{-1} (13%) at the landscape scale (Table 3). When using equivalent masses to compare both surveys, the RMSE at the field scale was reduced by 50% (11.4 instead of 22.5 t C ha^{-1}) especially for fields of unit 4 (61% of reduction), while a reduction of 21% was reached at the landscape scale (1.4 instead of 6.7 t C ha^{-1}) (results not shown).

Sources. The sources of uncertainty in the SOC stock propagated from different variables can be plotted for each scale and

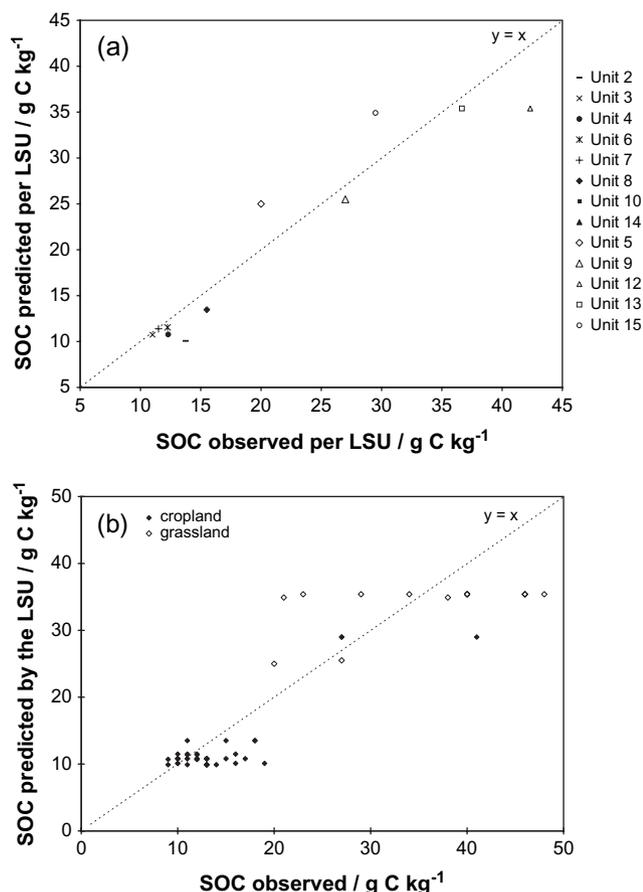


Figure 2 Comparison between the soil organic carbon (SOC) content predicted by the landscape units (LSU) defined in Goidts & van Wesemael (2007) and observed in an independent dataset “POLLUSOL” (Bock *et al.*, 2003) at (a) the landscape scale (mean SOC content of each LSU in both databases) and at (b) the soil profile level (SOC content predicted by the LSU for each available soil profile in POLLUSOL).

Table 4 Soil organic carbon (SOC) content in the first soil horizon of the landscape units (LSU) monitored (SOC₂₀₀₅) with their number of soil profiles (n) and estimated standard deviation (S C LSU). The number of soil profiles available for validation in the POLLUSOL database is presented (i_{val}) together with the corresponding mean SOC content (SOC_{POLLUSOL}). The mean error between both surveys is shown (ME), as well as the root mean square error of prediction (RMSEP) when using SOC₂₀₀₅ as a SOC reference for the soil profile in the corresponding LSU in POLLUSOL. The validated standard deviation of the LSU (S C LSU_{val}) and its coefficient of variation (CV) are also given

Land use	LSU	n	SOC ₂₀₀₅		i _{val}	SOC _{POLLUSOL}		ME		RMSEP		S C LSU _{val} ^a		CV
			/g C kg ⁻¹			/g C kg ⁻¹		/g C kg ⁻¹ /%		/g C kg ⁻¹ /%		/g C kg ⁻¹ /%		
Cropland	unit 1	29	10.1	2.0	na	/	/	/	/	/	/	2.0	20	
	unit 2	24	10.1	1.8	4	13.8	-3.7	36	5.3	52	5.3	52		
	unit 3	38	10.7	2.8	3	11.0	-0.3	3	1.4	13	2.8	26		
	unit 4	47	10.8	1.6	13	12.3	-1.5	14	2.5	23	2.5	23		
	unit 10	21	9.9	3.6	7	12.3	-2.4	24	2.9	29	3.6	36		
	unit 6	29	11.5	1.2	4	12.3	-0.8	7	2.4	21	2.4	21		
	unit 7	43	11.4	2.5	2	11.5	-0.1	1	0.5	4	2.5	22		
	unit 8	44	13.5	2.9	4	16.0	-2.0	29	3.5	26	3.5	26		
	unit 14	23	29.0	6.6	3	31.7	-2.7	9	7.1	24	7.1	24		
Grassland	unit 5	28	25.0	8.5	1	20.0	5.0	20	(Δ = 5.0) ^b	(41)	8.5	34		
	unit 9	9	25.5	7.6	1	27.0	-1.5	6	(Δ = 1.5) ^b	(23)	7.6	30		
	unit 11	12	24.2	8.2	na	/	/	/	/	/	8.2	34		
	unit 12	22	35.4	10.6	6	42.3	-6.9	20	8.4	41	10.6	30		
	unit 13	26	35.4	13.6	3	36.7	-1.3	4	15.3	16	15.3	43		
	unit 15	32	34.9	7.7	2	29.5	5.4	16	10.1	32	10.1	29		
Mean cropland ^c		33	13.0	2.8	4	15.0	-1.7	11	3.2	21	3.7	29		
(Total cropland ^d)		(298)			(40)		(-1.8)	(13)	(3.5)	(25)				
Mean grassland ^c		22	30.6	9.3	2	31.1	0.1	≈ 0	8.1	26	10.4	33		
(Total grassland ^d)		(129)			(13)		(-2.4)	(7)	(10.2)	(28)				
Mean per LSU		28			4		-1.0	5	5.1	24	6.1	30		
Total		427			53		-1.9	10	5.9	30				

^aThe final validated standard deviation of each LSU corresponds to the maximum of both S C LSU and RMSEP.

^bAs only one soil profile was available for validation, the absolute difference between the SOC predicted and the SOC observed (Δ) is presented instead of the RMSEP.

^cMean per LSU under the same land use.

^dInvolving all the soil profiles under the same land use.

land use considered, and according to the presence of rock fragments in the LSU (Figure 4). For non-stony LSU (Figure 4a), the main source of uncertainty in the SOC stock was the SOC concentration (representing on average 47% of the total SOC stock variability). However, at the field scale, the uncertainty that had the highest influence was the variability in the BD for cropland (34%) and the variability in the first horizon thickness for grassland (51%) (Figure 4a). For stony LSU, the main sources of uncertainty in the SOC stock were more diverse (Figure 4b). The variability in the SOC concentration and the rock fragment content represented on average about the same percentage of the total SOC stock variability across all scales (18 and 20% respectively). The variability in the rock fragment content had the highest influence on the SOC stock variability at the field scale for cropland (35%) and for grassland (23%), and also at the sample scale for grassland (38%) (Figure 4b). The variability in the SOC concentration was the main source of SOC stock variability for stony cropland at the

sample (26%), microsite (16%) and landscape (23%) scales, and for stony grassland only at the microsite scale (25%). The variability in the first horizon thickness represented the main source of uncertainty in the SOC stock for stony grassland at the landscape scale (24%) (Figure 4b).

Covariances increasing the SOC stock variability were only observed if rock fragments were present and were due to the interactions between the first horizon thickness and the BD, and between the SOC and the rock fragment content (Figure 4b). For non-stony soils, covariances decreasing the SOC stock variability were mainly due to the interactions between the SOC concentration and the BD, and between the SOC concentration and the first horizon thickness. For stony soils, interactions between the SOC concentration and the BD, between the rock fragment content and the first horizon thickness and between the BD and the rock fragment content led to negative covariances decreasing the SOC stock variability (results not shown). Negative covariances were larger than positive ones.

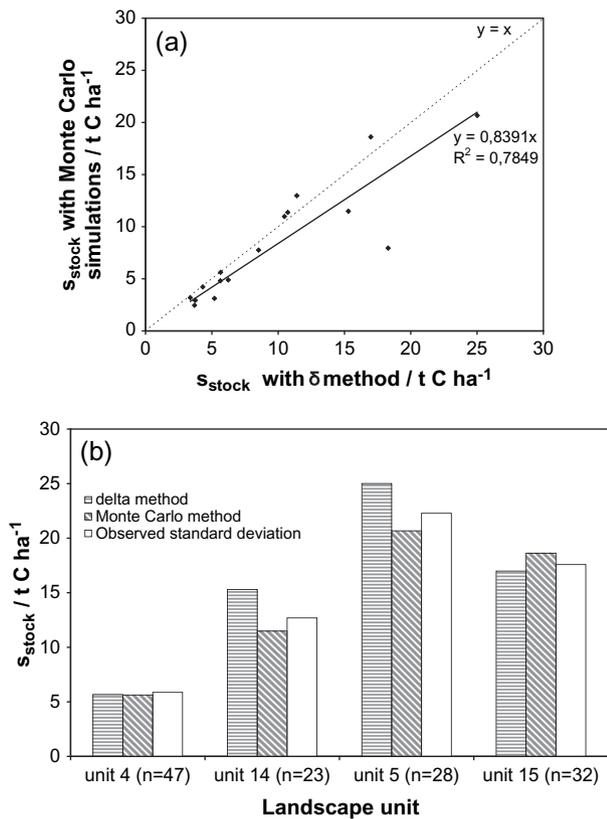


Figure 3 Comparison of the estimated standard deviation on soil organic carbon (SOC) stocks (s_{stock}) evaluated with the δ method and the Monte Carlo simulations method, (a) across all scales and (b) with a focus at the landscape scale (the observed standard deviation of each landscape units – LSU – is also presented, see Table 1 for details on the LSU).

The impact of the scale and the land use on the SOC stock variability was also highlighted. The CV of the SOC stocks increased from the sample scale (5 to 12%) to the landscape scale (15 to 35%) (Table 2). This was especially true for LSU under grassland (units 5 and 15) and under stony cropland (unit 14), while there was a small difference in CV across the scales for non-stony cropland (unit 4) probably due to the homogenisation of the soil surface through agricultural practices (Table 2). The land use also affected the CV of SOC stock which was higher by 37% for LSU under grassland compared to LSU under cropland (results not shown).

Discussion

Method used to assess the uncertainties in the SOC stock

The methodology used to assess the uncertainties in the SOC stock provided an estimate of the different sources of errors involved in the SOC stock variability at different scales. Both precision (s) and accuracy (ME) were estimated for several

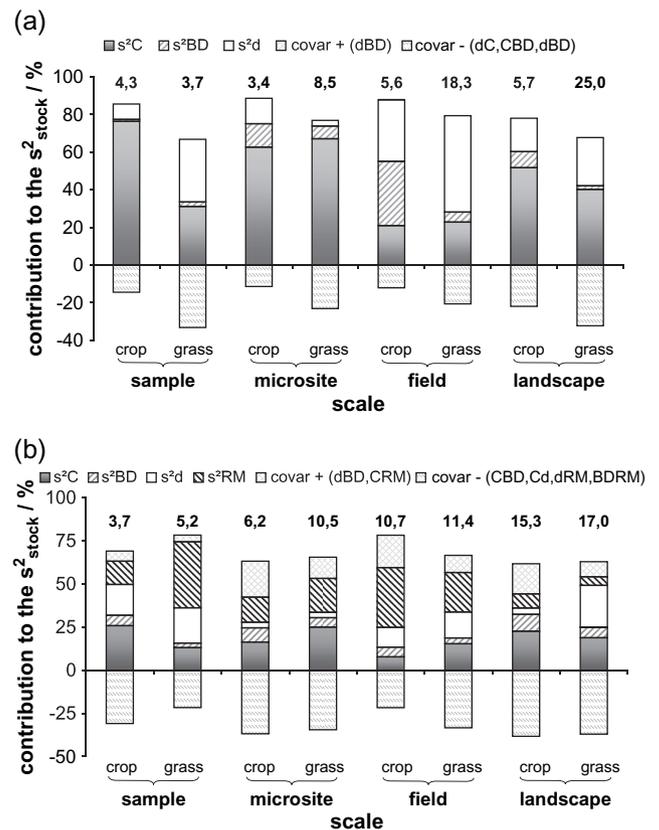


Figure 4 Sources of variability in the soil organic carbon (SOC) stock of 4 landscape units (LSU) at different scales (sample, microsite, field and landscape). A distinction between non stony LSU (units 4 and 5) (a) and stony LSU (units 14 and 15) (b) is done. s^2_C , s^2_{BD} , s^2_d and s^2_{RM} represent individual relative contribution (%) to the total SOC stock variance (s_{stock}^2) of, respectively, the SOC content (C), the bulk density (BD), the sampling depth (d) and the rock mass fragment (RM), while $covar$ are the contribution of covariances respectively increasing (+) or decreasing (-) s_{stock}^2 (the variables involved in $covar$ are specified between brackets). The value of the SOC stock standard deviation ($s_{stocks} / t C ha^{-1}$) is also given above each bar (values are taken from Table 2).

scales and types of LSU. Furthermore, the interactions between input variables (covariances) were taken into account in the error propagation, allowing both the δ method and the MC simulations to give an integrated picture in contrast to “local” approaches, i.e. excluding interactions (Muleta & Nicklow, 2005; Post *et al.*, 2008). However, at the field scale, only 2 replicates per field in non-stony LSU were available for the assessment of the precision on each input variable. Some caution is therefore needed when interpreting the results obtained at that scale. Covariances were only observed at the landscape scale while they were indirectly estimated for the finer scales based on the assumption of no scale-dependence of these correlations within one LSU. However, this assumption should be tested with a more adequate nested sampling scheme (Lark, 2005).

The confidence in the error propagation results was provided by the cross-check of both deterministic and stochastic methods, and by the agreement of the SOC stock CV value across scales with those reported by other studies (Wilding *et al.*, 2000 and Conant *et al.*, 2003 at the microsite scale, Robertson *et al.*, 1993 and Morton *et al.*, 2000 at the field scale, Kern, 1994, Milne & Brown, 1997 and Sleutel *et al.*, 2003 at the landscape scale). However, there was a tendency of the δ method to overestimate s_{stock} by 17% compared to the MC simulations (Table 2, Figure 3). This overestimation was proportional to the decrease in the sample size available to assess s_{stock} with the δ method (results not shown) and to the increase in the standard deviation itself (Figure 3a). This trend has been reported by Jones (1989) with an overestimation of first order Taylor series ranging between 1.8 and 16.9% compared to MC simulations. Despite this overestimation, the δ method is useful to identify the contribution of each term of various types of equations to the final variability observed on the result, provided that uncertainties in individual terms and interaction can be estimated.

Main sources of uncertainty in the SOC stocks

As expected, the spatial variability had an important impact on the SOC stock as shown by the increase of the SOC stock CV across scales (from 5 to 35%, Table 2). This increase in the SOC stock CV mainly corresponded to the increase in the SOC concentration CV (Table 2). Besides, both CVs had similar magnitudes (except for the field scale). This might permit using the SOC concentration CV as a surrogate of the SOC stock CV in cases where only SOC concentration data are available.

The main variables contributing to the SOC stock variability differed according to the scale considered, the land use and the stoniness. *For non-stony soils*, the SOC concentration variability was the main origin of the uncertainties in SOC stocks, except at the field scale (Figure 4a). This variability in the SOC concentration was due to different factors according to the land use. As the SOC concentration variability in cropland (unit 4) does not strongly increase from the sample scale onward (sample: 1.3 g C kg⁻¹, microsite: 0.9 g C kg⁻¹, field: 0.8 g C kg⁻¹, landscape: 1.6 g C kg⁻¹; Table 2 and Figure 4a), the laboratory precision appears to be the main source of the SOC concentration variability. A different situation prevails for grassland (unit 5) as the SOC concentration variability increases strongly from the sample scale onward (sample: 1.1 g C kg⁻¹, microsite: 3.7 g C kg⁻¹, field: 3.4 g C kg⁻¹, landscape: 8.5 g C kg⁻¹; Table 2 and Figure 4a), which suggests that the spatial variability has a higher impact than the laboratory precision. At the field scale, the most important source of SOC stock variability was the variability in the thickness of the first horizon for grassland and the variability in the BD for cropland (together with the variability in the plough layer depth) (Figure 4a). This highlights the fact that a rigorous methodology for soil sampling (based on fixed and/or pedological hori-

zons depths) as well as several samples are needed to overcome this variability from both the surveyor and the environment, along with the use of equivalent masses for SOC stock comparison. As the CV of the BD did not vary very much across scales (1 to 9%, Table 2), fewer samples for the BD than for the SOC concentration will be needed to achieve a given level of confidence, which is also reported by Don *et al.* (2007).

For stony soils, rock fragments were the main source of SOC stock variability at the field scale for cropland and at the field and sample scale for grassland, while the variability in the SOC concentration predominated at the other scales (except for grassland at the landscape scale where it was the thickness of the first horizon). However, the influence of the rock fragment content variability might be overestimated at the field scale for cropland as a CV close to the one observed at the landscape scale was initially assumed. This would suggest that the SOC concentration variability is the main contributor to the SOC stock variability for stony cropland, despite the presence of rock fragment content. The increase of this SOC concentration variability across scales suggests that the spatial variability in the SOC concentration is the main source of uncertainty to overcome for stony cropland (Table 2). For stony grassland, the influence of the SOC concentration variability is only highlighted at the microsite scale, while the variability in the rock fragment content and the first horizon thickness are predominant. Increasing the sampling density for these variables is therefore greatly needed.

Accuracy and precision of the SOC stock monitoring implemented

The re-sampling of locations by different surveyors was done within a radius of less than 11 m on average due to available information on the geographical coordinates, general topography and detailed soil profile. This imprecision was smaller than the one found in a similar study (about 15 m in England and Wales, DEFRA, 2003) and should allow each location re-sampled in the network to meet the requirements of a SOC monitoring site such as defined by Morvan *et al.* (2008) (i.e. to be geo-referenced with a precision inferior to 10 metres and to have undergone at least one survey with future planned surveys on the same location).

No bias was observed between different surveys, except in the sampling depth and particularly for cropland (ME of 3.4 cm – 12%). As croplands are ploughed, the thickness of the first horizon changes through the year and is difficult to identify, even though the average plough depth between both surveys was similar (validated by questionnaires to the farmers) and the sampling was only allowed on fields that had not recently been ploughed. This bias in sampling depth might be due to the different seasons in which the two surveys took place (February to June for the first survey and August to October for the second), and consequently led to a bias in the SOC stock of about 15%. Ideally, sampling should therefore be carried out during the same season.

These imprecisions from the re-sampling were reflected at the field scale by a RMSE in each variable ranging from 12 to 31% for one location (especially in the sampling depth for both types of land use, followed by the BD for cropland and the SOC concentration for grassland, Table 3). The RMSE in the SOC stock had a higher range (from 30 to 54%), except if equivalent masses were considered for comparison between surveys (range from 14 to 31%). Although the location re-sampled was within 11 m of the original soil profile, the magnitude of the uncertainties were quite high, showing that a high precision must be achieved to detect small changes through time at one location. However, at the landscape scale, the RMSE in each variable from an imprecise re-sampling ranged from 1 to 10% (with the highest RMSE in the sampling depth), while an average RMSE of 13% was achieved in the SOC stock (or of 3% using equivalent masses for comparison). These uncertainties were more acceptable, thanks to the number of locations taken into account at an aggregated level (the LSU).

The error in the SOC concentration from the laboratory was of the same order as the one from an imprecise re-sampling and should therefore not be neglected, especially for soils with low SOC concentration (Table 3). The negative bias in SOC concentration between our database and POLLUSOL might be due to the slightly different method to measure the total OC for the latter and to the possible underestimation of the correction factor used by the laboratory (1.3) to rectify the incomplete OC oxidation of the Walkley & Black method (Letten *et al.*, 2007).

The average RMSE of the SOC monitoring implemented when predicting the SOC concentration through space using the LSU approach was high (6.1 g C kg⁻¹ - 30%, with a range from 20 to 52%, Table 4) but comparable to errors of prediction using dynamic SOC stock modelling at the landscape unit scale (e.g. a RMSE of 31% was found for soil types of Southern Illinois with the CENTURY model, Yadav & Malanson, 2008, and a RMSE of 61% for soil types of Northern Belgium with the DNDC model, Sleutel *et al.*, 2006). However, fewer data are needed per stratum in our approach (about 28 locations per LSU compared to an average of 348 locations or cells per soil type in Sleutel *et al.*, 2006). Increasing the level of stratification might improve the prediction of the LSU monitored but would also increase the amount of data needed.

Therefore, the impact of these uncertainties on our previous regional assessment of the SOC stock change between 1955 and 2005 can be determined. As both sampling campaigns took place throughout all the year, there should be no bias in the sampling depth. Besides, equivalent masses were used for the SOC stock comparison, and the same methodology for laboratory SOC analyses was used. However, an imprecise re-sampling of the locations may have occurred. Therefore, assuming that this imprecision is similar to the one found in this study between two different surveyors, a similar RMSE in the SOC stock at the landscape scale (1.4 t C ha⁻¹) can be assumed and compared to the SOC stock change observed in Goidts & van Wesemael (2007) (i.e. an average change of -5.8 t C ha⁻¹ for LSU under cropland and 21.9 t C ha⁻¹ for LSU under

grassland). This RMSE represents between 6 and 24% of the average SOC stock change detected (or between 31 and more than 100% if non-equivalent masses had been used for comparison).

The potential of the SOC monitoring implemented to detect SOC stock changes through future re-sampling (i.e. the minimum detectable difference in SOC stock allowed - MDD) can also be estimated based on the number of locations available and the standard deviation of the SOC stock estimated in this study. As about 28 benchmarked soil profiles per LSU are available in our design (paired sampling), and based on the MDD formula from Zar (1999) (Note 5), the MDD represents on average 20% of the initial SOC stock (11 t C ha⁻¹, Table 5). The time needed to detect such a change varies according to the rates of SOC stock changes observed : from 63 years for "business-as-usual" rates of SOC stock changes observed in our study area (Goidts & van Wesemael, 2007), to 11 years for higher rates of SOC stock changes (approximately 1 t C ha⁻¹ year⁻¹ for improvement in agricultural practices, Freibauer *et al.*, 2004) (Table 5). This highlights the difficulty of detecting SOC stock changes within the timescale of policymakers.

Practical considerations for a SOC stock monitoring scheme

Improvements in SOC stock assessments depend on the scale of interest and should mainly focus on the decrease of the SOC concentration variability when a similar pedological context is encountered. This can be achieved by using other techniques for SOC analyses than the Walkley and Black method, such as C-N analysers which can improve the precision by reaching an average CV lower than 3% (Bowman *et al.*, 2002). Storing dry samples is highly recommended to avoid any dependence of the technique chosen. Using composite samples decreases the spatial variability (and cost) of SOC concentration at small scales, which is especially needed for grassland. Increasing the sampling density or the level of stratification (according to the main driving factors of the SOC concentration) might also help to reduce the SOC concentration spatial variability at larger scales, but will induce higher costs of surveys. In order to detect SOC changes over time, a precise re-sampling of the locations is highly recommended (through benchmarked sites), especially if the rates of SOC changes are small, such as the rates observed in our study area between 1955 and 2005. Ideally, an additional sampling scheme allowing the quantification of uncertainties should be implemented together with the monitoring scheme in order to properly use the results obtained.

Additional improvements can be made to reduce the variability in the BD and the sampling depth. Using pedotransfer relationships instead of BD measurements may only be useful if they are validated for the study area (which is rarely done). As collecting BD in stony soils is challenging, using composite samples or taking larger soil volumes can reduce the error. The sampling depth can be fixed arbitrarily or according to soil horizons. The latter allows consideration of homogeneous processes (e.g. rhizosphere dynamics) and might lead to more consistent

Table 5 Minimum detectable differences (MDD) in soil organic carbon (SOC) stock of the landscape units (LSU) monitored in CARBOSOL, and time (*t*) needed to detect these MDD according to different rates of SOC change (*r*)^a

Land use	LSU	n	MDD ^b		<i>t</i> ^c	
			/t C ha ⁻¹	/%	for <i>r</i> = <i>r</i> _b	for <i>r</i> = <i>r</i> ₊
Cropland						
	unit 1	29	5.1	13	51	5
	unit 2	24	15.5	38	155	15
	unit 3	38	6.0	14	60	6
	unit 4	47	4.2	11	42	4
	unit 10	21	12.2	28	122	12
	unit 6	29	5.8	14	58	6
	unit 7	43	4.6	11	46	5
	unit 8	44	6.4	15	64	6
	unit 14	23	11.8	18	118	12
Grassland						
	unit 5	28	13.8	19	34	14
	unit 9	9	21.2	37	53	21
	unit 11	12	13.4	20	33	13
	unit 12	22	13.9	18	35	14
	unit 13	26	19.5	29	49	19
	unit 15	32	12.7	20	32	13
Mean Cropland (Total)		33 (298)	7.9	18	79	8
Mean Grassland (Total)		22 (129)	15.7	24	39	16

^aWith *r*_b the rates of SOC change observed between 1955 and 2005 or “business as usual” (*r*_b = 0.1 t C ha⁻¹ year⁻¹ for cropland and *r*_b = 0.4 t C ha⁻¹ year⁻¹ for grassland, Goidts & van Wesemael, 2007); and with *r*₊ the rates of SOC change following improvement in agricultural management (*r*₊ = 1 t C ha⁻¹ year⁻¹ on average for cropland and grassland, Freibauer *et al.*, 2004).

^bAssuming a re-sampling of the soil profiles of the LSU monitored (paired sampling).

^c*t* = MDD / *r*.

BD data. Equivalent masses should be used for comparison over time to avoid important errors as shown by Ellert *et al.* (2002) and this study (reduction of the error up to 21% at the landscape scale and to 50% at the field scale). This implies taking samples down to a sufficient depth, because equivalent masses might involve the consideration of greater depths.

The design chosen for the regional SOC stock monitoring in southern Belgium “CARBOSOL” was based on a stratified sampling (each stratum corresponding to a landscape unit - LSU). However, only the most representative strata were sampled. As the total area is not covered, spatial modelling is still needed to have a complete picture of the study area. Different approaches can be used for the regionalization of the SOC stocks, either empirical modelling (Zirlewagen *et al.*, 2007; Meersmans *et al.*, 2008) or process-based modelling (Milne *et al.*, 2007; Yadav & Malanson, 2008), but additional uncertainties in the parameters are then involved (Post *et al.*, 2008).

Conclusions

The monitoring of soil organic carbon (SOC) stocks is challenging as it involves several variables subject to various sources of

errors. If these uncertainties are not reduced, they can be larger than the SOC stock changes observed. This study provided an overview of the sources and magnitude of uncertainties across different scales in the SOC stock monitoring implemented in southern Belgium, which can be indicative for other studies focusing on SOC stocks. As the sources of uncertainties on the SOC stocks varied according to the scale and the landscape unit (LSU) considered, designs for SOC stock assessment should be adapted accordingly. Recommendations are also given to reduce the main sources of errors, i.e. from the SOC concentration laboratory analyses (e.g. by using C-N analysers), from the SOC concentration spatial variability (by using composite samples, benchmarked sites, high sampling density or stratified sampling) and from the comparison of non-equivalent masses. These recommendations will hopefully help to improve future SOC stock assessment. With low rates of SOC change, the present inventory configuration requires several decades to register a significant difference, and high rates of change (e.g. 1 t C ha⁻¹ year⁻¹) would be needed to detect on the order of a 10-year time horizon. Therefore, a more optimal design (reducing uncertainties) would increase the detectability of SOC changes (lower rates per year) at shorter time scales.

Notes

1 The accuracy refers to the difference between the true (or reference) value and the estimated value, while the precision refers to the agreement among repeated measurements.

2 From the northwest to the southeast of Wallonia, there is an increase in precipitation (from 800 to 1200 mm) along with elevation (from 180 to 690 m), a decrease of temperature (from 10 to 8°C), a shift from deep sandy loam and silty soils to shallow silt loam and stony soils, and a shift from intensive crop-based agriculture to more extensive cattle breeding (for further details, see Goidts & van Wesemael, 2007).

3 The term “rock fragments” refers to the particles 2 mm or larger in diameter and includes all sizes that have horizontal dimension less than the size of the pedon (Miller & Guthrie, 1984).

4 Note that $\sigma_{dRM} = -\sigma_{d(1-RM)}$, etc.

5 $MDD_{paired} = \sqrt{\frac{s_d^2}{n}} (t_{\alpha(2),v} + t_{\beta(1),v})$ where s_d^2 is the variance estimate of the difference in SOC stock between paired locations (assumed to equal s_{stock}^2 as the difference is not yet known), n is the number of locations in the LSU, t is the t -statistic at a given significance level (α) and power ($1 - \beta$) (using $\alpha = 0.05$ and $\beta = 0.1$), considering a two-sided (2) test with v the degree of freedom.

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