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A multiple regression approach to assess the spatial distribution of Soil Organic Carbon (SOC) at the regional scale (Flanders, Belgium)

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Abstract

Estimates of the amount of Soil Organic Carbon (SOC) at the regional scale are important to better understand the role of the SOC reservoir in global climate and environmental issues. This study presents a method for estimating the total SOC stock using data from Flanders (Belgium). More than 6900 SOC measurements from the national soil survey (database 'Aardewerk') are combined with a digital land use map and a digital soil map of Flanders. The spatial distribution of the SOC stock is studied in its relation to factors such as soil texture, soil moisture (drainage class) and land use. The resulting map with a resolution of 15 m consists of different classes forming a combination of these environmental factors. The results show that the lowest SOC amount (kg m^{-2}) is stored under cropland whereas the highest amount is found under grassland. Regarding the effect of soil properties, a significant correlation between SOC stock and depth of the ground water table is observed. Sandy loam soils stock the lowest SOC amount (kg m^{-2}), whereas clay soils retain the highest SOC amount. First, the mean SOC amounts of the land use–soil type classes are calculated and assigned to the corresponding cells in order to obtain a total SOC stock with its spatial distribution for Flanders. Then, a multiple regression model is applied to predict the SOC value of a particular land use–soil type class on the map. This model is based on the observed relationships between SOC and land use–soil type characteristics, using the entire dataset. The first approach does not allow to obtain a (reliable) SOC value for all land use–soil type classes due to a lack of samples in some classes. A major advantage of the regression model approach is the attribution of class specific SOC values to each land use–soil type class, regardless of the number of observations in the classes. Consequently, by applying the model approach instead of the mean approach, the area for which a reliable SOC estimate could be obtained increased by 8.1% (from 9420 km^2 to 10179 km^2) and the total predicted SOC stock increased by 10.1% (from 88.7±5.6 Mt C to 97.6±1.1 Mt C).

Keywords: Soil organic carbon; Soil type; Land use; Modeling; Multiple regression analysis; Flanders; Belgium

1. Introduction

It is generally recognized that soils represent a major reservoir in the global C-cycle. Soils contain more organic carbon than the atmosphere and biosphere together (e.g. Grace, 2004). Nevertheless, the role of this reservoir in global climate and environmental issues is not clearly understood. Moreover, an important part of the missing atmospheric carbon sink is most probably situated in the soil reservoir (e.g. Schimel et al., 2001).

With the ratification of the Kyoto Protocol, Flanders has to reduce its CO_2 emission level with 5.2% compared to its 1990 emissions. This goal has to be achieved in the period 2008–2012 (VMM, 2004). Articles 3.3 and 3.4 of the Kyoto Protocol allow the participating countries to take activities such as improved management of agricultural land or reforestation into account in order to realize this reduction (Dendoncker et al., 2004). As a result of agro-environmental and regional policies, the Belgian carbon mitigation potential by improved management is estimated at 0.47% to 0.90% of the greenhouse gas emission in 1990 (Dendoncker et al., 2004). Other European studies show that land use change and management practices

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can even play a more important role in achieving the Kyoto goals (Cannell et al., 1999; Smith et al., 2000; Janssens et al., 2005).

The first studies on soil organic carbon examined the SOC stock at a global scale (Bolin, 1970; Bohn, 1982; Parton et al., 1987; Batjes, 1996). The global SOC pool is estimated at 1200 to 1600 Gt C (Wang et al., 2003). However, the great spatial variability of SOC values within the mapping units is an important source of uncertainty in these assessments (Liebens and Van Molle, 2003).

More accurate SOC estimates at the sub-regional scale (country, state) are essential to better understand the significance of the soil reservoir. In studies at the regional scale, different data sources and a large variety of spatial analysis techniques have been used, often within a GIS environment. A bottom up approach is common in these surveys: the study area is stratified by its land use and/or soil type and for each land use–soil type class, the mean SOC mass is calculated from point measurements of SOC that can be attributed to the corresponding polygons/grid-cells on the map. Nevertheless, the selection of the type of SOC database, the land use and/or soil map, the mapping resolution, bulk density or other information and choice of reference depth can have a great influence on the final SOC stock estimation.

Kern (1994) compared three different approaches in his study to obtain the spatial pattern and total amount of SOC in the USA. For each approach a different combination of SOC, soil, and ecosystem data was used, resulting in total SOC stock estimations ranging from 78.0 Giga (10^9) ton carbon (Gt C) to 84.5 Gt C (Kern, 1994). Several authors showed another example of the influence of different databases and maps on national SOC stock estimations in China ranging from 92 Gt C (Wang et al., 2003) to 120 Gt C (Ni, 2001). Although the vegetation map of China was used in both studies, Wang et al. (2003) combined this map with SOC data from the national soil surveys, whereas Ni (2001) used a soil texture map and mean SOC densities from earlier studies.

Batjes and Dijkshoorn (1999) illustrated that reference depth has an important influence on the total SOC stock. They calculated that in the Amazon region the top 30 cm of the soil contains 52% of the total amount of carbon in the top 1 m.

Using different spatial resolutions, Batjes (2000) found that the total SOC stock of South America ranges from 149.1 Gt C to 159.7 Gt C for the first meter of the soil.

The accuracy of the land use and bulk density information used also plays a very important role in the assessment of SOC contents. Howard et al. (1995) used the dominant soil series and land cover type to calculate the total amount of SOC in the first meter of Great Britain's soil at 21.8 Gt C. The geographical distribution of the SOC was mapped for a 10 km grid. Based on a more realistic land use distribution and more accurate information about bulk density of the peat soils in Scotland, Milne and Brown (1997), recalculated the total national SOC amount for a resolution of 1 km, at 9.8 Gt.

Lettens et al. (2004) estimated Belgian SOC stock at 181 Mega (10^6) ton carbon (Mt C) in the upper 30 cm and 280 Mt C in the upper 1 m, by intersecting the soil association map and the land use map of Belgium at a resolution of 250 m. In this study SOC data were obtained from a national soil survey, resulting in the soil database called 'Aardewerk' (1950–1970) (Lettens et al., 2004). More recent inventories allowed Lettens et al. (2005) to calculate the amount of SOC in Belgium for the year 2000 at 264 Mt C for the upper 1 m (Lettens et al., 2005).

For Flanders SOC estimates for the top 1 m of soil were published by Liebens and Van Molle (2003) and Sleutel et al. (2003a). Liebens and Van Molle (2003) combined carbon measurements of the national soil survey (database Aardewerk, 1950–1970) with information from the digital land use map of Flanders and the soil map of Belgium. They illustrated that total SOC stock estimation ranges from 125.6 to 134.9 Mt C due to the influence of different SOC density estimations and various spatial distribution models (Liebens and Van Molle, 2003). Sleutel et al. (2003a) used a dataset with 190,000 SOC measurements to calculate SOC amount stored in Flemish cropland soil by agro-pedological–administrative region. In this study, the total SOC stock of cropland soils is estimated at 28.2 Mt C (Sleutel et al., 2003a).

Comparison of studies at the national level, revealing remarkable differences in SOC stock estimates, emphasizes the need for more detailed research (Rusco et al., 2001). Errors associated with assigning mean SOC content from a small number of samples to mapping units can be an important source of discrepancies. Jones et al. (2004) used a pedo-transfer rule to predict mapping unit specific SOC content in order to correct for these errors. The pedo-transfer rule is defined as a series of 'if–then' conditions with soil, land use and climate as input variables. Using this method the geographical distribution of organic carbon content in European top soils, at a resolution of 1 km, was obtained (Jones et al., 2004).

In the present study, SOC measurements from the national soil survey (1950–1970, database 'Aardewerk') are used to estimate Flanders SOC stock. The spatial distribution is mapped at a resolution of 15 m by combining a digital soil map and a digital land use map of Flanders. Many land use–soil type combinations resulting from the overlay of the soil map and the land use map were characterized by no or low number of point measurements of SOC. Consequently, using the often-used mean method, i.e. by assigning mean SOC values of the soil type–land use class to the corresponding areas on the map, no or unreliable SOC values are obtained for these classes. Hence, a multiple regression model is constructed predicting a reliable SOC amount for each land use–soil type combination to overcome this problem. In order to evaluate this approach, SOC calculations and spatial distribution resulting from both methods, i.e. the mean and model approach, are compared.

2. Materials and methods

2.1. SOC data

Information from the Belgian National Soil Survey (1947–1974) was compiled in a digital database, called Aardewerk (Van Orshoven and Vandenbroucke, 1993). This database

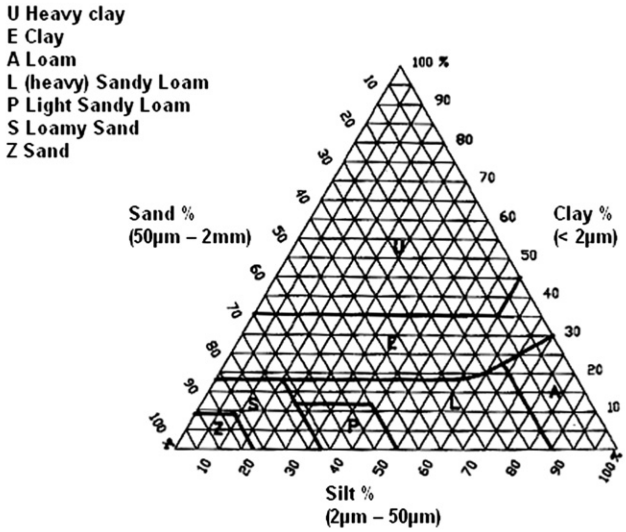

Fig. 1. Belgian soil texture classification triangle (after Ameryckx et al., 1995).

contains pedologic information from soil profiles sampled over the whole of Belgium. For Flanders, Aardewerk contains almost 9000 soil profiles representing 49,000 horizons. The profiles in the dataset are provided with information about land use, texture and drainage class, classified according to the Belgian soil classification system (Fig. 1 and Table 1). Furthermore, for each horizon the percentages of sand, silt and clay are given, as well as the amount of SOC (%), determined by wet oxidation using the bichromate method of Walkey & Black (1934) (Van Orshoven and Vandenbroucke, 1993).

More than 6900 profiles, including information about soil type, land use and SOC content, were selected from Aardewerk. In most cases the first meter of soil contains approximately 5 horizons. The SOC contents (%) of each horizon are transformed into SOC mass densities (kg m^{-3}) by multiplying the SOC content of the horizon by the soil bulk density (kg m^{-3}). Because of incomplete oxidation of carbon when using the Walkley & Black method, a correction factor of 1.33 is applied (Schumacher, 2002):

$$\mathrm{SOC}_D = \rho_s * \frac{\mathrm{SOC}}{100} * 1.33 \tag{1}$$

where: SOC_D = SOC density of the horizon (kg m^{-3})
ρ_s = bulk density of the soil (kg m^{-3})
SOC = SOC content of the horizon (%)

Bulk density data are not given in the dataset Aardewerk. Consequently, the required bulk density values for this study are derived from a pedotransferfunction (PFT). Boucneau et al. (1998) compared different PTF's for predicting the soil bulk density for Flemish soils. The dataset used by Boucneau et al. (1998) contains 40 soil profiles, representing major soil series in northern Belgium. For the present study, of all the useable functions, the general PTF of Manrique and Jones (1991) shows the best correlation between observed and predicted values (Boucneau et al., 1998). Hence, the general PTF of Manrique and Jones (1991), which only uses SOC content as input variable, is selected to calculate the bulk density of the soil (ρ_s; Eq. (2)).

$$\rho_s = 1.66 - 0.318 * \sqrt{\mathrm{SOC}} \tag{2}$$

The SOC mass per unit surface area (kg m^{-2}) of a profile is calculated as the weighted average of the SOC mass density (kg m^{-3}) of every horizon, where the thickness of the horizon (T_i) is the weighing factor, multiplied by the reference depth (D_r). To facilitate comparison with international literature a reference depth of 1 m is selected, as this is the most common reference depth used in related studies (e.g. Kern, 1994; Batjes, 2000; Sleutel et al., 2003a; Lettens et al., 2004; Eq. (3)).

$$\mathrm{SOC}_m = \frac{\sum_{i=1}^{n} \mathrm{SOC}_{Di} * T_i}{\sum_{i=1}^{n} T_i} * D_r \tag{3}$$

where: SOC_m = SOC mass per unit surface area (kg m^{-2})
SOC_{Di} = SOC density of the ith horizon (kg m^{-3})
T_i = thickness of the ith horizon (m)
n = number of horizons

The thickness of the last horizon till reference depth (1 m) can be calculated using Eq. (4).

$$T_n = D_r - \sum_{i=1}^{n-1} T_i \tag{4}$$

where: T_n = thickness of the last (nth) horizon to the reference depth (m)
T_i = thickness of the ith horizon (m)
D_r = reference depth (m)

Table 1
Belgian drainage classification system as a function of the soil texture: (Heavy clay (U), clay (E), sandy loam (L), loam (A), light sandy loam (P), loamy sand (S), sand (Z)) after Ameryckx et al. (1995)

Drainage class	Definition	Natural draining	Depth oxidation horizon (cm) (min. depth water table)		Depth reduction horizon (cm) (max. depth water table)
			Text. A, L,E, U	*Text. Z, S, P*	
a	Very dry	Very strong	–	–	–
b	Dry	Strong	>120	90–120	–
c	Moderate dry	Moderate-strong	80–120	60–90	–
d	Moderate wet	Moderate	50–80	40–60	–
e	Wet with reduction horizon	Moderate-bad	30–50	20–40	>80
f	Very wet with reduction horizon	Bad	0–30	0–20	40–80
h	Wet	Moderate-bad	30–50	20–40	–
i	Very wet	Bad	0–30	0–20	–
g	Extremely wet	Very bad	0	0	<40

2.2. Maps

The digital land use map of Flanders, with a resolution of 15 m, was derived from Landsat7-ETM+images acquired in 2001. Classification of these images was accomplished with a semi-automatic bayesian classification algorithm, using a field inventory for the training of the classifier. The classification obtained was refined to 18 land use classes using external road and waterway information, the digital soil association map and the CORINE land cover dataset (OC GIS Vlaanderen, 2002). For the present study, four aggregated classes are extracted from the digital land use map of Flanders: forest, grassland, cropland and heath.

The soil map of Belgium is based on the National Soil Survey (1947–1974). Since 2001, the “Ondersteunend Centrum (OC) GIS Vlaanderen” distributes a digital version of the soil map of Belgium (OC GIS Vlaanderen, 2001). Based on a morphogenetic classification system for the majority of the area and a geomorphological classification for the Polders, Coast and Dunes region the digital soil map containes, 4500 unique soil codes. From this map a texture–drainage class map was constructed by extracting the texture-and drainage class information from the soil code for each morphogenetic classified area. Soils belonging to the unit Polders, Coast and Dunes were not classified based on drainage and texture (morphogenetic) but on geomorphology. Nevertheless, the textural characteristics of these geomorphologic soil type classes are well described (OC GIS Vlaanderen, 2002). Based on this information a reclassification was performed. This resulted into five corresponding texture groups, differing significantly in their SOC content: i.e. sand, a combination of sand (or sandy loam) and clay textured soil layers, clay, heavy clay (with peat) and land dunes. The Belgian soil drainage classes were defined based on the depth of occurrence of oxidation and reduction properties in the soil profile. These depths correspond to the minimum and maximum ground water depth, or the position of the winter and summer ground water table, respectively (Ameryckx et al., 1995). Fig. 1 and Table 1 show the Belgian soil texture and drainage classification system.

The study area was stratified by overlaying the soil type map and the reclassified land use map. The resulting map consists of different land use–soil type classes and has a resolution of 15 m.

2.3. Calculation of total SOC stock

Two methods were applied to determine the spatial distribution of SOC. In a first approach, called mean approach, the SOC data from Aardewerk are grouped into 252 possible land use–soil type classes, based on land use (grassland, cropland, forest and heath), drainage (Fig. 1) and texture (Table 1) classification of the database. For each land use–soil type class the mean SOC mass per unit surface area (kg m^{-2}) is calculated and attributed to the corresponding grid-cells in the constructed land use–soil type map with a resolution of 15 m.

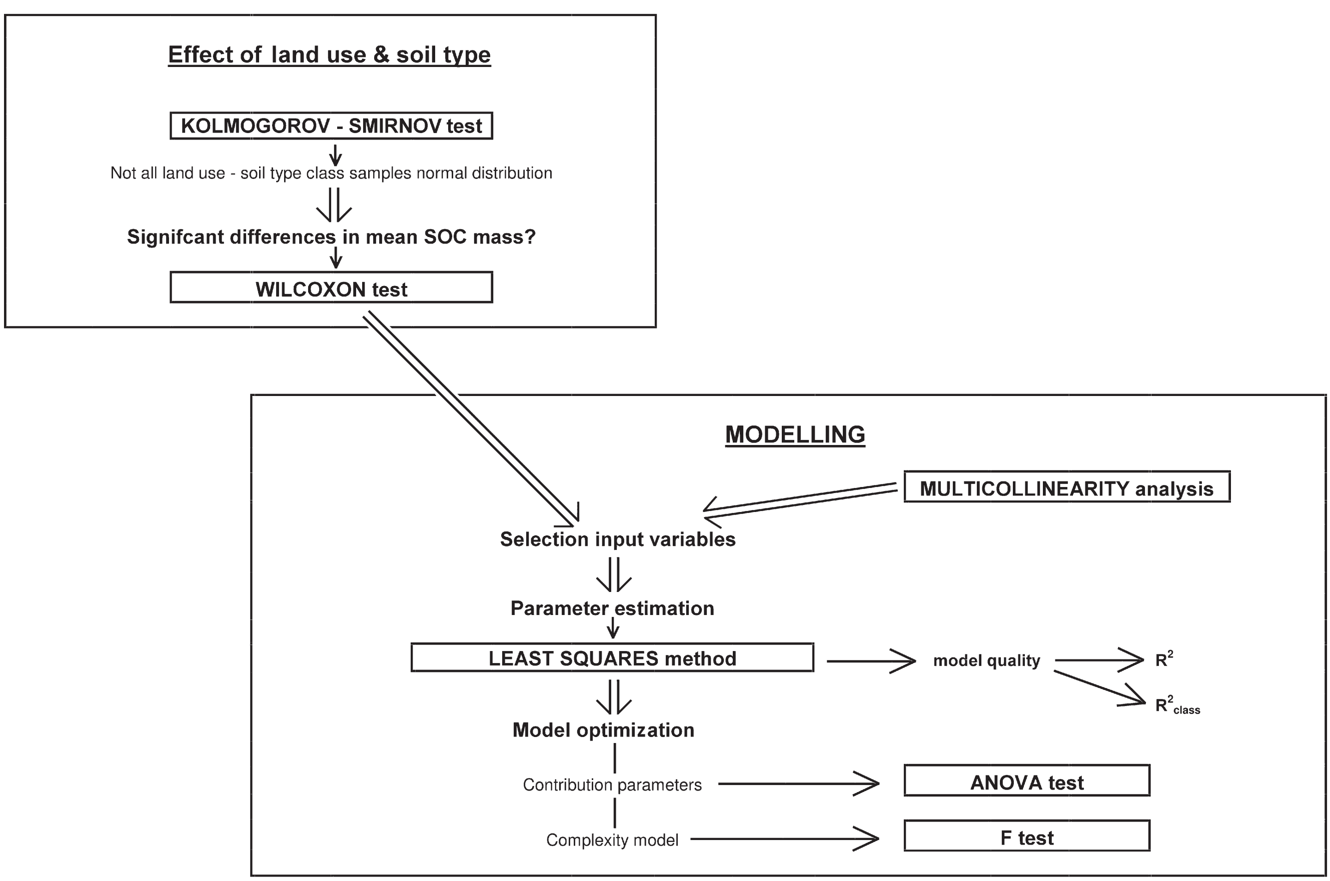

Fig. 2. Flowchart of the statistical analysis.

For classes with less than 10 samples, the mean SOC mass obtained is considered not representative. Consequently, these values were not taken into account during the mapping. These classes represent 7.46% of total study area.

In a second approach, called “model approach”, a regression model predicting the SOC stock for each land use–soil type class on the map, is constructed, based on all observations. Land use, texture (geometric mean particle size (D_g), proportion of particle size classes: sand, silt and clay) and drainage (depth of the water table) are the input variables for the model.

Finally, the total amount of SOC in the study area is calculated by multiplying the area of each land use–soil type class by the SOC mass per unit surface area (kg m^{-2}) for that class, and then summing the SOC masses obtained for all the classes (Eq. (5)).

$$\mathrm{SOC}_T = \sum_{i=1}^{n} \mathrm{SOC}_{mi} {*} A_i \quad (5)$$

where: SOC_T=total amount of SOC in the entire study area (kg)

SOC_{mi}=SOC mass per unit surface area of land use–soil type class i (kg m^{-2})

A_i=area of land use–soil type class i (m^2)

n=number of land use–soil type classes

2.4. Statistical analysis

Statistical analysis (Fig. 2) on the results were carried out using the software packages SPSS 11.5 and MATLAB 6.1. A Kolmogorov–Smirnov test (e.g. Chakravarti et al., 1967) indicated that for many land use–soil type combinations SOC data are non-normally distributed. Therefore, the Wilcoxon test (e.g. Kanji, 1994) is applied to detect significant differences in SOC content. Based on this analysis and a multi-collinearity analysis, input variables for a multiple regression model are selected. Model parameters are estimated with a Least Squares (LS) estimator. Analysis of Variance (ANOVA) ($p<0.05$) is used to evaluate the contribution of the different input variables to model prediction. In order to verify if an increase of the complexity of the model leads to a significant improvement of its quality (R^2), an F-test is applied. Due to the large amount of

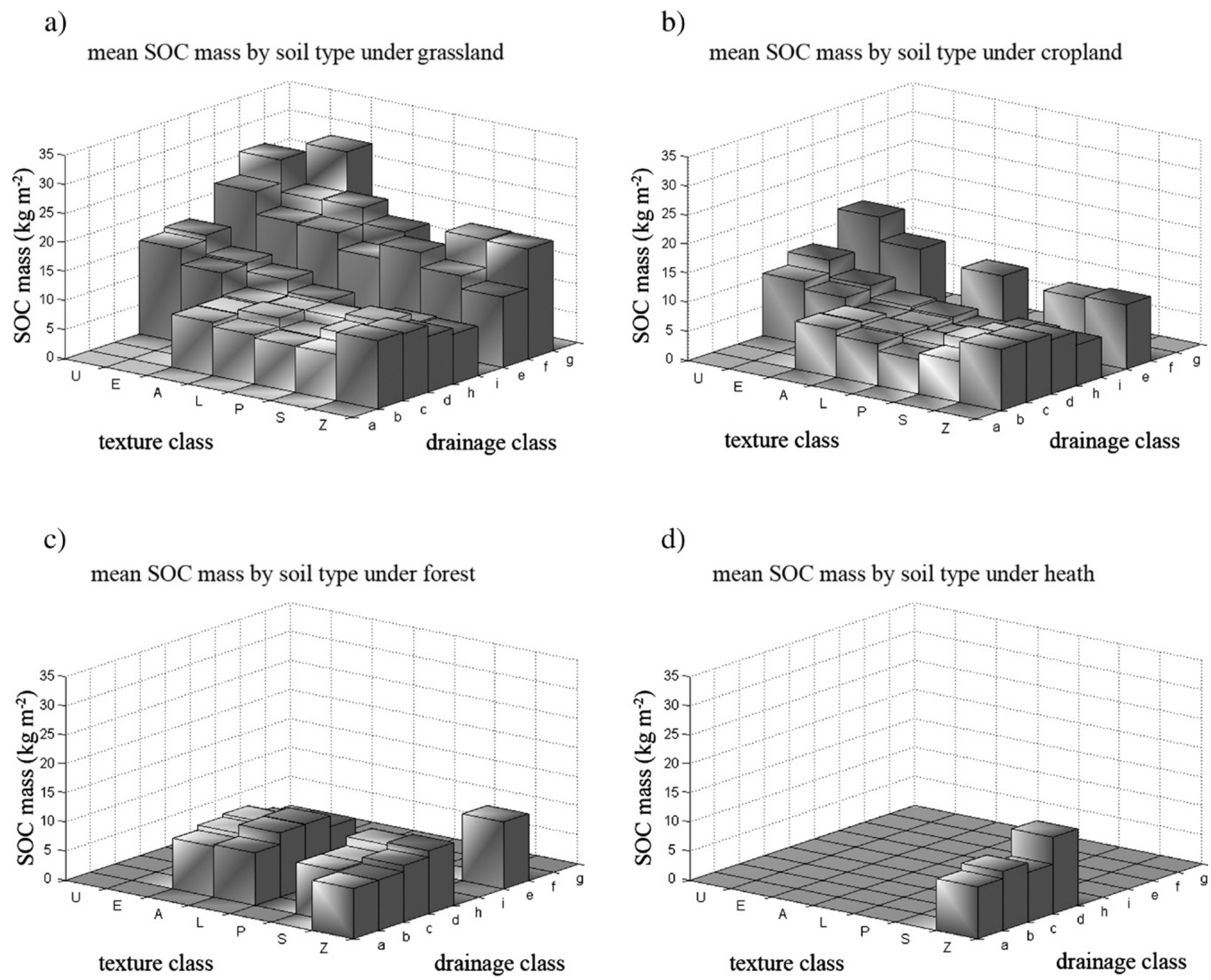

Fig. 3. Mean SOC masses (kg m^{-2}) by texture–drainage class for different types of land use: a) pasture, b) cropland, c) forest, d) heath.

data even a very small increase of R^2 ($p>0.01$) is to be considered significant. Therefore, the difference between the observed mean value of a class with more than 10 samples and the predicted value for that class (R^2_{class}) is also assessed.

3. Results and discussion

3.1. Mean approach

For 101 of the 252 possible land use–soil type combinations no soil data are available in Aardewerk. Because of the spatial autocorrelation of soil texture, drainage and land use, these land use–soil type classes were scarce and only covered 0.74% of the total study area. For 64 combinations, containing more than one but less than 10 samples, mean SOC mass is not calculated because the sample size is considered insufficient for calculating a representative mean value. These classes represent 6.72% of the total study area, but describe extreme environments and so they are characterized by very high/low SOC contents.

Consequently, for only 87 out of 252 classes mean SOC masses are calculated. The number of samples, mean SOC mass per unit area and corresponding standard deviations of the different land use–soil type classes are given respectively in e-Table 1, e-Table 2 and e-Table 3 (Meersmans, 2007). Fig. 3 shows the mean SOC masses per unit area. Probability values of Wilcoxon tests detecting significant differences in SOC content between two land use, drainage or texture classes are given in e-Tables 4,5 and 6 (Meersmans, 2007).

3.1.1. Land use

The results indicate that for almost every land use–soil type class the lowest amount of SOC (kg m^{-2}) can be found under cropland (Fig. 3). Liebens and Van Molle (2003) obtained a similar result using the same dataset but a different method. These results are in accordance with the findings of Paustian et al. (1997). They found that the amount of SOC decreases with increasing physical disturbance of the soil. Plowing appears to be the most important explanatory factor as it causes disaggregation and loss of internal physical protection of SOC against oxidation (Lal et al., 1997). In 18 of the 30 soil types a significant lower mean SOC mass ($p<0.05$) was found under cropland than under grassland. Comparing cropland with forest, 10 of the 15 soil types have significant lower mean SOC mass in cropland ($p<0.05$) (e-Table 4; Meersmans, 2007). For the majority of the soil types the highest amount of SOC is found under grassland. On the other hand, the difference in SOC between forest and grassland is very small for most texture–drainage classes; only in 2 of the 15 cases a significant difference in mean SOC mass at 0.05 level was detected (e-Table 4; Meersmans, 2007). This is in accordance with observations of Lettens et al. (2005) on Belgian soils, indicating that SOC amounts under forest and grassland were comparable and generally higher than the SOC stocks under cropland. When comparing the amount of SOC between different land use classes, the reference depth is very important: the SOC stock is much higher under forest than under grassland when only the topsoil (i.e. the first 20 cm) is taken into account (Wang et al., 2004).

3.1.2. Drainage

For almost every land use–texture combination the same trend was observed (Fig. 3): the amount of SOC increases from drainage class b to drainage class f or g. This indicates that high amounts of SOC can be found in poorly drained soils. For almost all land use–texture classes, the mean SOC masses (kg m^{-2}) in wet to extremely wet soils with a reduction horizon less than 1 m deep (drainage classes e, f, g), are significantly higher ($p<0.01$) than those in the better drained soils without a reduction horizon (but with an oxidation horizon) (b, c, d, h).

In 10 out of the 13 land use–texture classes mean SOC mass is significantly higher ($p<0.01$) in wet soils with a reduction horizon (e) than in wet soils without a reduction horizon (h) (e-Table 5; Meersmans, 2007). The reduction horizon is an indicator for the maximum depth of the ground water table. This means that for soils belonging to drainage classes e, f and g ground water is permanently present in the soil profile. In soils with drainage classes b, c, d and h the water table is only periodically present. The amount of free oxygen atoms is lower in water than in air. Consequently, oxidation of carbon is lower in wet soils (with the presence of a permanent ground water table) as compared to dry soils, where saturated conditions occur only periodically.

The relationship between SOC and the minimum depth of the ground water table is weaker than with the maximum depth of the ground water table (Table 2). Generally, it can be stated that the effect of the minimum depth of the groundwater table on SOC depends on texture class, whereas texture class doesn't affect the impact of the maximum depth of the ground water table on SOC.

For agricultural soils with a fine texture (i.e. (heavy) clay (texture class E, U) and loam (A) soils) the mean SOC mass in wet soils with strongly fluctuating depth of the ground water table (i.e. maximum depth not present in the profile and minimum depth within the topsoil, represented by drainage class h) is higher as compared to the better drained soils with a larger minimum ground water table depth (b, c, or d). Only for

Table 2
Correlation coefficients between different site variables: sand, silt and clay content (%), geometric mean particle size (Dg), acidity (pH), minimum and maximum depth of the ground water table (h_2o_{min}, h_2o_{max}), amount of SOC in kg m^{-2} (SOC)

	Sand (%)	Silt (%)	Clay (%)	Dg	pH	h_2o_{max} (m)	h_2o_{min} (m)	SOC (kg m^{-2})
Sand (%)	1.000							
Silt (%)	−0.970	1.000						
Clay (%)	−0.707	0.521	1.000					
Dg	0.897	−0.844	−0.723	1.000				
pH	−0.506	0.460	0.461	−0.498	1.000			
h_2o_{max} (m)	−0.085	0.132	−0.088	−0.050	−0.010	1.000		
h_2o_{min} (m)	−0.438	0.501	0.091	−0.050	0.125	0.498	1.000	
SOC (kg m^{-2})	0.022	−0.079	0.168	0.020	−0.029	−0.520	−0.306	1.000

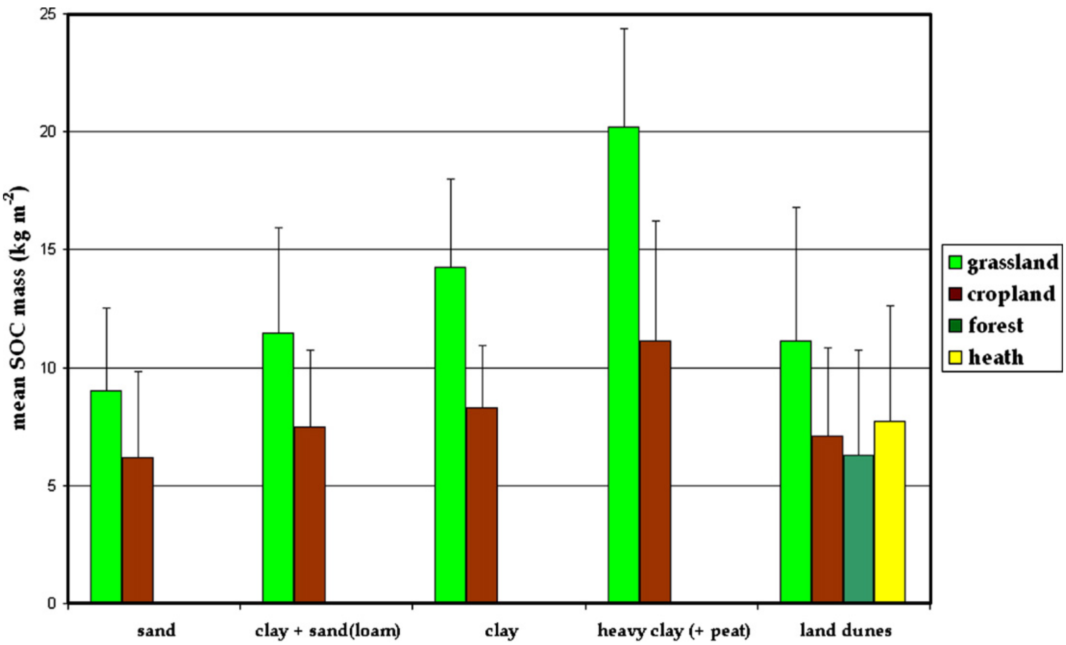

Fig. 4. Mean SOC mass (kg m^{-2}) per land use–soil type class for the coast, polders and dunes area.

loam (A) soils under grassland, the difference between wet soils without a reduction horizon (h) and moderate wet soils without a reduction horizon (d) is significant at 0.01 level. Sand (Z) soils under cropland and grassland show an opposite trend: mean SOC mass in wet soils without a reduction horizon (h) is lower than in drier soils belonging to drainage classes b, c, or d. Under cropland the difference between wet soils without a reduction horizon (h) and moderate wet soils without reduction horizon (d) is significant ($P<0.01$) (e-Table 5; Meersmans, 2007). This can be explained by the very high input of manure due to intensive livestock agriculture on dry sand soils in the Campine area, situated in North Flanders (Sleutel et al., 2003a).

The positive correlation between soil wetness and SOC found in this study indicates a negative effect of soil drainage on the SOC stock. This finding is in accordance with the international literature (Bouwman, 1990; Davidson, 1995; Tan et al., 2004; Ungaro et al., 2005). Furthermore, different studies identified the importance of the ground water level on the SOC stock in wetlands (Updegraff et al., 2001; Lloyd, 2006). Bouwman (1990) estimated that the soil can lose 10 ton C ha^{-1} y^{-1} after draining. This implies that protection of poorly drained areas such as peat lands, is very important in the context of global warming (Bouwman, 1990).

3.1.3. Texture

Heavy clay (U) and clay soils (E) store significantly ($p<0.05$) more SOC than all other soil texture classes for most land use–drainage class combinations (e-Table 6; Meersmans, 2007). Because clay soils are mostly characterized by poor drainage, they contain less air and therefore have lower SOC oxidation rates. Regardless of the drainage status of the soil, small voids in clay soils promote aggregation and physical protection of SOC against oxidation (Bouwman, 1990). Under cropland and grassland, the lowest mean SOC masses occur within light sandy loam (P) soils. The SOC amounts in dry sandy soils (Za, Zb, Zc) are remarkably high under cropland. Under cropland, for dry to moderate wet soils without reduction horizon (b, c, and d) soils with a sand texture (Z) show significantly higher ($p<0.01$) mean SOC masses than finer textured soils (A, L, P and S) (e-Table 6; Meersmans, 2007). Under grassland, the difference is only significant ($p<0.05$) for dry soils (b). The high SOC value under agricultural sand (Z) soils is not in accordance with the international literature where a clear positive linear relationship is found between SOC mass and clay content or clay + silt content (Zinn et al., 2005). This implies that lowest amounts of SOC are expected in sand soils (Z), as this texture class is characterized by the lowest clay (or clay + silt) content of all texture classes.

Under cropland the differences between sandy soils (Z) and loam, (light) sandy loam or loamy sand soils (A, L, P, S) become smaller with increasing soil moisture. These differences are not significant under wet conditions (e and h). Under grassland, these wet soils (e and h) show significantly lower ($p<0.01$) mean SOC masses for sand soils (Z) than for loam soils (A) (e-Table 6; Meersmans, 2007). The unexpected high mean SOC content for dry sandy soils under agricultural land use can again be explained by the high input rate of manure, due to intensive livestock agriculture on this soil type in the north of Flanders (Sleutel et al. 2003a; van Wesemael et al., 2005).

The difference in mean SOC between two texture classes was significant ($p<0.05$) in only 1 out of 19 cases under forest. For the same 19 inter texture class tests, a significant difference was observed in 5 cases for grassland and in 13 cases for cropland. This could possibly be a consequence of the much higher number of observations under agricultural land use (cropland and pasture) than under forested land, as the number of observations affects the probability values of the Wilcoxon tests. Nevertheless, agricultural management and particularly manure production, has an important impact on SOC stock and varies by texture in Belgium (van Wesemael et al., 2005). Furthermore, in the present study, the high input rate of manure in sand soils appears to have a great influence on the differences in SOC between sand and other texture classes under agricultural land uses.

3.1.4. Coast, dunes and polders

Coast, dunes and polders cover 7.1% of the study area. Although a different classification system was used for this region, a close relation between both classification systems exists. This allowed grouping the soil codes into 5 corresponding texture groups: sand, combination of sand (or sandy loam) and clay textured soil horizons, clay, heavy clay (with peat) and land dunes. For these groups the database Aardewerk contains more than 9 samples only for cropland and grassland. For the land dunes the database includes enough samples ($n>9$) for each land use type (grassland, cropland, forest and heath). Mean SOC contents of these classes are illustrated in Fig. 4. The mean SOC mass under grassland is higher than under cropland. A positive correlation between clay content and mean SOC content was observed.

A last land use class is formed by the peat soils, characterized by an exceptionally high SOC content (Houghton, 1999). For Flanders the mean SOC for this class was calculated at 42.7 kg m^{-2}. This value is close to the peat SOC densities reported by Liebens and Van Molle (2003) and Lettens et al. (2004), respectively 44.9 kg m^{-2} and 45.6 kg m^{-2}. However, the occurrence of these soils is very restricted in the study area: only 0.03% of the surface is covered by peat soils.

The distribution of SOC in Flanders based on the mean SOC mass for each land use–soil type class is mapped in Fig. 5. White spots on the map are urban areas or land use–soil type classes without mean SOC value (i.e. less then 10 representative samples). The big white spots correspond to the most important cities or large military domains.

3.2. Model approach

Based on the above-mentioned determining factors and further analysis a regression model is developed, using the entire dataset. This model is used to predict a general SOC value for each land use–soil type class found on the map. This allows the production of class-specific SOC values for each of the 252 possible land use–soil type combinations. Consequently, a more comprehensive estimation of the spatial distribution of the total SOC stock in Flanders can be obtained than the one using the mean approach.

The depth of the ground water table represents the drainage status of the soil in the regression model. The drainage classes from the database are quantified by taking the middle value of the interval defined by both the minimum and maximum depth of the water table (h_2o_{min} and h_2o_{max}; Table 1). For classes where maximum and/or minimum depth of the water table are not given or are deeper than 1–2 m, a value of 150 cm was used.

Table 2 shows the correlation coefficients between the different site variables. SOC shows a negative correlation with the maximum depth of the water table ($r=-0.520$). Furthermore, SOC is also correlated with the minimum depth of the ground

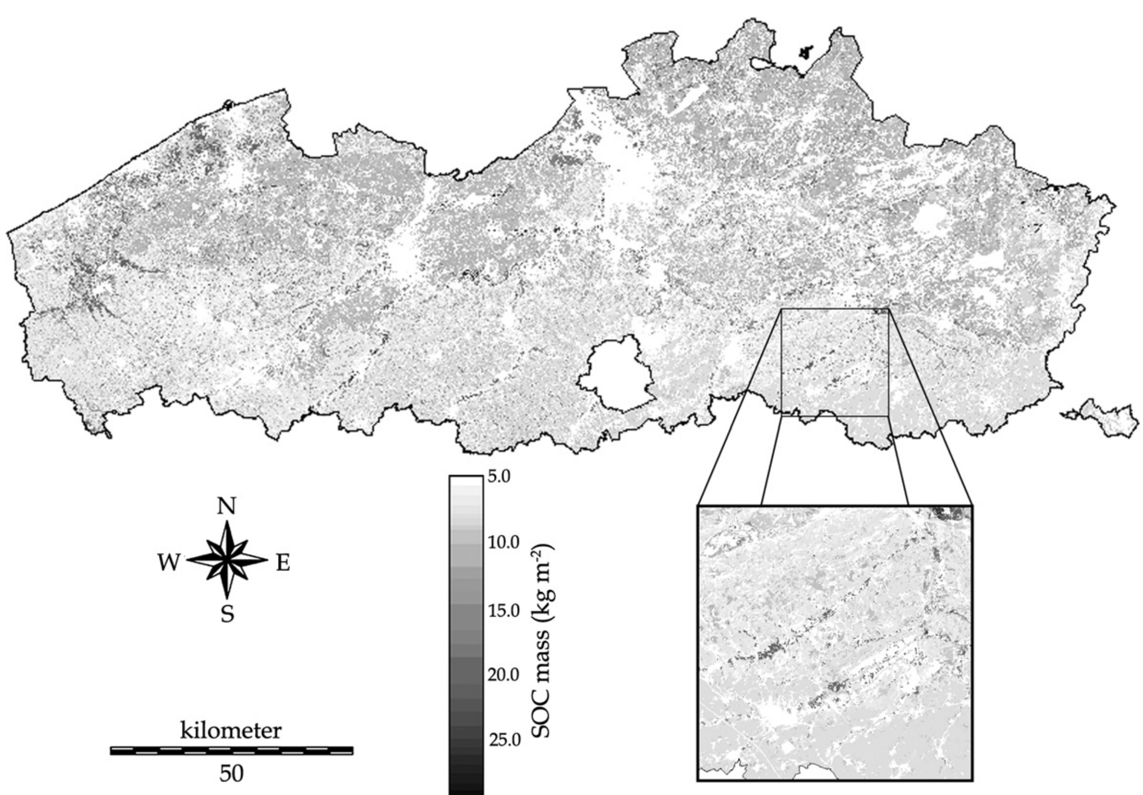

Fig. 5. SOC distribution map for Flanders (Belgium) based on mean SOC mass for each land use–soil type class (kg m^{-2}).

Table 3
Predicted value, standard error and 95% confidence interval of model parameters

	Value	Std. error	95% confidence interval	
a	−10.120	0.292	−9.537	−10.704
b	0.074	0.011	0.097	0.052
c	−2.643	0.646	−1.351	−3.936
d	0.031	0.005	0.040	0.021
e	10.025	1.005	12.034	8.015
f	−2.925	0.394	−2.137	−3.712
g	0.168	0.011	0.189	0.146
h	8.491	1.433	11.357	5.625
i	2.334	0.558	3.451	1.217
j	−1.997	0.410	−1.176	−2.818
γa	22.471	0.566	23.604	21.339
γb	24.090	0.467	25.023	23.156
γw	25.490	0.591	26.672	24.309
γh	24.584	0.743	26.070	23.098

water table (r=−0.306) and with clay content (r=0.168). The mutual correlation of the (minimum and maximum) depth of the ground water table and the clay content is lower than 0.70, which is, according to Buijs (2000), the maximum value allowing for the input of these three variables together in the model. Consequently, these variables were selected as most important input variables for the model. Based on regression analysis across map units of area-weighted estimates of SOC, clay content and drainage class in Kansas and Montana (USA), Davidson (1995) also found a remarkably stronger (negative) correlation between SOC content and drainage class, as compared to the positive correlation with clay content.

Land use was accounted for in the model by adding a land use specific constant. From previous studies (Tan et al., 2004), it is known that relationships between site variables and SOC content are land use specific. Tan et al. (2004) constructed a different linear regression model for each land use type in order to predict the SOC content in relation to texture, drainage, slope gradient and topography. We constructed a single model by estimating parameter values for more than 1 land use. For example, for the variable "maximal depth of the ground water table (h_2o_{max})" one parameter value is estimated for all land uses. Nevertheless, because the land use specific effects of some variables on SOC, some land use specific parameter values were determined in the proposed model.

A statistical tool was used for the decision of calculating land use specific parameters. The quality of model variables and their individual contribution to the predictive power of the model were evaluated by using the 95% confidence interval of each parameter (ANOVA test (p<0.05), Table 3). Moreover, an F-test was used

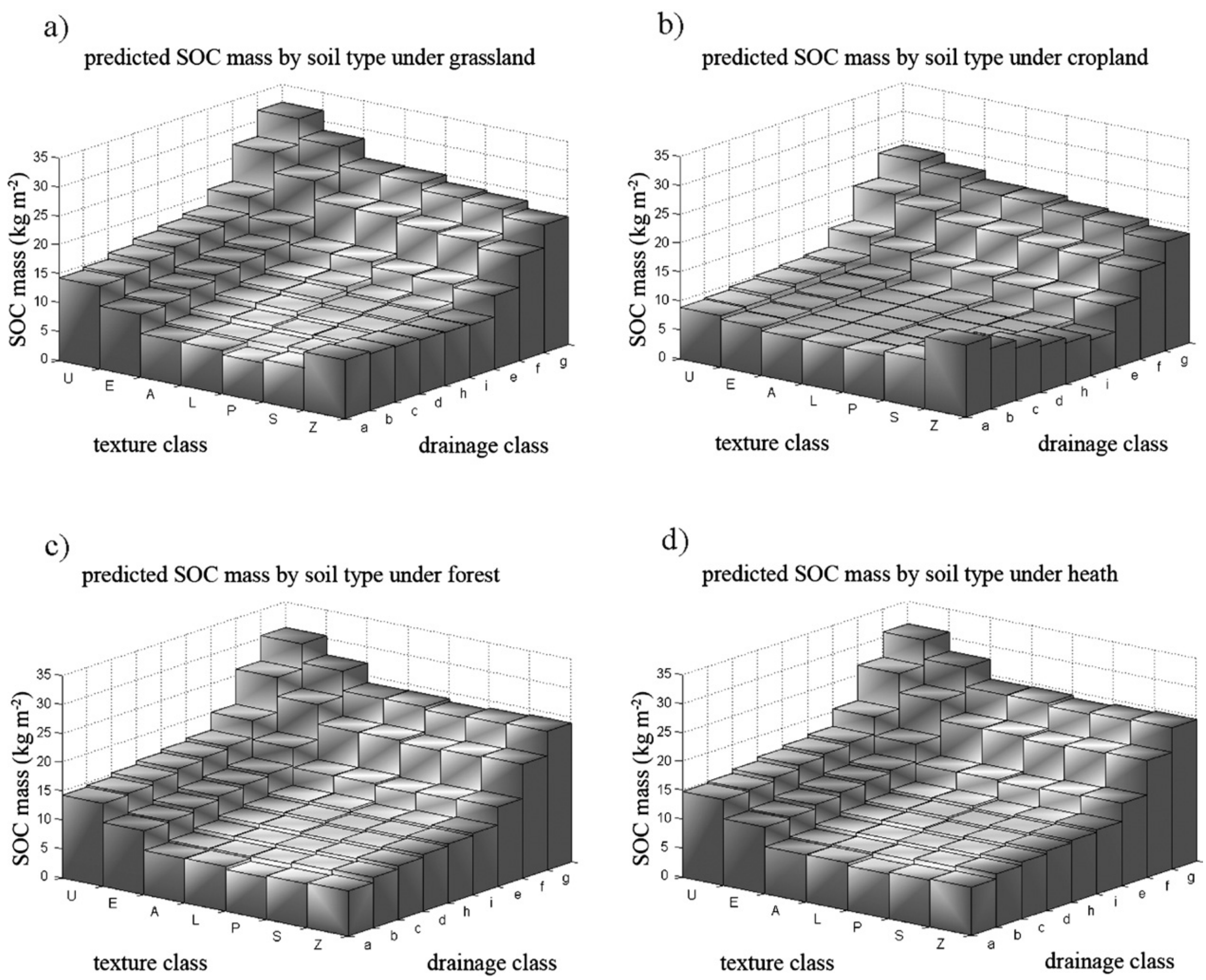

Fig. 6. Predicted SOC mass (kg m^{-2}) by drainage–texture class based on the regression model for different land use types: a) pasture, b) cropland, c) forest, d) heath.

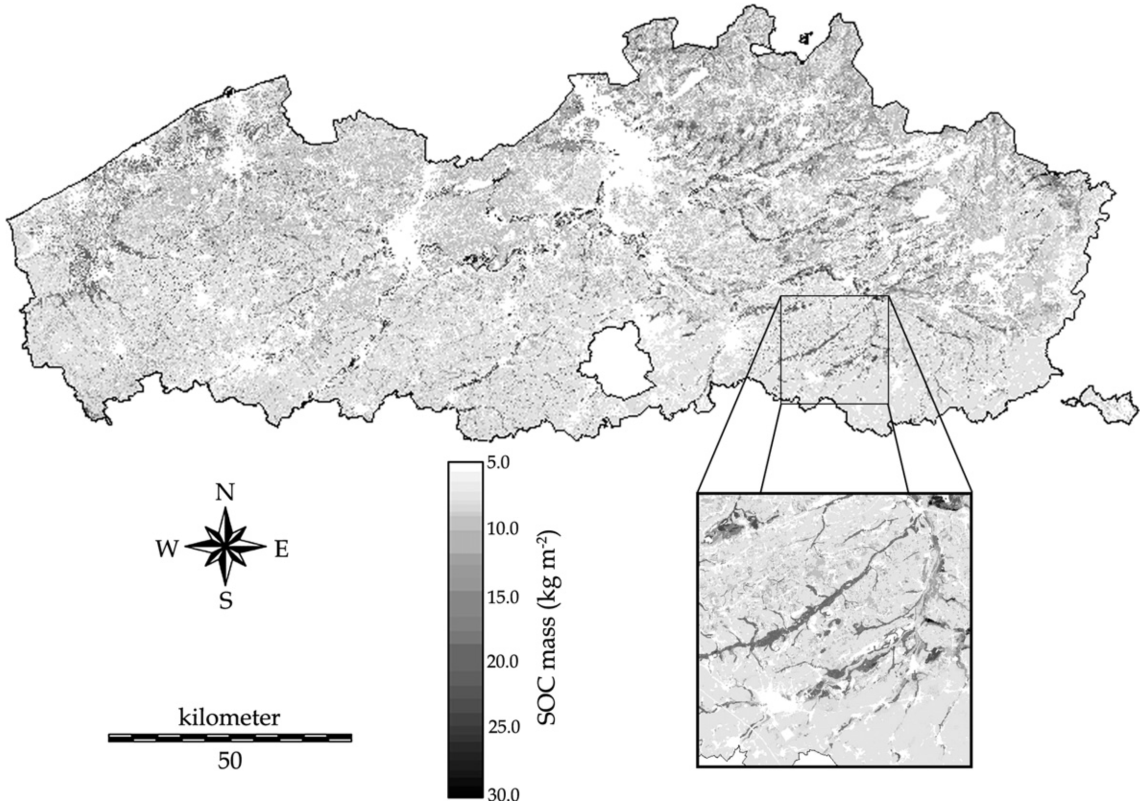

Fig. 7. SOC distribution map for Flanders (Belgium) based on predicted SOC mass for each land use–soil type class obtained by the use of a regression model (kg m^{-2}).

to check if an increase in model quality, by adding a new variable, resulted in a significant improvement of model quality (R^2).

The remarkable higher SOC mass densities in well-drained sand soils compared to the SOC mass densities of well-drained loam soils under agricultural land (Fig. 3) indicates that for Flanders, a linear relationship between clay content and SOC mass does not completely reflect the variation in SOC content due to texture. Therefore it was decided to integrate the geometric mean particle size (Dg) in the model (Eq. (6)):

$$\mathrm{Dg} = \exp\left(\sum_{i=1}^{n} f_i * \ln(M_i - N_i)\right) \tag{6}$$

where: f_i: relative proportion particle diameter size class i

M_i: particle diameter upper bound of particle diameter size class i

N_i: particle diameter lower bound of particle diameter size class i

The geometric mean particle size is very weakly correlated with SOC content (r=0.02) and is strongly correlated with clay content (r=0.72) (Table 2). However, adding this variable to the model considerably improved the quality of the model (higher R^2). The ANOVA test showed that for cropland and grassland, an interaction term between Dg^2 and h_2o_{min} had a significant contribution to the model performance (Table 3). This indicates that the influence of soil moisture on SOC content depends on texture. Furthermore, based on the ANOVA test, for cropland an interaction term between (1-clay%) or (silt%+sand%) and h_2o_{min} is added to the model. Finally, the following regression model is constructed:

$$\begin{aligned}
\mathrm{SOC}_{cropland} &= a^*h_2o_{max} + (b^*clay\% + c^*Dg \\
&\quad + d^*(silt\% + sand\%)^*h_2o_{min} + e^*Dg^{2*}h_2o_{min} \\
&\quad + f^*h_2o_{min}) + \gamma_{cropland} \\
\mathrm{SOC}_{pasture} &= a^*h_2o_{max} + \left(g^*clay\% + c^*Dg + h^*Dg^{2*}h_2o_{min}\right. \\
&\quad \left. + f^*h_2o_{min}\right) + \gamma_{pasture} \\
\mathrm{SOC}_{forest} &= a^*h_2o_{max} + (g^*clay\% + i^*Dg + j^*h_2o_{min}) + \gamma_{forest} \\
\mathrm{SOC}_{heath} &= a^*h_2o_{max} + (g^*clay\% + i^*Dg + j^*h_2o_{min}) + \gamma_{heath}
\end{aligned}$$

where: h_2o_{max}=maximum depth of the ground water table (reduction horizon)

h_2o_{min}=minimum depth of the ground water table (oxidation horizon)

clay%=percentage of clay

silt%=percentage of silt

sand%=percentage of sand

Dg=geometric mean particle size

a,…, j, γ_i=model parameters

Table 4
Total SOC stock (Mega ton) and total study area (km^2) according to mean and model approach

	Total SOC stock (M ton)	Total study area (km^2)
Mean approach	88.66±5.63	9419.8
Model approach	97.61±1.05	10179.0
Difference (%)	10.11	8.06

Table 5
SOC stock (Mega ton) and area (km^2) according to morphogenetic and geomorphologic classified soils and peat soils

	Morphogenetic class		Geomorphologic class (coast, polder, dunes)	Peat
	Mean approach	Model approach		
Area (km^2)	8692.2	9451.4	724.5	3.1
SOC stock (M ton)	80.78±5.53	89.74±0.26	7.75±1.02	0.13±0.06

For morphogenetic classified soils SOC stock and area resulted from mean and model approach are given separately.

Small local disturbances in physical soil properties or management practices can have a great effect on the SOC content of the soil. This means that the investigated system is typically characterized by a lot of noise and outliers. Consequently, a quite low determination coefficient (R^2) is expected even for models describing the system very well. The constructed model has a R^2 value of 0.36. Despite the presence of the most important factors in this model, many factors influencing the SOC status, are not included (e.g. soil management, erosion). Introducing these variables in the model could eventually result in an increase of R^2. Determination coefficient values for each land use are: 0.21 under cropland, 0.47 under grassland, 0.24 under forest and 0.18 under heath. Grassland has a significant higher R^2 value compared to other types of land use, indicating a better fit of the system by the model and/or less noise compared to other types of land use.

However, comparing the mean and predicted SOC mass of each land use–soil type class an R^2_{class} value of 0.92 was obtained. This indicates that the model is a good predictor for mean SOC mass by land use–soil type class. The use of R^2 or R^2_{class} to describe the performance of the model depends on the research objectives. When using the model as a pedo-transfer function to predict the SOC amount, given the input variables for a specific sample, it is recommended to use the R^2 value as an indication of the predictive power of the model. The R^2_{class} value gives an indication of model performance when the model is applied to produce regional estimates from a set of spatial data, as it then integrates information from the area as a whole and not from one sample. Fig. 6 lists the mean SOC masses by drainage–texture class for different land use types predicted by the regression model. Fig. 7 represents the SOC distribution based on predicted SOC masses (mean approach) for each land use–soil type class.

Because the model approach allows us to assign a specific SOC value to each land use–soil type class, a more comprehensive estimate of the spatial distribution of the total SOC stock in Flanders is obtained (Fig. 7) compared to the mean approach. A clear relationship with the fluvial pattern now appears in the resulting map. Based on the mean approach, the total amount of SOC is calculated at 88.66±5.63 Mt C for an area of 9419.8 km^2. With the model approach, a total SOC stock of 97.61±1.05 Mt C is predicted for an area of 10179.0 km^2. The increase of 8.1% in the area to which a SOC value could be attributed, by using the model approach instead of the mean approach, results in an increase of 10.1% in the total calculated SOC stock (Table 4). Table 5 illustrates the calculated total SOC stock and study area according to morphogenetic and geomorphologic classified soils and peat soils. For the morphogenetic classification, the results of the mean and model approach are given separately. This table indicates that using the model approach the standard error on the total calculated SOC stock is 25 times lower. The same trend is observed on the SOC value errors of the individual land use–soil type classes, as this error ranges between 1.54 and 17.45 (kg m^{-2}) for the mean approach and between 0.10 and 0.77 for the model approach. This can be explained by the fact that following the model approach a class specific SOC value is predicted, which is based on all samples (>6900), while following the mean approach for this calculation only a small part of dataset was used, because the dataset was initially divided in 252 classes.

The additional area taken into consideration mainly consists of poorly drained valley soils, rich in SOC. These soils have high SOC values. Fig. 8, represents the geographical distribution of the difference in estimated SOC mass between the model

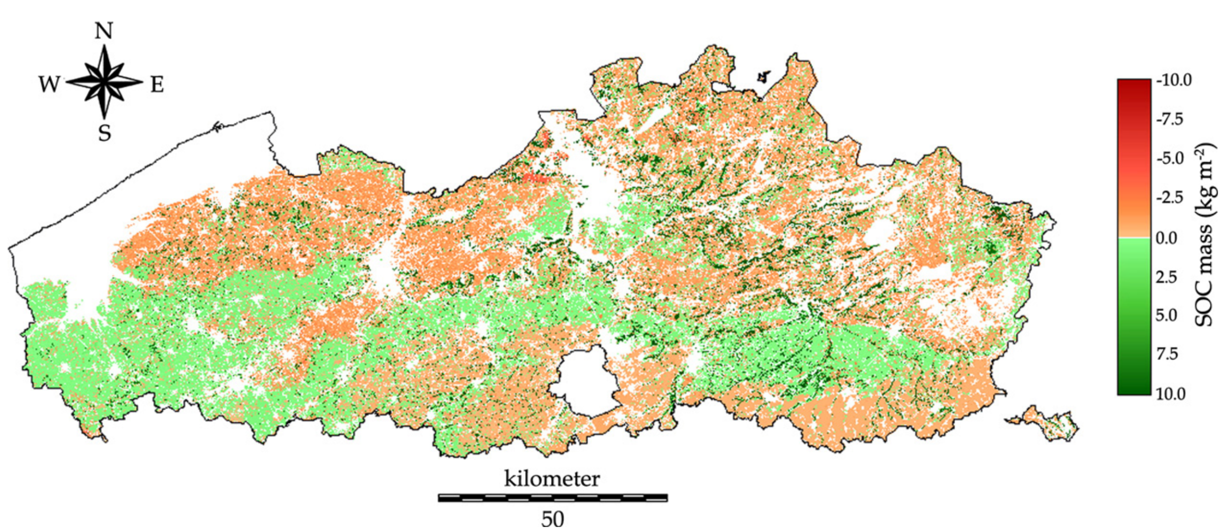

Fig. 8. Spatial distribution of the difference between predicted SOC mass (method 2) and mean SOC mass (method 1) (Fig. 7 – Fig. 5).

and the mean approach. This difference map clearly shows that the model approach predicts a lower SOC stock for the Loam region (south and south-east of Flanders) and a higher SOC stock for the Sandy Loam region (central and south-west of Flanders) compared to the mean approach.

A comparison with previous studies assessing the SOC stock in Flanders, reveals that the total SOC amounts predicted in this study are lower than the 125.6–134.9 Mt C predicted by Liebens and Van Molle (2003). Total SOC stock under cropland, estimated at 53.2 Mt C, is remarkably higher than the 28.2 Mt C predicted by Sleutel et al. (2003a). The main reason for this difference is the area assigned as cropland, which is much lower in the study of Sleutel et al. (2003a) than in this study, respectively 3594 km^2 and 6244 km^2. Nevertheless, mean SOC densities of cropland and grassland are comparable to earlier studies. The mean SOC density under grassland (11.4 kg m^{-2}) for this study is lower than those reported by Lettens et al. (2003) (11.7 kg m^{-2}) and Liebens and Van Molle (2003) (12.9 kg m^{-2}). For cropland, the calculated mean SOC mass density (8.5 kg m^{-2}) for this study is higher than the values published by Liebens and Van Molle (2003) (7.4 kg m^{-2}), Sleutel et al. (2003a) (7.8 kg m^{-2}) and Sleutel et al. (2003b) (8.3 kg m^{-2}), but lower than the one found by Lettens et al. (2004) (8.9 kg m^{-2}). The latter studies used mean SOC values by land use–soil type classes to obtain a total Flemish SOC stock. This study shows that the use of the presented SOC mass regression model, instead of mean SOC masses, results in much lower standard errors on calculated SOC masses of individual classes and consequently on total SOC stock of the study area. As the model approach allows the prediction of a SOC value for each land use–soil type class, regardless of the number of observations, this study is characterized by a more detailed classification. Moreover the present study has a finer mapping resolution compared to previous estimations.

4. Conclusions

Land use has an important impact on the amount of SOC. In Flanders, the lowest amounts of SOC are stored under cropland, regardless of soil type. For most soil types, the highest amounts can be found in grasslands. The amounts of SOC in forested soils are comparable to those in grasslands. Ground water level appears to be the best predictor for SOC content in Flanders. A strong negative correlation between the SOC stock and depth to ground water table was found. In wet soils the oxidation of SOC is limited by the low amount of free oxygen atoms. Although the results indicate that texture plays a less important role than the drainage condition, a positive correlation between SOC content and clay content is observed. In general, clay rich soils retain the highest amounts of SOC whereas sandy loam soils stock the lowest quantities. The masses of SOC stocked under dry sandy soils in this study are surprisingly high, probably as a result of the very high input of manure and slurry from intensive livestock breeding.

Depending on the method applied, the total SOC stock in Flemish soils was assessed at 88.7±5.6 or 97.6±1.1 Mt C. An important advantage of using SOC values predicted by the regression model is the possibility to derive reliable class specific SOC values for land use–soil type classes with a no or a limited number of observations. Using the model approach, a large area of poorly drained valley soils rich in SOC, were included in the calculation of total SOC stock. While the total area for which SOC stocks could be calculated increased by 8.1%, the total predicted SOC stock increased by 10.1% using the model approach instead of the mean approach. The use of the model approach results in a more comprehensive spatial distribution of the total SOC stock in Flanders compared to the use of mean values directly obtained from the observations, and shows a clear relation between the fluvial pattern and the amount of SOC. Moreover, this study shows that the application of a regression model approach instead of a mean approach results in remarkable lower standard errors of land use–soil type class specific SOC values and total SOC stock estimation.

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