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An exponential change decline function to estimate soil organic carbon stocks and their changes from topsoil measurements

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Summary

Soil organic carbon (SOC) stocks and their changes are important indicators in ecosystem service assessments. Routine soil inventories are often limited to the topsoil, even though a non-negligible fraction of SOC is known to be stored in deeper horizons. To assess SOC stocks and their changes in the upper metre of the soil profile, vertical extrapolation of topsoil SOC measurements is necessary. The commonly used exponential decline function is not valid, however, for soil types in which subsurface horizons with a larger SOC content ('anomalies') occur. Here, we propose an exponential change decline function to account for these profile anomalies. Therefore, we applied the exponential decline function to the difference between the recent (2008–11) and historical (1947–74) SOC contents in the topsoil and compared the results with those derived by the original method. We applied the exponential change decline function to 54 041 agricultural land units (7159 km^2) in Flanders (Belgium) and were able to model specific profile characteristics such as spodic horizons, plaggic topsoil and peat substrates. For these particular land units, the exponential decline function underestimated SOC stocks; therefore, it compromised an in-depth assessment of changes in SOC stocks over time. This study shows that the exponential change decline function is promising for certain soil types and will contribute to the more accurate assessment of ecosystem service indicators. In addition, we emphasize the need for more detailed descriptions of subsoil reference profiles, sampled by pedogenetic horizon rather than by fixed depth interval to optimize calibration of the decline functions.

Highlights

- When recent soil sampling is limited to the topsoil, extrapolation is needed to assess subsoil SOC stocks.
- We modified the exponential decline function to model SOC-rich subsurface horizons with the integration of legacy data.
- An appropriate extrapolation approach is essential for in-depth SOC assessments.
- Detailed subsoil data are needed to optimize the calibration of the decline functions.

Introduction

Soil has the largest pool of organic carbon in terrestrial ecosystems (Batjes, 1996); therefore, soil organic carbon (SOC) stocks and their changes are often considered key indicators in ecosystem service assessments (Layke *et al.*, 2012). The storage and sequestration of carbon in soil contribute to regulation of the global climate (MEA, 2005; Layke *et al.*, 2012) and improve the chemical and physical properties of soil for plant growth and microbial activity, which are closely related to the productive capacity of soil (Tiessen *et al.*, 1994). Preventing carbon losses and where possible increasing stocks are especially important to secure the soil quality of agricultural ecosystems on which we rely for food security (Powlson *et al.*, 2011). Earlier regional and countrywide studies in Western Europe, and Belgium in particular, reported a decrease in SOC stocks in agricultural soil during the last two

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decades. This has been explained mainly as the result of a decrease in applications of animal manure, increased depth of ploughing and an increase in temperature through climate change (Sleutel *et al*., 2003; Smith *et al*., 2007; Mestdagh *et al*., 2009; Taghizadeh-Toosi *et al*., 2014).

Most studies focus on the topsoil (i.e. the upper 15–30 cm of the profile) to estimate regional SOC stocks (Minasny *et al*., 2013). However, a considerable (Batjes, 1996; Jobbágy & Jackson, 2000) and more stable (Rumpel & Kögel-Knabner, 2011) fraction of the total stock is estimated to be stored in the subsoil and should not be neglected in ecosystem service assessments. Limiting assessment to the topsoil only is likely to result in an incomplete understanding of changes in SOC stocks (Chapman *et al*., 2013). In most national monitoring programmes the upper 15–30 cm only of soil is sampled; therefore, subsoil data are often lacking (Lettens *et al*., 2005; Minasny *et al*., 2013; Gregory *et al*., 2014). In such cases, estimates of the vertical distribution of SOC are required to assess stocks in the upper metre. In general, the SOC content is found to decrease exponentially with depth (Russell & Moore, 1968). Therefore, Hilinski (2001) proposed an exponential decline function, which was applied by Sleutel *et al*. (2003), Meersmans *et al*. (2009) and Hobley & Wilson (2016). Other proposed mathematical expressions comprise logarithmic (Jobbágy & Jackson, 2000), power (Bennema, 1974) and spline functions (Webster, 1978). The popularity of the exponential function is because it can model changes in the profile with depth for biological and related soil properties and because of its mathematical simplicity (Minasny *et al*., 2013). However, the assumption of exponential decline is not valid when soil horizons with a large SOC content occur, such as in spodic horizons, plaggic topsoil and peat substrates (Webster, 1978; Sleutel *et al*., 2003). Given their considerable spatial extent, these soil types cannot be neglected. Podzols are estimated to cover 14% of Europe (they are the dominant soil of the northern latitudes (European Commission, 2005)) and 12% of Flanders, Belgium (Dondeyne *et al*., 2015). Plaggic Anthrosols occupy approximately 500 000 ha and occur mainly in northwest Germany, the Netherlands and northeast Belgium (Giani *et al*., 2014).

In the second half of the 20th century, a large number of soil profiles were described and their horizons analysed on various key soil properties in the context of intensive soil sampling campaigns to produce soil maps in several countries and regions. Such legacy soil profile descriptions are a valuable resource for extending the information content of soil maps with quantitative data on historical SOC stocks (Ottoy *et al*., 2015). Moreover, these datasets also contain reference data about the dependence of the SOC content with depth and can be used to calibrate vertical extrapolation functions (Sleutel *et al*., 2003; Mestdagh *et al*., 2009). In many of these datasets, profile descriptions are available for the major soil map units (SMUs) only and so are lacking for the many minor SMUs. The SMUs are often generalized spatially to achieve complete cover of the vertical sequence of horizons, their thickness and SOC content (Lettens *et al*., 2004). In earlier research we were able to attach at least one historical profile to 18 731 of 18 809 land units (defined as a combination of SMU and land cover type) or 98.7% of the non-built-up area in Flanders, Belgium, based on a multi-level generalization approach from which we derived regional SOC stocks for the upper 100 cm (Ottoy *et al*., 2015).

In this paper we propose an approach to compute recent (2008–11) regional SOC stocks for the upper metre of soil from topsoil measurements. The approach takes advantage of historical profile data (1947–74). To account for profile anomalies related to spodic, plaggen or peat horizons we did not assume that SOC contents decrease exponentially with depth (i.e. from the recently measured content in the topsoil to the residual content at the base of the profile) (Hilinski, 2001). Instead, we applied the exponential decline function to the difference between the recent and historical contents in the topsoil and assumed an invariant SOC content at the base of the profile. We evaluated the approach by comparing these results with those derived by the original extrapolation function; first for specific land units under agriculture and next for the regional aggregation of all agricultural land units in Flanders. The results are used to assess the changes in SOC stocks between 1960 and 2010.

Materials and methods

Study area and available data

The SOC stocks were calculated for agricultural soil in the region of Flanders (north Belgium), which covers an area of 13 522 km^2. This area is characterized by a maritime temperate climate, with a mean annual temperature of 9.8–10.5 °C and a mean annual precipitation of 733–832 mm (Peel *et al*., 2007). The soil texture shows a marked change from north to south with a decrease in sand and an increase in silt content.

Recent measurements. Between 2008 and 2011, 96 849 soil samples were taken from agricultural land in Flanders by the Soil Service of Belgium (Maes *et al*., 2012). The measurements were limited to a topsoil of 23 cm for arable land and 6 cm for grassland. The SOC content (%) was determined by a modified version of the Walkley & Black (1934) method. Following Lettens *et al*. (2005), a factor of 1.14 was applied to calculate total SOC contents. To protect the privacy of farmers' field data, the data were made available as 3-year averages for each possible combination of municipality (n = 308) and agricultural region (n = 7) for arable land and grassland separately.

Legacy data. Together with the soil map of Belgium (cartographic scale of 1:20 000; OC GIS-Vlaanderen, 2001), an extensive historical soil profile dataset is available for Belgium (Van Orshoven *et al*., 1993). The derived Aardewerk-Vlaanderen-2010 database comprises the location and descriptive data of 7020 soil profiles and descriptive and analytical data of 42 529 associated horizons, sampled between 1947 and 1974 in Flanders. The SOC content was determined by the classic Walkley & Black (1934) method and a correction factor of 1.32 was applied. With this database, the Aardewerk-STAT method enabled us to compute statistical soil profiles using different levels of generalization (Ottoy *et al*., 2015).

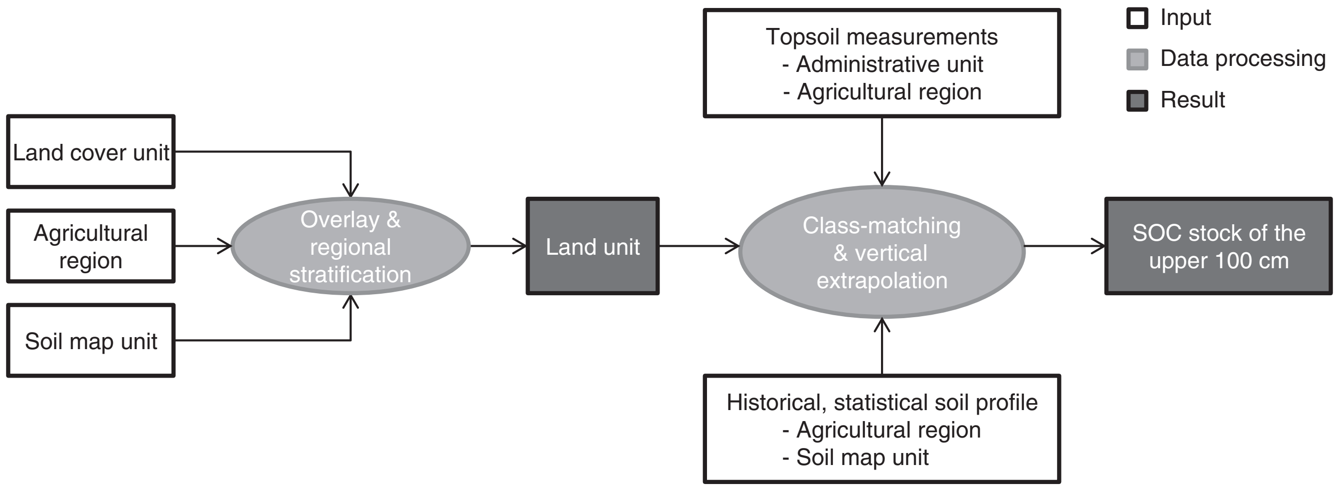

Figure 1 Schematic overview of the sequential procedures followed in this study. A differentiation is made between inputs, data processing methods and results.

Statistical soil profiles summarize the data related to a set of matching profiles and associated horizons. In the present study, for each SMU the most detailed level was selected for which a minimum of one matching profile was found. For each horizon in the statistical soil profile, quantitative characteristics were derived, such as SOC content.

Land cover map. Spatial data for the agricultural fields were retrieved from the ECOPLAN land cover map with a spatial resolution of 5 m × 5 m (Vrebos, 2015). The land cover classes were aggregated into three types: arable land, grassland and other land cover.

Land units

Land units (LUs) were defined by a topological overlay of the soil map, the aggregated land cover map, the agricultural region map and the municipal boundaries. Based on the combination of agricultural region and municipal code, each LU under arable land and grassland was linked with the average topsoil SOC content. For each combination of agricultural region, SMU and land-use type, an historical, statistical soil profile was retrieved by the Aardewerk-STAT method for the most detailed level of generalization and linked with the corresponding LU (Figure 1).

Vertical extrapolation models

Two vertical extrapolation methods were used to model SOC content below the depth of tillage: (i) the original exponential decline function of Hilinski (2001) and (ii) the same function but applied to the change between the recent and historical SOC contents, further termed the exponential change decline function.

Exponential decline function (EDF). To model the presence of the plough layer like Meersmans *et al*. (2009), the SOC content was considered to remain constant for the depth of tillage (*td*), after which it was assumed to decrease exponentially according to the general equation of the exponential depth function proposed by Hilinski (2001):

$$\begin{cases} z \le td \ : \quad C(z) = C_0, & (1) \\ z > td \ : \quad C(z) = C_\mathrm{b} + \left(C_0 - C_b\right) e^{-k_\mathrm{ED} z}, & (2) \end{cases}$$

where $C(z)$, C_b and C_0 are the SOC contents (g OC g^{-1} dry soil) at depth z (cm), the base of the profile and the surface, respectively. In Equation (2), z was considered to be the mean depth below the plough layer. The value of parameter k_ED (cm^{-1}) determines the shape of the exponential decline curve. A larger k_ED value corresponds to a stronger decrease in SOC with depth.

Exponential change decline function (ECDF). By applying the exponential depth extrapolation function to the change between the recent and historical contents (ΔC), Equations (1) and (2) were adapted to Equations (3) and (4), respectively. If we assume that SOC content at the profile base has not changed ($\Delta C_\mathrm{b} = 0$), which accords with Sleutel *et al*. (2003), Equation (4) can be simplified to Equation (5). This latter equation can be used to estimate the recent SOC content at depth z (cm):

$$\begin{cases} z \le td \ : \ \Delta C(z) = C_0 - C_{\mathrm{hist},0}, & (3) \\ z > td \ : \Delta C(z) = \Delta C_\mathrm{b} + \left(\Delta C_0 - \Delta C_\mathrm{b}\right) e^{-k_\mathrm{ECD} z}, & (4) \end{cases}$$

$$z > td \ : \ C(z) = C_{\mathrm{hist},z} + \left(C_0 - C_{\mathrm{hist},\,0}\right) e^{-k_\mathrm{ECD} z}, \quad (5)$$

where $C_{\mathrm{hist},z}$ and $C_{\mathrm{hist},0}$ are the SOC contents (g OC g^{-1} dry soil) of the historical soil profile at depth z (cm) and at the surface, respectively. Similar to Equation (2), z in Equation (5) represents the mean depth below the plough layer.

Model calibration and validation

The values of the model parameters C_b, k_{ED} and k_{ECD} were estimated using a separate set of 17 profiles sampled in 2012 (Van de Vreken *et al*., 2016). In the 17 fields where these profiles were observed, an historical soil profile was also available. Of these 17 profiles, 10 were under arable land (five in the north-eastern Campine region and five in the south-eastern Loam belt) and seven under grassland (four in the Campine region and three in the Loam belt). The SOC content (%) was determined with an elemental analyser for fixed depth intervals: 0–30, 30–60 and 60–90 cm for arable land, and 0–10, 10–20, 20–30, 30–60 and 60–90 cm for grassland. To model the plough layer, the first interval of the reference data (0–30 and 0–10 cm) was set according to the boundaries of the topsoil measurements (0–23 and 0–6 cm). Figure 2 shows that the SOC content of the second interval was derived by proportional weighting (according to depth fraction) of the SOC content of the associated original intervals. Similarly, the corresponding historical profiles were generalized to the same depth intervals. By pooling the data points that belong to each combination of agricultural zone (Campine region or Loam belt) and land use type (arable land or grassland), the parameters C_b, k_{ED} and k_{ECD} were estimated with the nlstools package of R-software (Baty *et al*., 2015). Each model was validated by a leave-one-out cross-validation.

As for relations established earlier between the parameter value and soil texture (Sleutel *et al*., 2003; Mestdagh *et al*., 2009), we used the estimated parameter values of the Campine region for the Dunes and Sandy region because all three agricultural regions are dominated by soil with a sandy texture. The estimated parameter values of the Loam belt were used for the three remaining agricultural regions characterized by finer soil textures (Polders, Sandy loam region and Pasture area Liège).

The SOC stocks and their change

The SOC content of each horizon i (OC_i) for each LU was obtained by applying Equations (1)–(3) and (5) to the recent topsoil measurement as the C_0 value, the estimated C_b, k_{ED} and k_{ECD} parameters and the SOC contents of the horizons in the corresponding historical, statistical profile as C_{hist} values. Next, the SOC stock was calculated to a reference depth of 100 cm with Equation (6). Extrapolation to 100 cm, outside the calibration range of 90 cm, was necessary to compute changes in SOC stocks over time. The difference was limited to 10 cm; therefore, we assume it has a minor effect only on the resulting SOC stocks.

$$\mathrm{SOC} = \sum_{i=1}^{n} \left(\mathrm{OC}_i \times \mathrm{BD}_i \times d_i\right), \tag{6}$$

where SOC ($\mathrm{kg\,OC\,m^{-2}}$) is the SOC stock in the upper metre, n is the total number of horizons, BD_i ($\mathrm{kg\,m^{-3}}$) is the bulk density of horizon i and d_i (m) is the thickness of horizon i. Because there were no measurements of bulk density, it was estimated by the pedotransfer function of Rawls (1983):

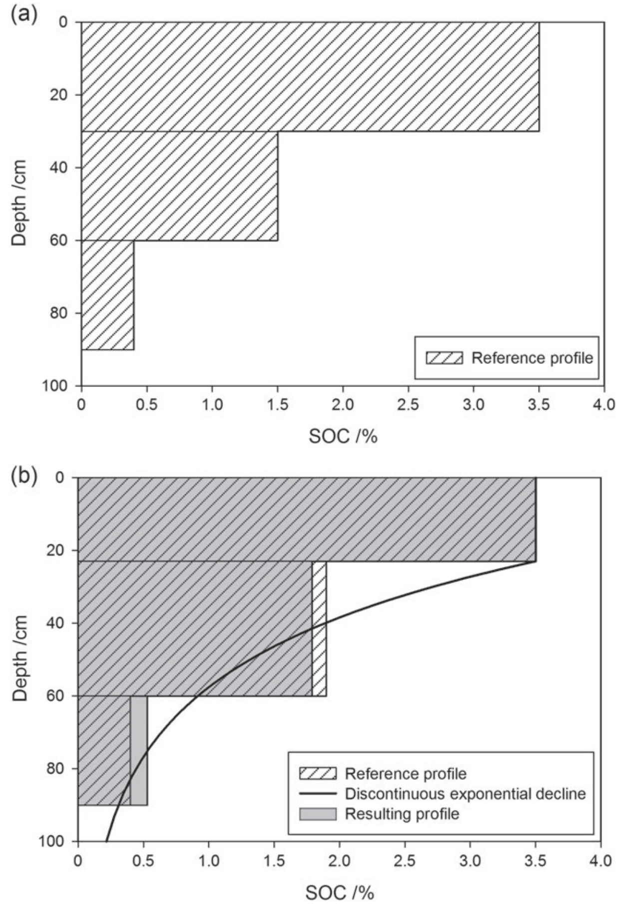

Figure 2 Overview of the original (a) and adapted (b) depth intervals in a typical calibration profile under arable land. The resulting profile was derived by assigning the fitted soil organic carbon (SOC) content of the mean interval depth to the associated interval.

$$\mathrm{BD} = \frac{100}{\frac{\mathrm{SOM}}{\mathrm{BD_{SOM}}} + \frac{100-\mathrm{SOM}}{\mathrm{BD_{MF}}}}, \tag{7}$$

where SOM (%) is the soil organic matter content (SOC content × 2, analogous to Lettens *et al*. (2004)), BD_{SOM} is the bulk density of soil organic matter ($0.224 \times 10^3\ \mathrm{kg\,m^{-3}}$) and BD_{MF} is the bulk density of the mineral fraction, reported by Lettens *et al*. (2004). The bulk density of peat soil was set to $0.31 \times 10^3\ \mathrm{kg\,m^{-3}}$ (Batjes, 1996). The estimated bulk density values probably underestimated the true bulk density because soil compaction of the upper horizons is widespread through the frequent use of heavy machinery. Underestimation of the bulk density leads to an underestimate of the SOC stocks.

The changes in SOC stock were calculated for each LU as the difference between the resulting recent stock (Equation (6)) and the historical stocks obtained in Ottoy *et al*. (2015). This analysis was carried out for LUs that were under agriculture in both periods.

Table 1 Estimated parameter values (± standard error) of the exponential decline function (EDF, Equation (2)) and exponential change decline function (ECDF, Equation (5)) and goodness-of-fit assessment on both the training set (train) and after leave-one-out cross-validation (LOOCV)

	Arable land		Grassland	
Extrapolation function	Campine region	Loam belt	Campine region	Loam belt
EDF				
k_{ED}	0.017 ± 0.017	0.050 ± 0.002	0.040 ± 0.012	0.060 ± 0.005
C_b	0.000 ± 1.233	0.183 ± 0.014	0.347 ± 0.302	0.536 ± 0.084
d.f.	8	8	14	10
R^2_{train}	0.77	0.99	0.73	0.97
$RMSE_{train}$	0.31	0.01	0.38	0.13
$RMSE_{LOOCV}$	0.35	0.02	0.43	0.20
ECDF				
k_{ECD}	0.025 ± 0.016	0.077 ± 0.020	0.051 ± 0.023	0.115 ± 0.025
d.f.	9	9	15	11
R^2_{train}	0.66	0.56	0.85	0.96
$RMSE_{train}$	0.43	0.11	0.50	0.24
$RMSE_{LOOCV}$	0.41	0.09	0.60	0.34

d.f., degrees of freedom; R^2, coefficient of determination; RMSE, root mean squared error.

Because both estimates of SOC stocks rely on estimates of bulk density by a pedotransfer function that uses SOC content as a predictor, the resulting changes in carbon stocks need to be treated with caution (Smith *et al*., 2007).

Results

Areal cover and calibration

A total of 56 339 land units (LUs) were considered, of which 30 585 LUs (170 959 polygons covering 396 855 ha) represented arable land and 25 754 LUs (227 077 polygons covering 352 918 ha) represented grassland. Of these land units, 2298 LUs (33 875 ha) had been classified as built-up areas and were omitted from further analysis. The model parameter values were estimated by non-linear regression (Table 1). The larger was the k_{ED} or k_{ECD} value, the greater was the decrease in depth of topsoil SOC or the change in topsoil SOC, respectively. The C_b value represents the residual SOC content at the base of the profile, which was larger under grass than under arable land. For grassland soil in the Campine region, the exponential change decline function had a larger R^2, but also larger training and cross-validation errors than the exponential decline function, whereas for the other three combinations the exponential decline function resulted in a better fit. The standard errors were larger in the anomaly-rich Campine region than in the Loam belt, especially for the parameters of the exponential decline function.

Vertical distribution of SOC

Figure 3 illustrates the vertical distribution of SOC for four distinct LUs. The distribution for a Nudiargic Luvisol in the Loam belt under arable cultivation (Figure 3a) showed an exponential decline for both functions, but it was greater when fitted by the exponential change decline function than by the exponential decline function. This resulted in larger estimates of SOC stocks for the exponential decline function (Table 2). Figure 3(b–d) shows the distribution for three LUs in the Campine region with an ‘irregular’ distribution of SOC: a Gleyic Podzol under grass, a Plaggic Anthrosol under arable land and a Gleyic Cambisol (Thaptohistic) under grass, respectively. The exponential change decline function only was able to fit LU-specific characteristics such as the spodic horizon (Figure 3b), the thick plaggic horizons (Figure 3c) and the peat layer (Figure 3d). This is reflected in the mean SOC stock (Table 2), which is larger for the estimates based on the exponential change decline function. Depending on the extrapolation method used, the SOC stock in the Gleyic Podzol increased with the exponential change decline function and decreased with the exponential decline function.

Regional SOC stocks and changes

Both extrapolation functions led to differences in total and mean SOC stocks (Table 3). With the exponential decline function, the total SOC stock in the upper metre of agricultural soil in Flanders was estimated to be 102 297 kt OC, 51 070 kt OC under arable land and 51 227 kt OC under grassland. The estimate of total SOC stocks was less (81 517 kt OC) with the exponential change decline function. Mean SOC stocks in the upper metre under grassland (12.5–15.7 kg OC m^{-2}) were greater than those under arable land (10.4–13.1 kg OC m^{-2}).

Under arable land, both functions indicated that the largest mean stocks were in the regions characterized by sandy soil: the Dunes, Sandy region and the Campine region. Furthermore, these regions were characterized by the largest difference in estimated mean stocks. Under grass, the exponential decline function predicted large mean stocks in the same sandy regions and Polders, whereas the exponential change decline function identified the Pasture area Liège as an important SOC pool. The geographical distribution of SOC stocks estimated by the two functions and corresponding differences in stocks (Figure 4) showed that the larger estimates

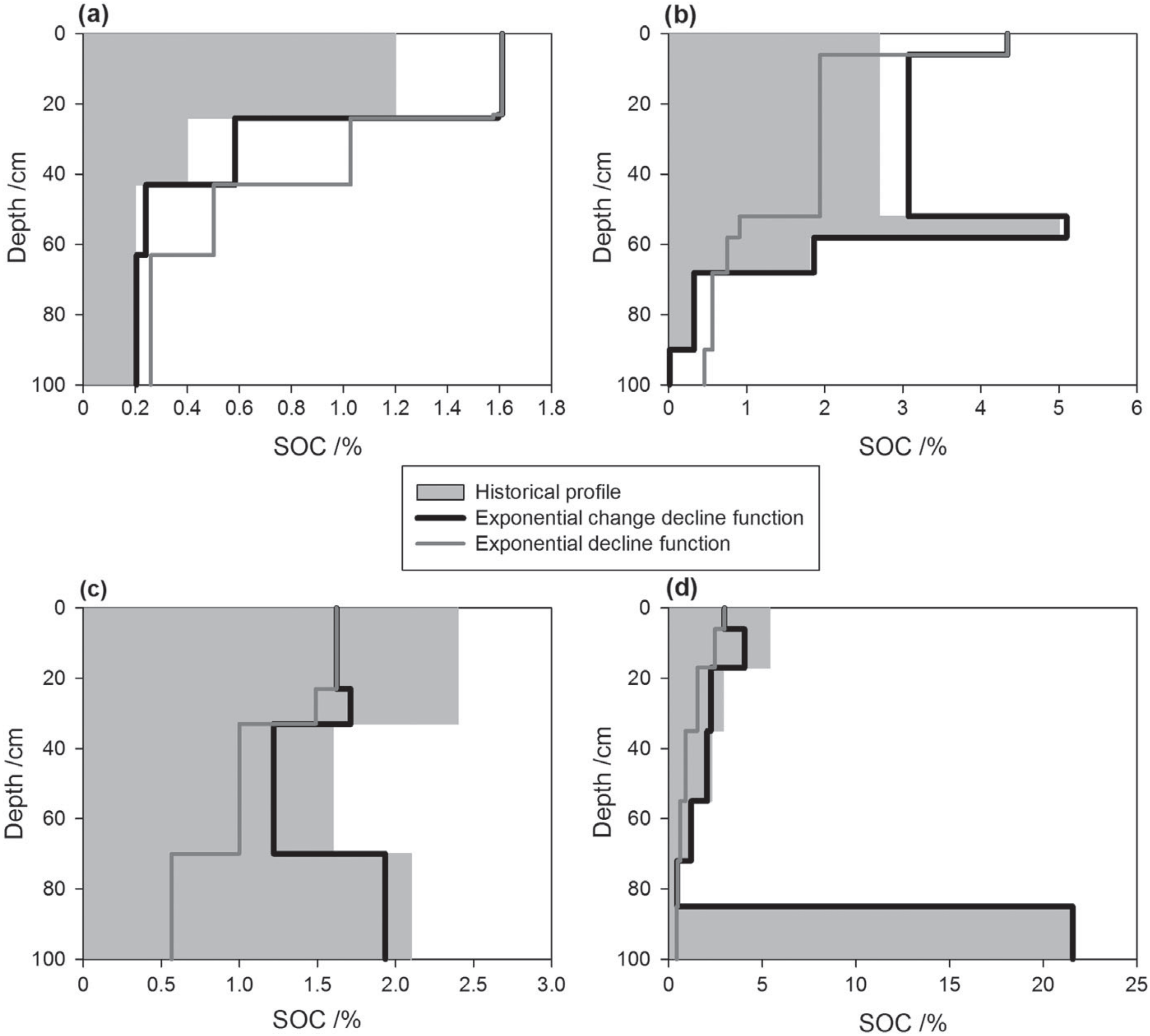

Figure 3 The modelled vertical distribution of soil organic carbon (SOC) content with the exponential change decline function (black lines) and the exponential decline function (grey lines), together with the historical SOC profile (grey bars) of four land units (LUs): (a) Nudiargic Luvisol in the Loam belt under arable land, (b) Gleyic Podzol in the Campine region under grass, (c) Plaggic Anthrosol in the Campine region under arable land and (d) Gleyic Cambisol (Thaptohistic) in the Campine region under grass.

of stocks made by the exponential decline function were more widespread, whereas the larger estimates made by the exponential change decline function were for the scattered 'anomalous' LUs.

The 50-year evolution of SOC stocks from a comparison of the stocks estimated for 2010 with the historical stocks derived from Ottoy *et al*. (2015) can be shown spatially (Figure 5). The western part of Flanders acted mainly as a sink of CO_2 during this 50-year period, whereas the SOC stock in the Campine region decreased. Because the exponential decline function resulted in larger estimates of stocks for 2010, the increases were larger and the decreases were less pronounced. In 1960, the mean SOC stocks under arable land and grass were 8.3 and 12.8 kg OC m^{-2}, respectively, in the upper metre. Overall, SOC stocks under arable land increased and the magnitude of increase depended on the vertical extrapolation function applied: +4.8 kg OC m^{-2} with the exponential decline function and +2.1 kg OC m^{-2} with the exponential change decline function. For grasslands, however, the results showed an increase of 2.9 kg OC m^{-2} for the exponential decline function and a decrease of 0.2 kg OC m^{-2} for the exponential change decline function.

Table 2 Mean soil organic carbon (SOC) stocks (kg OC m^{-2} in the upper 1 m) derived by applying the exponential change decline (ECDF) and exponential decline function (EDF), together with the historical SOC stock of four distinct land units (LUs)

Soil map unit	World Reference Base classification	Agricultural region	Administrative region	Historical SOC stock / kg OC m^{-2}	SOC stock ECDF / kg OC m^{-2}	SOC stock EDF / kg OC m^{-2}
Aba1	Nudiargic Luvisol	Loam belt	23 009	6.21	7.83	9.79
Sdg	Gleyic Podzol	Campine region	11 009	22.70	25.16	18.23
Zam	Plaggic Anthrosol	Campine region	24 001	25.09	20.48	14.40
vSep	Gleyic Cambisol (Thaptohistic)	Campine region	13 006	38.34	34.59	14.85

Table 3 Total (kt OC) and mean (kg OC m^{-2}) stocks in the upper 1 m estimated by the exponential change decline function (ECDF) and exponential decline function (EDF) of arable land and grassland soils aggregated by agricultural zone

	Arable land					Grassland				
		EDF		ECDF			EDF		ECDF	
Agricultural region	Area / ha	Total stock / kt OC	Mean stock / kg OC m^{-2}	Total stock / kt OC	Mean stock / kg OC m^{-2}	Area / ha	Total stock / kt OC	Mean stock / kg OC m^{-2}	Total stock / kt OC	Mean stock / kg OC m^{-2}
Dunes	230	44	18.9	32	14.0	1702	353	20.7	238	14.0
Polders	39 436	4448	11.3	4371	11.1	26 223	4451	17.0	3890	14.8
Sandy region	95 011	15 212	16.0	10 821	11.4	100 072	16 510	16.5	11 918	12.1
Sandy loam region	140 919	13 031	9.2	10 501	7.5	94 645	13 448	14.2	9315	9.8
Campine region	69 169	14 203	20.5	11 122	16.1	88 226	14 126	16.0	13 769	15.6
Loam belt	42 750	4003	9.4	3487	8.2	14 243	2013	14.1	1566	11.0
Pasture area Liège	1056	129	12.3	111	10.5	2216	326	14.7	377	17.0
Total	388 572	51 070	13.1	40 445	10.4	327 327	51 227	15.7	41 072	12.5

Discussion

Limitations of recent SOC inventories

Ecosystem service assessments rely on detailed estimates of SOC stocks and changes in them. Taking the topsoil into account only would result in an incomplete understanding of the changes in SOC stocks (Chapman *et al*., 2013). Because of the limitations of recent soil inventories (i.e. topsoil measurements that are often spatially aggregated), vertical extrapolation is necessary (Minasny *et al*., 2013). The estimated k_{ED} parameters are similar to those found in earlier studies (Sleutel *et al*., 2003; Mestdagh *et al*., 2009); they show that the larger parameter values are for agricultural regions characterized by finer soil textures. The estimated values of C_b reflect the residual SOC stock at the base of the profile, and are similar to those observed by Meersmans *et al*. (2009) and Hobley & Wilson (2016). Hobley & Wilson (2016) stressed the effect of land use, climate and site factors on the resulting parameter values. The larger uncertainties in the parameter values from the exponential decline function in the Campine region probably result from the anomalous profiles in which the SOC content does not decline exponentially with depth (Sleutel *et al*., 2003). Although the concept of the exponential change decline function was clearly promising for these particular LUs, the function's overall predictive performance was not convincing for our full dataset. We assume that SOC measurements by depth interval rather than horizon-based values in our reference dataset partly explain the smaller R^2 and larger root mean squared errors, especially for the arable LUs in the anomaly-rich Campine region. Depth intervals of 30 cm often mask the spodic horizon, which can be as narrow as 6 cm in our legacy database (Figure 3b). To increase the accuracy of estimates of SOC stocks, we support the recommendations by Wiesmeier *et al*. (2012); they proposed that soil should be sampled by horizon down to the parent material.

The added value of legacy data

Legacy data are, in contrast to recent inventories, often characterized by more vertical detail. Therefore, historical soil profile descriptions provide a valuable source of information on the assumed invariant sequence of horizons and their historical SOC contents (Ottoy *et al*., 2015), and so are essential for model calibration (Sleutel *et al*., 2003; Mestdagh *et al*., 2009). Legacy datasets are important sources of information, in particular for LUs with an anomalous distribution of SOC with depth. This 'irregular' distribution cannot be fitted by the exponential decline function and subsoil data are lacking in recent measurements. Figure 3 shows that the addition of LU-specific data points (i.e. $C_{hist,z}$ values) led to more reliable estimates.

The integration of legacy data not only allowed us to obtain information at depths below the topsoil, but also enabled us to differentiate spatially between the LUs. Recent topsoil measurements

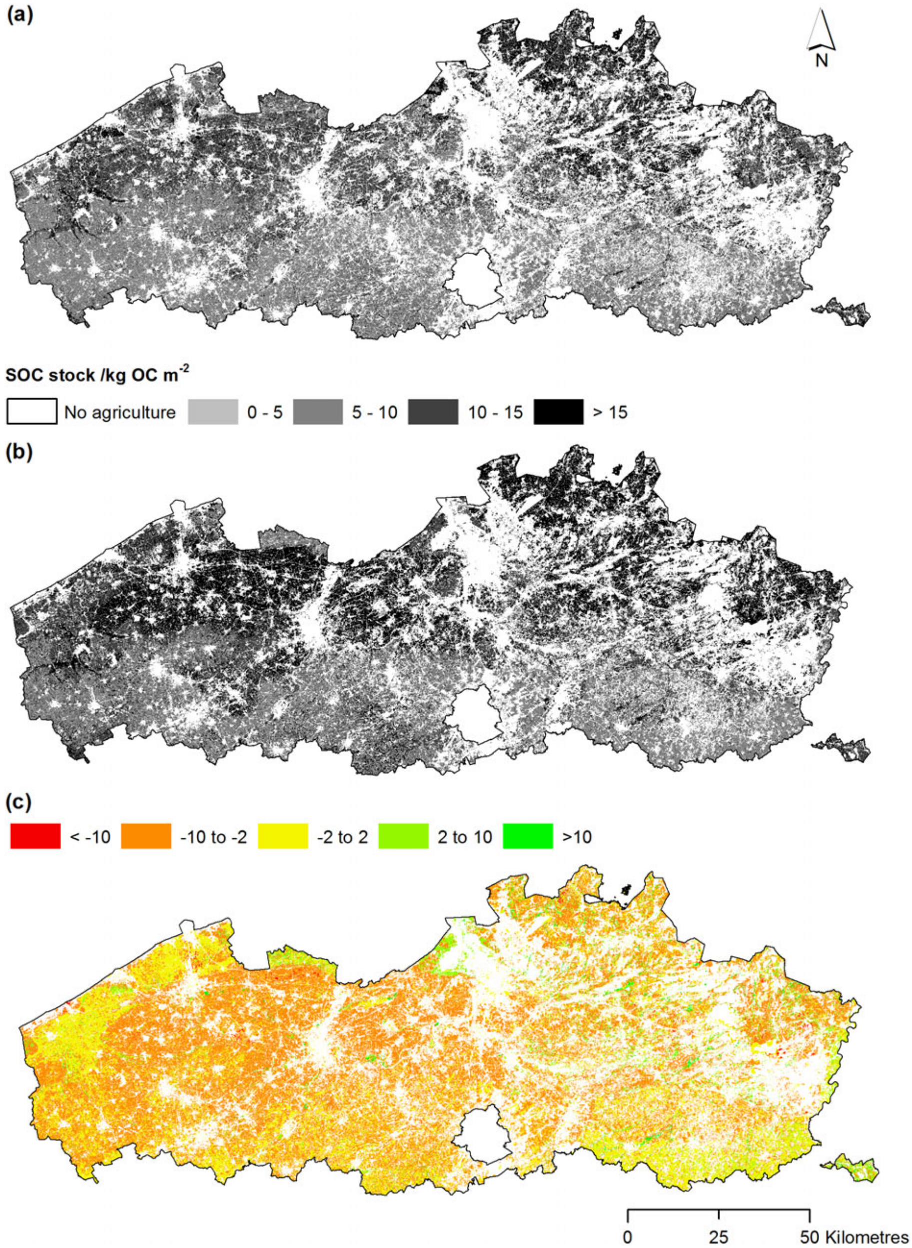

Figure 4 Spatial distribution of the estimated soil organic carbon stock (kg OC m^{-2} in the upper metre) of agricultural soil using (a) the exponential change decline function and (b) the exponential decline function. The difference in stock between (a) and (b) is given in (c).

were aggregated to give average values; therefore, LUs in the same municipality and agricultural zone were not only assigned the same C_b value, but also the same C_0 value. For the exponential change decline function, the integration of LU-specific $C_{hist,z}$ and $C_{hist,0}$ values enabled a detailed spatial differentiation between different LUs.

Regional SOC stocks

The exponential decline function has been applied by Sleutel *et al*. (2003), Mestdagh *et al*. (2009) and Meersmans *et al*. (2009), but our modified function has, to the best of our knowledge, not been applied before. For stocks under arable cultivation our results were 10.4–13.1 kg OC m^{-2} in the upper metre, whereas the mean estimates of Meersmans *et al*. (2009) and Sleutel *et al*. (2003) were smaller, 8.2 and 7.8 kg OC m^{-2}, respectively. Our estimated SOC stock under grass by the exponential change decline function (12.5 kg OC m^{-2}) is within the range of earlier assessments, 11.1 kg OC m^{-2} by Meersmans *et al*. (2009) and 14.3 kg OC m^{-2} by Mestdagh *et al*. (2009), whereas the estimate by the exponential decline function (15.7 kg OC m^{-2}) exceeds these values. The larger estimates of SOC stocks for arable LUs in the sandy regions can be explained by the relatively small value for k_{ED} of 0.017, which is smaller than those of Sleutel *et al*. (2003) and Meersmans *et al*. (2009), which were 0.022 and 0.028, respectively. The large estimates for LUs under grass result from the large C_b values. Given the

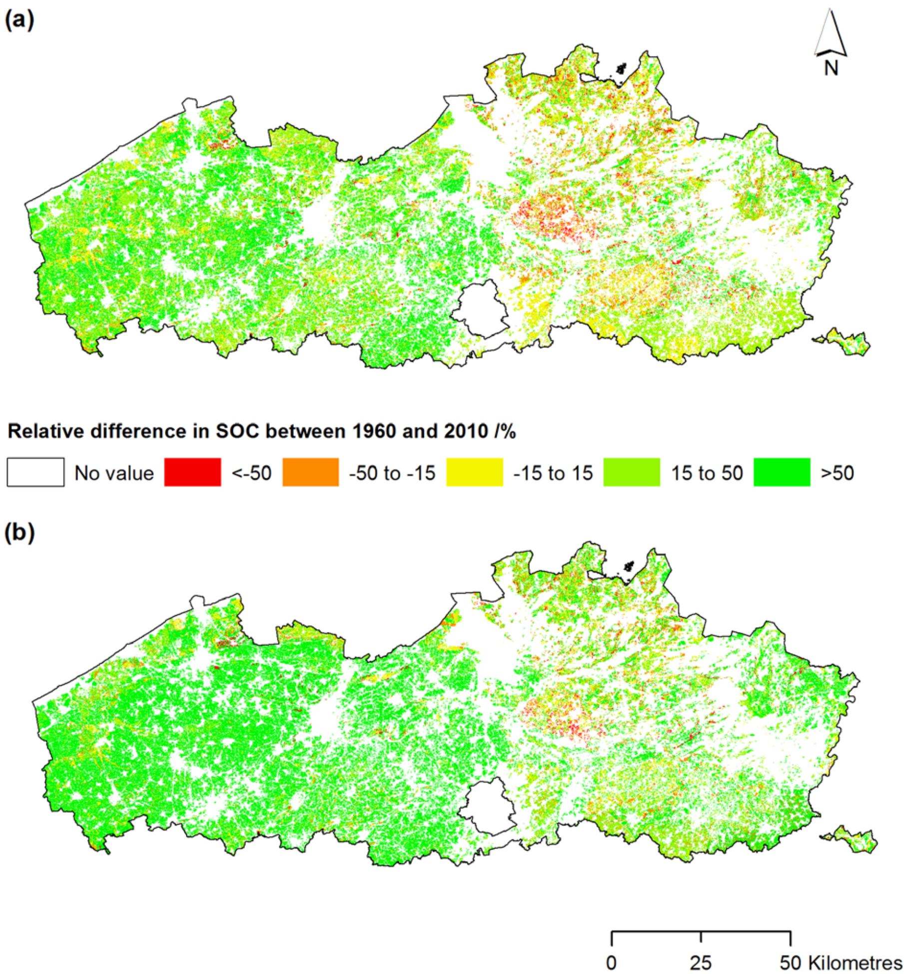

Figure 5 Relative changes in the soil organic carbon (SOC) stock in the upper metre (%) between 1960 and 2010 for agricultural soil from the 2010 estimates by (a) the exponential change decline function and (b) the exponential decline function.

large uncertainty identified for this parameter, caution is required when comparing our estimates with those of others.

The estimated stocks of SOC and distributions of the four LUs studied enabled a more detailed comparison. Even though their estimated stocks are within the ranges found by earlier studies that used horizon-based profile descriptions (Wiesmeier *et al*., 2012; Gregory *et al*., 2014), it is clear that the exponential change decline function only was able to model the specific profile characteristics adequately. The importance of these LUs in SOC assessments had already been identified by Springob *et al*. (2001) in Germany, who explained larger SOC contents in arable sandy soil by the input of organic matter through soil development (e.g. podzolization) and historical land-use practices (plaggen management). In Podzols, an SOC-rich spodic horizon occurs below the topsoil. Plaggic Anthrosols are characterized by an SOC-rich plaggen topsoil, which can have a thickness of more than 100 cm (Giani *et al*., 2014). Podzols and Anthrosols cover 12 and 11% of the Flemish region, respectively; they are situated mainly in the Campine and other sandy agricultural regions in the northwest (Dondeyne *et al*., 2015). At the European level, Podzols are estimated to cover 14% of the area (European Commission, 2005). Anthrosols have not been mapped consistently; therefore, their estimated spatial extent of 0.1% is probably underestimated (European Commission, 2005). Under- or over-estimation of the total SOC stock, either by inconsistent mapping or by incorrect vertical extrapolation, compromises the in-depth assessment of changes in SOC over time.

The exponential decline function on average predicted larger stocks than the exponential change decline function, which is remarkable for the anomaly-rich sandy regions. We assume that underestimation of these anomalies by the exponential decline function is offset by larger, probably overestimated, predictions for the other LUs.

Changes in SOC stocks

The results for particular land units (Table 2 and Figure 3) have shown clearly the importance of a suitable method of extrapolation to assess changes in SOC stocks over time. Because the exponential decline function led to larger estimates of the SOC stock, the increases were larger, whereas the decreases were less pronounced. Earlier (topsoil) assessments detected an overall increase in SOC stocks after 1960, which was explained mainly by changes in the intensity of manure application and historical land-use (van Wesemael *et al*., 2010; Meersmans *et al*., 2011). Around 1960, soil still suffered from a lack of organic amendments during the war and post-war periods. More intensive manure applications explain the increases in SOC stocks between 1960 and 2010. However, after implementation of the law to restrict manure application in 1991 SOC stocks have been decreasing (Sleutel *et al*., 2003; Lettens *et al*., 2005). The larger increase since 1960 in the Sandy region can be explained by a threefold increase in manure input around 1990 (van Wesemael *et al*., 2010). For some LUs, especially poorly drained grassland soil, the SOC stocks decreased with artificial drainage after 1960 (van Wesemael *et al*., 2010; Meersmans *et al*., 2011). Although the Campine region stored one of the largest amounts of SOC in Flanders, this stock has shown the largest decrease during the past 50 years. van Wesemael *et al*. (2010) explained this decrease by the abandonment of plaggen management in the late 19th century. Our results indicate that this historical land management practice is an important determinant of the spatial variation in SOC stock, but its effect is decreasing.

Conclusions

We have shown that the exponential change decline function can overcome shortcomings of recent soil inventories and can improve estimates of SOC stocks and changes in these. By including specific data on the land units, our method resulted in more spatially detailed estimates than the commonly used exponential decline function. It was particularly promising for soil types in which SOC-rich subsurface horizons occur. The function's overall performance, however, was not convincing for our full dataset. This is probably a result of the coarse resolution of the depth intervals in our reference dataset, which can mask these SOC-rich horizons. Therefore, we support the recommendations mentioned earlier for future soil inventories and emphasize the need for more detailed subsoil reference profiles, sampled by pedogenic horizon. When sampling by horizon is not feasible practically, the resolution of the depth intervals should be increased. The availability of such reference datasets should enable a more detailed calibration and validation of the models used above.

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