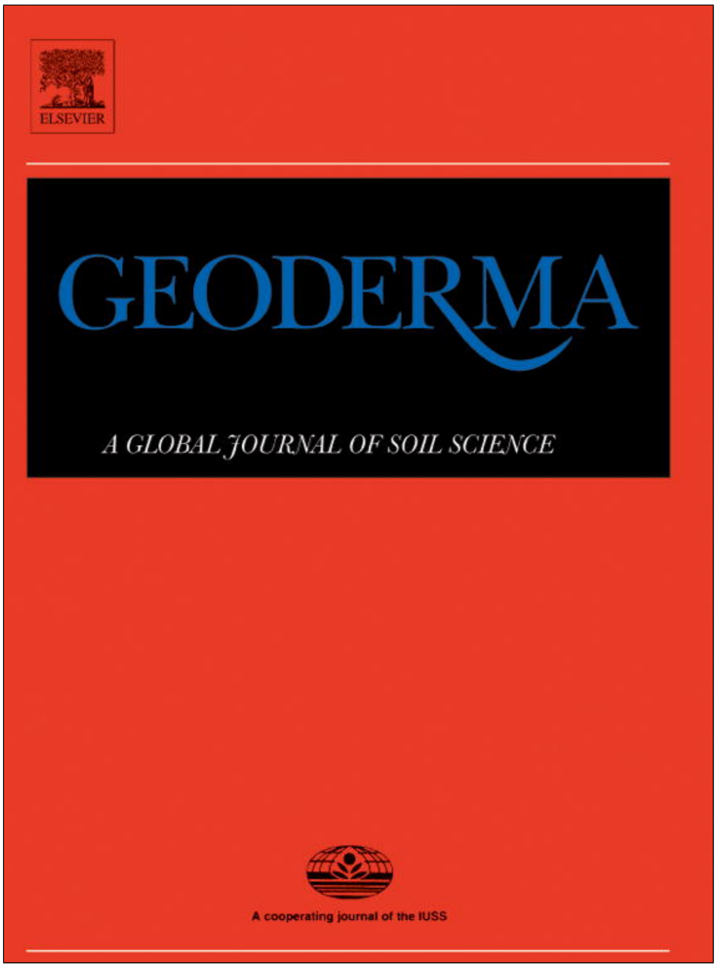
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Organic carbon stocks in agricultural soils in Ireland using combined empirical and GIS approaches

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A B S T R A C T

Substitution of the Intergovernmental Panel on Climate Change (IPCC) default methodology by country-specific activity data is recommended for improved estimation of baseline soil organic carbon (SOC) stocks and their changes. In the Republic of Ireland (ROI), previous studies focused either predominantly on grassland or on all land cover types but were depth-limited. To improve the accuracy, Tier 2 approaches are proposed by the IPCC. This requires an analysis of high spatial resolution databases (such as the Irish NSDB – National Soil Database) and maps, collated for major land cover, soil types and land use areas in Ireland. In this study, data were overlaid using ArcGIS to derive information for disaggregated soil types and agricultural land use areas. Empirical models were developed using separate measurement data to estimate the NSDB-derived SOC concentrations for deeper layers, using a depth distribution function and the bulk density (ρ_d) using pedotransfer functions. The soil type specific models ($R^2=0.87$–0.99) had an improved estimate of SOC densities when mineral and organic soils (peat) were treated separately. The estimated SOC densities for grasslands on mineral plus organo-mineral soils at the 0–10, 0–30, 0–50 and 0–100 cm depths were 52.2, 127.1, 170.9 and 213.8 t C ha^{-1}, respectively. For arable lands, the corresponding SOC densities were 29.9, 81.3, 117.6 and 167.5 t C ha^{-1}. Nationally, for all soil types, the corresponding stocks (the products of SOC density and land cover area) were estimated to be 246.9, 608.1, 829.5 and 1079.3 Tg for grassland, and 13.5, 36.7, 50.2 and 67.0 Tg for arable lands in the three soil layers. The total national SOC stocks were estimated to be 888 at 0–30 cm and 1832 Tg at 0–100 cm reference depths. For the complete soil profile, including peats >100 cm depth, the national estimate was 2824 Tg. The combined empirical models and Geographical Information System technique provide robust estimates of SOC stocks for disaggregated land covers and soil types, enabling Ireland to consider moving from Tier 1 to Tier 2 accounting methodology. This improved national inventory of the ROI is important for estimates of the C stock related to the Land Use, Land Use Change and Forestry (LULUCF) categories.

1. Introduction

Recent international negotiations, though yet to be finalized, have concluded that significant reductions in anthropogenic greenhouse gas (GHG) emissions are required to keep global temperature below 2 °C relative to pre-industrial times (COP 16, 2010; The Cancun Agreements). It is recognized within the United Nations Framework Convention on Climate Change (UNFCCC) that significant efforts are required to place global agriculture and food production on an environmentally sustainable, climate resilient low carbon pathway. Globally, agricultural activity is estimated to be responsible for approximately 14% of anthropogenic GHG emissions (Intergovernmental Panel on Climate Change, IPCC, 2007). However, in the Republic of Ireland (ROI) the current estimate is 30% (McGettigan et al., 2010). Despite a recent decrease in Irish national GHG emissions (due to the economic downturn, EPA, 2010), agricultural emissions remain a significant component of Ireland's emissions profile. Improved agricultural management practices have the potential to reduce GHG emissions from agricultural sectors (Smith et al., 2008). The SOC pool, one of the most important reservoirs of the global-C cycle, may have the potential to act as major source or sink of GHGs due to its large extent and active interaction with the atmosphere (Gal et al., 2007; Lal, 2004).

The Tier 1 approach, based on readily available activity data and default emission values as per IPCC guidelines, is used to establish trends in carbon stocks (IPCC, 1996, 2006). Whereas Tier 2 emphasises

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the development of country and regional specific emission factors for key activities, and Tier 3 requires additional resources to develop more sophisticated methodologies including modelling approaches, leading to provide improved estimates of GHG budgets. The higher tiers reflect more robust emission accounting, which are required to identify more specific mitigation options across land use management (LUM) and land use change (LUC). Due to the lack of detailed, spatially explicit activity data, about 56% of the Annex-I countries use IPCC Tier 1 methods and about 25% use Tier 2 methods within their inventory procedure (Lokupitiya and Paustian, 2006). In progressing to a Tier 2 approach, robust country-specific research and activity data are essential to reflect the diversity of practices which influence soil carbon within a country, and to further refine their analysis to include regional variation. This is also relevant to LULUCF sector, and that quantification of baseline SOC stocks across soil depth associated with the variety of land uses and practices is required to assess the change in SOC with LUC. This is highly relevant for sustainable management of the soil and thereby identification of the source and sink categories for offsetting GHG emissions. However, the application of improved technologies to increase soil carbon sequestration, though limited by saturation and resiliency, could counteract the benefit of carbon sequestration by enhancing the emissions of potent GHGs such as N_2O and CH_4 (Mosier et al., 1998; Six et al., 2004) and these need to be taken into account for mitigation/offsetting.

With reference to the Kyoto Protocol, and accounting rules set out within the Marrakech Accords (UNFCCC, 1998, 2002), it is relevant that revisions to inventory methodology are compatible with the net-net accounting rules. This includes the comparison of emissions and removals during the first commitment period (2008–2012), and the second commitment period (2013 to either 2017 or 2020 to be decided) of the Kyoto Protocol from cropland, grazing land management, and revegetation with the base year (UNFCCC, 2011). Recently, in a number of countries, pedotransfer functions and regression modelling, taking into account soil, land use, drainage, climate, etc. have been used to obtain a more complete and detailed spatial distribution of SOC stocks (e.g. Jones et al., 2004; Meersmans et al., 2008, 2009; Scott et al., 2002; Sleutel et al., 2003; Soussana et al., 2004). However, enormous uncertainty prevails with national SOC stock estimates, and often a description of the vertical distribution of SOC with depth and its spatial variation is lacking. The SOC distribution with depth has been examined either by grouping the measurements into fixed depth increments or by fitting continuous functions to the data (e.g. Omonode and Vyn, 2006). Exponential functions have been widely used (e.g. Hilinski, 2001; Meersmans et al., 2009; Sleutel et al., 2003; Soussana et al., 2004) while logarithmic, power or polynomial functions have also been employed (e.g. Arrouays and Pélissier, 1994; Bernoux et al., 1998; Jobbagy and Jackson, 2000). In line with commitments under the UNFCCC, the Republic of Ireland publishes annual estimates of changes in SOC stock (McGettigan et al., 2010). Due to limited country-specific data (except forestry), the ROI uses the IPCC Good Practice Guidance Tier 1 methodology (IPCC, 1996, 2006) but is committed to achieve Tier 2 or better methodology. In the ROI, previous studies predominantly focused on grassland (Brogan, 1966; McGrath, 1973, 1980; McGrath and McCormack, 1999) and afterwards successful interpolations for SOC values to map the SOC distribution at a finer resolution using coupled geostatistics and GIS techniques was limited to the near surface soil (McGrath and Zhang, 2003; Zhang and McGrath, 2004). Estimates of SOC stocks in the ROI up to now were derived mainly from: national data including Co-ordination of Information on the Environment (CORINE) land cover map; the General Soil Map (GSM); and UK datasets (e.g. SOC concentrations and bulk densities for specific soil types) with limited spatial resolution (Eaton et al., 2008; Tomlinson, 2005). In temperate regions, the differential estimates of SOC density for arable lands have been reported to be 24–43% lower than for grassland (e.g. Lettens et al., 2004; Liebens and Van Molle, 2003; Meersmans et al., 2009, 2011). In the ROI, the previously estimated SOC density difference for 0–30 cm falls within the ranges (13–25%) (Eaton et al., 2008; Xu and Kiely, 2009).

To reconcile the above discrepancies and the lack of information on SOC stocks for disaggregated agricultural land covers and soil types, a more detailed spatial assessment of baseline SOC stocks is required. Data on measured SOC concentrations and bulk densities are required which would reflect the SOC stocks (Gifford and Roderick, 2003; Lee et al., 2009) and combined with modelling and GIS techniques is a suitable technique to estimate soil C stocks of disaggregated agricultural land covers (Cruickshank et al., 2000; Eaton et al., 2008; Tomlinson, 2005; Xu and Kiely, 2009; Xu et al., 2011; Zhang et al., 2011). Recent works (Lewis, 2012; Lewis et al., 2012) show that in a pristine blanket peatland that both the SOC and bulk density remain essentially constant from the 10 cm depth to the bottom of the soil profile (in some cases > 5 m). The objectives of this study were: (i) to collate spatially explicit pedon data and land areas for disaggregated agricultural land covers available in the ROI; (ii) to develop empirical models from measured data to estimate SOC concentrations and bulk densities up to 100 cm depth; (iii) to estimate SOC density (i.e. the product of SOC concentration and bulk density) for selected grid-points of the NSDB using the models (from (ii) above), relating to the Great Soil Groups and Indicative Soil Types; and (iv) to calculate the national SOC stocks, disaggregated into grassland and arable lands using the highest resolution spatial data available.

2. Methodology

2.1. Data acquisition

Data were collated for land cover, land use, soil type and soil organic carbon (SOC) concentration and related properties to estimate the SOC densities (the product of SOC concentration and soil mass per unit area) and thereby stocks (the product of SOC density and land cover area) for disaggregated agricultural land cover classes in the ROI. The approach was to develop empirical models using pedon data available in the ROI and use these to estimate the SOC densities at increments of 10 cm down to 100 cm soil depth. For this, currently available relevant higher spatial resolution maps and databases were acquired. The steps followed a conceptual framework are shown in Fig. 1.

Measured SOC concentration data to a depth of 10 cm were acquired from the National Soil Database (NSDB) of the ROI (Fay et al., 2007). The NSDB is a soil geochemistry database for a total of 1310 fixed sampling sites on the national grid-arrays (10 km × 10 km segment). Land cover at the sampling sites comprised of grassland, arable, forestry, and peat land types. In a later study, measurements of SOC concentration and bulk density (ρ_d) data to a depth of 50 cm were made at 69 selected sites of the NSDB (Kiely et al., 2009). For validation of models, independent but limited datasets on SOC concentrations and bulk density measured recently across soil depths (> 100 cm) in projects of Teagasc (Irish Agriculture and Food Development Authority) were also collated and interpolated to match with soil depths (Diamond and Sills, 2011; Richards et al., 2009). These include soils of county Waterford and of three profiles per location for arable lands (Oak Park only) and grassland (Johnstown Castle and Oak Park). Three data-points under grassland were also taken from the datasets used for model development and the overall number of GSGs under a land cover ranged from 1 to 12 (total 40 data-points).

To integrate the measurement data (Kiely et al., 2009), the CORINE map (a computer-aided visual interpretation of satellite imagery) was initially used to identify land cover classes based on the year 2000 (CLC, 2000; CORINE is managed in Ireland by the Environmental Protection Agency, EPA, Ireland; and the analysis is

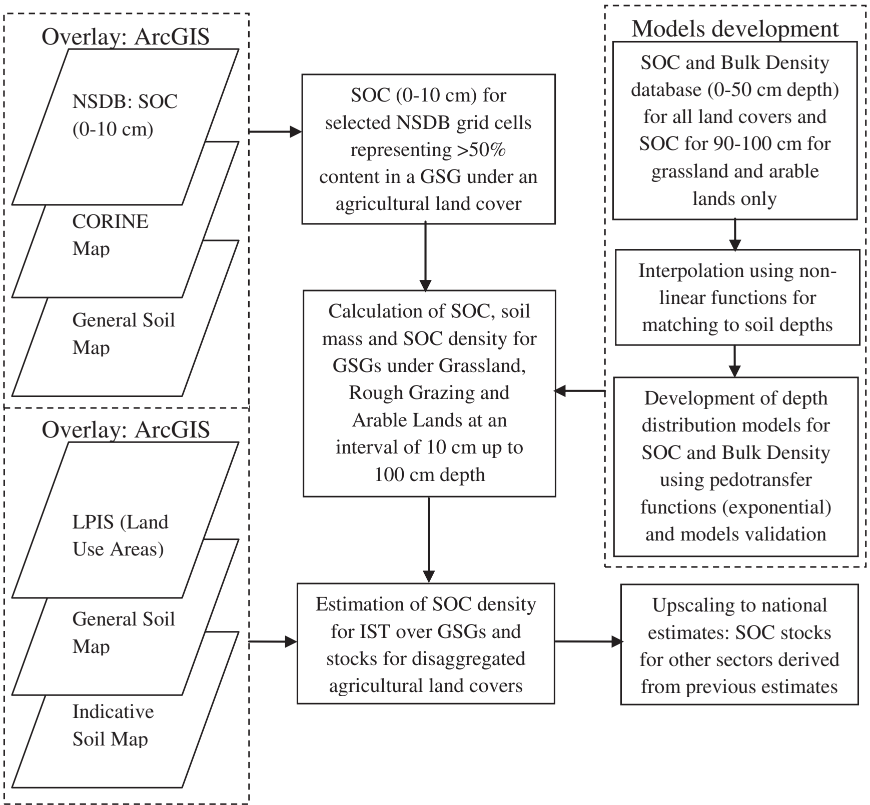

Fig 1. Flow paths of methodologies to estimate organic C stocks in soils under disaggregated agricultural land covers and to develop empirical models using measured pedon data (NSDB = National Soil Database, SOC = Soil Organic Carbon, GSG = Great Soil Group, LPIS = Land Parcel Information System, IST = Indicative Soil Type).

supported by the large volume of ancillary data). The CLC comprises 44 land cover classes, covering agriculture as well as natural habitats and urban areas. We used a subset of land cover classes as devised by Eaton et al. (2008). Agricultural sectors (grassland, rough grazing, arable and heterogeneous agricultural areas/other) were chosen, linking soil attributes to land management that affects SOC. The selected agricultural land covers in combination with ArcGIS (version 10, ESRI, Ireland), a complete Geographical Information Systems (GIS) and Mapping Software System, were used to elucidate SOC contents derived from the NSDB within a land cover and also between the land covers.

The second edition of the General Soil Map (GSM) of Ireland (scale 1:575,000; Gardiner and Radford, 1980) published by the then An Foras Talúntais (currently Teagasc) describes ten Great Soil Groups (GSG), comprising soil associations with variable representations of principal soil type. The NSDB was overlaid on the combined GSM and CORINE 2000 maps to estimate the SOC for a specific GSG under each given land cover. Ten GSGs (Brown Podzolics, Grey Brown Podzolics, Brown Earth, Gleys, Podzols, Rendzinas, Lithosols, Regosols, Basin peats and Blanket peats) predominantly fall within the agricultural land covers. Basin and Blanket peats were merged into one as ‘Peats’ while Regosols were omitted as it holds no agricultural land covers. Based on the similarity/difference in soil physico-chemical properties, the first four and the next three were classified as mineral and organo-mineral soils, respectively. The EPA Indicative Forestry Soils (IFS) map, herein termed as an Indicative Soil Map (ISM), was used to derive a set of Indicative Soil Types (IST) for each combination of land cover/land use and GSGs. In this updated system, the mineral soils are classified on the nature of their parent rock (acid or basic), deep or shallow, and wet or dry. Peats are classified by location, elevation and evidence of human modification.

2.2. Data compilation

In the NSDB, there was a lack of high spatial resolution data, referring especially to disaggregated agricultural land covers and soil types. In this study, we have extended the analysis to better represent the diversity of soil type and vegetation in the landscape. In this analysis, some attention was focused, where certain land uses were assigned to inappropriate soil types, and also where the soil data layers do not agree. For this, the CORINE land cover, the GSM and the NSDB spatial data were imported into ESRI ArcGIS. Buffer zones were defined with a 1 km radius centred on the NSDB sample grid-points as illustrated in Fig. 2. To ensure that the SOC data from the NSDB are representative of the local landscape, only those sites where the GSG and the land cover identified by the NSDB soil survey team with > 50% of the buffer zone were selected for further analysis. This resulted in a subset of 1028 of the total of 1310 NSDB sample points. These included 350 for grassland, 51 for rough grazing, 46 for arable lands and 581 sites for other land cover type. In this analysis, we only consider agriculture land cover types. By adding soil attributes from the GSM, further information on the GSG corresponding to a land cover were recorded. The SOC content (10 cm depth) in the NSDB was used as the only source of accounting its stocks for various land covers (and/or land uses), and GSGs/ISTs.

Kiely et al. (2009) determined both the SOC concentration and the ρ_d up to a 50 cm depth by collecting soil samples at a selected 69 sample points from the NSDB. Values for both parameters were sorted according to land cover and thereafter GSGs within a land cover. Sampling increments between the SOC and ρ_d did not match well; therefore the data were interpolated with soil depth using non-linear relationships down to 50 cm. To reduce uncertainty arising through interpolation, the function fitting analysis was tightly

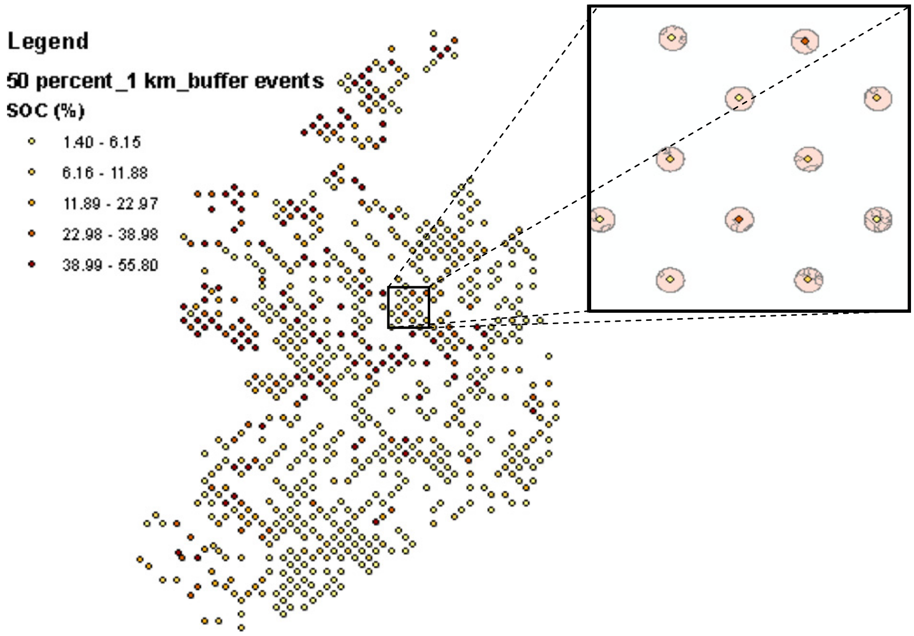

Fig. 2. Selected 1 km buffer zone on Irish National Grid-points representing soil organic carbon (SOC) concentration (%) under a land cover contains a Great Soil Group (GSG) >50% area (zoom box) (Fay et al., 2007).

constrained to be consistent with the original data for SOC and ρ_d of Kiely et al. (2009) at the measurement depths to develop equations to model both SOC and ρ_d.

To estimate SOC_{ref} (baseline) stocks for the disaggregated land cover and soil type (coupled GSGs and ISTs), the Land Parcel Information System (LPIS) database (2004) maintained by Department of Agriculture, Fisheries and Food, Ireland (DAFF) were sorted into two categories: grassland and non-grassland, using ArcGIS. A total of 703,181 grassland polygons were identified and 180,584 non-grassland. These polygons were then integrated with the GSM and ISM, from which an estimate of land areas for all soil types under a land use was derived (Fig. 2). The LPIS database provided a reasonably robust indication of general land use classes, but disaggregation of grassland was poor. The Central Statistics Office (CSO) agricultural statistics were used to address this issue. Areas for disaggregated agricultural land covers were devised as: grassland (Pasture, Rough, Hay, and Silage) and arable crops (Cereals, Roots + Tubers, Oilseed + Forage + Fodder + Silage, and Horticulture + Fruits + others). In the LPIS (2004), a number of typographical errors were corrected within the arable land use by cross-checking with other attribute data such as crop varieties. The total area for grassland acquired from the LPIS was higher (4,333,008 ha) than the area estimated by the CSO (3,881,000 ha). However, it may be that the LPIS data represents the total farm area, whilst the CSO figures reflect active land usage in the year of survey. Also, farmers tend to leave less productive grassland fallow for short periods. The LPIS data does not capture the various grassland use practices, such as silage, hay, and rough grazing areas. This is due to how data are gathered by agencies and how farm surveys were evaluated. The proportions of CSO areas were considered to be more relevant for calculating the disaggregated areas for grassland activities, as the CSO survey explicitly collects data on agricultural usage. The total area of agricultural grassland is best represented by the LPIS analysis which collates high resolution spatial data.

It should be noted that great care is required in the overlay and geostatistical analysis of spatial data of different spatial resolutions. Low resolution data necessarily involves a high degree of spatial averaging and generalisation which can mask heterogeneity visible at higher resolutions. Overlay techniques may yield unrealistic outputs some of which are obvious; for example trees planted in small lakes and other errors may be more difficult to identify.

2.3. Development of empirical models

Empirical models were developed using the extended soil database of Kiely et al. (2009). The SOC concentration and ρ_d with depth up to 50 cm measured were fitted with an exponential function and extrapolated to 100 cm. Data for SOC and ρ_d were arranged according to the GSGs available under the agricultural land covers. Three approaches to develop empirical models were: (i) Soil Type Specific (STS) based either on the mean value of several measurement points or the measured single dataset available, and Land Cover Specific; (ii) the mean value of GSGs under a land cover (LCS-Mean); and (iii) all data points for GSGs under a land cover with removal of some outliers (LCS-All). The rough grazing showed evidence of bidirectional profile of SOC content with depths (Wall and Heiskanen, 1998) and in this case an LCS-mean approach was taken.

SOC contents at depths more than 10 cm were calculated using the empirical models developed from distribution ratios of the measured/interpolated SOC with depth as:

$$z > 10\,\text{cm} : \text{SOC}_z = a\,e^{(-k\times z)} \times \text{SOC}_{z10} \quad (1)$$

Where:

SOC_z	Soil organic carbon content (%) at z depth (from 10 to 100 cm)
a and k	Constants derived from the shape of the exponential part of the curve where 'a' is the initial state and 'k' the scale/depth constant of proportionality.
SOC_{z10}	Soil organic carbon concentration (%) at 10 cm depth from NSDB

Bulk density (ρ_d; g cm^{-3}) is not available from the NSDB. Therefore, empirical models were developed to calculate ρ_d from the pedotransfer function (herein SOC) irrespective of soil type, as:

$$z = 10-100\,\text{cm} : \rho_d = a\,e^{(-k\times \text{SOC}_z)} \quad (2)$$

2.4. Soil mass and SOC density

The SOC data of Kiely et al. (2009) have limited representation of GSGs for a variety of land covers (grassland, rough grazing and arable) and were used for the models development only. The depth distribution models were used to estimate SOC content at the NSDB sample points to 100 cm depth, but tightly constrained by the original 0–10 cm measurement data in each case. Where not available, the SOC contents across soil depths for the ISTs were derived from the values of the respective GSGs. Following the estimation of SOC content across soil depths for each soil type under the agricultural land covers derived from the NSDB, the soil depth (z = cm) was multiplied by Eq. (2) to get soil mass (SM_z, t ha^{-1}) as:

$$SM_z = z \times \rho_d \times 100 \tag{3}$$

Then, SOC content (%) for the respective incremental soil depth (0–100 cm) was multiplied by Eq. (3) to calculate SOC density (t C ha^{-1}), referring to SOCD (soil organic carbon density), for each soil type (GSG versus IST) under the agricultural land covers chosen.

$$SOCD_z = SM_z \times \frac{SOC_z}{100} \tag{4}$$

2.5. Total SOC stocks in disaggregated agricultural soils and national estimates

Total organic carbon stocks (TOCS) for the respective soil type under a land cover were pooled to represent specific reference soil depth (0–10, 0–30, 0–50 and 0–100 cm except for Rendzinas, which is assumed to be 50 cm due to the presence of rocks/gravels below this depth), as:

$$TOCS_{0-100} = \sum_{0}^{100} SOCD(z)dz \tag{5}$$

The TOCS for the disaggregated agricultural land covers were calculated by multiplying the respective areas derived from the LPIS with SOC stocks under a land use for grassland or a group of land use for arable lands using the stocks for soil types under the land cover. For national estimates, the TOCS for other land cover classes were adopted from Eaton et al. (2008). However, comparisons between studies were complicated due to different estimates of land cover areas. For example, Eaton et al. (2008) estimated the arable area, based on CORINE 2000, to be 153,835 ha greater than the estimate based on LPIS used here. Likewise, their grassland area was 550,690 ha less than what we estimate in this study. It can be assumed that these discrepancies are included in the other land cover classes also.

2.6. Statistical analysis and evaluation

An analysis of variance (ANOVA) for significant test of SOC content, its density and stocks (where applicable) among soil type under a land cover and between land cover classes, including for model validation, at 0.05 probability level was performed. In addition to the analysis of the coefficient of variations (CV) to compare the degree of uncertainty for variables within soil groups, two validation indices from the measured and predicted SOC content and bulk density across soil depths were computed. The indices were relative mean errors (RME), which is a measure of the bias of the predictions, and the root mean square error (RMSE), which is a measure for the accuracy of the predictions, follows:

$$\text{Relative mean error (RME)} = \frac{100}{n}\frac{\left(\sum_{i=1}^{n}(Mi-Pi)\right)}{Mt} \tag{6}$$

$$\text{Root mean square error (RMSE)} = \frac{100}{M}\left(\frac{1}{n}\sum_{i=1}^{n}(Pi-Mi)^2\right)^{\frac{1}{2}} \tag{7}$$

Where, Pi is the parameter value to a specific soil depth predicted by the model; Mi is the measured value for the same soil depth, n is number of sample population and $\bar{M}$ is the mean of all Mi values. One test was done to see the degree of closeness of the values simulated by the empirical models developed for accounting SOC content and ρ_d according to Eqs. (1) and (2) to the measured datasets up to 50 cm soil depth. The second aim was to validate the quality of the empirical models developed for the estimation of the two variables up to both 50 and 100 cm soil depth using independent datasets taken from others (Diamond and Sills, 2011; Richards et al., 2009). To test the significance of non-linear functional relationships, the ln-transformed linear bivariate fit (centred polynomial) model was followed. Calculation and statistical analyses were performed in Microsoft Excel Spreadsheet (v. 2010; Microsoft Corporation,) and JMP v.10 (SAS Inc., USA). For overlaying maps and geo-processing of data, ArcGIS version 10 (ESRI, Ireland) was used.

3. Results

3.1. Initial interpolation of measured pedon data and its quality evaluation

Of the 10 Great Soil Groups (GSG), soils sampled from the selected points of the NSDB by Kiely et al. (2009) represented only 7 for grassland, and 4 each GSGs for rough grazing and arable (Table 1). The initial interpolation of data for SOC and ρ_d mismatched across soil depth using non-linear relationships down to 50 cm which proved to be insensitive to both vegetation and GSGs. The SOC fitted well to an exponential function (R^2 = 0.67–0.99; majority > 0.90), whilst ρ_d showed good fit to a natural logarithmic function (ln, R^2 = 0.45–0.99, majority > 0.85) and both were significantly correlated from 0.05–0.001 levels of probability. The above interpolation was followed by the development of models and their statistical evaluations with the measured datasets, follows.

Overall, the 50 cm average standard errors of means across land covers and soil groups were very small (0.02–0.19%/g cm^{-3}). Irrespective of GSGs and land cover/land use, the non-linear functional relationships provided good estimates of SOC up to 50 cm depth (R^2: 0.93 to 0.99; $p \le 0.05$) and ρ_d (R^2: 0.58–0.99, $p < 0.05$), being lowest for the Peats (Table 1). Relative mean errors (RME) demonstrated slightly under- and over-estimations for SOC and ρ_d of the GSGs under both grassland and arable (<1.2%). A huge variation particularly for SOC under rough gazing (0.01–13.04%) was found, with the highest being for the Lithosols, Podzols and Peats. The RMSE were small for both variables under the land covers (0.18–15.11%) excluding the Brown Podozolics and Grey Brown Podzolics under grassland and in all soil groups under rough grazing (22.94–39.18%).

3.2. Development of empirical models to estimate soil organic carbon content

3.2.1. Depth distribution of soil organic carbon and validation of models

The non-linear (exponential) depth distribution models, developed using soil depth ratio functions, fitted well for all GSGs under the agricultural land covers (Table 2). These were confirmed by the R^2 of soil type specific approach, explaining 87 to 99% of the variance (Eq. (1)) at ≤0.05–0.001 levels of significance. The k values (scale constant, cm^{-1}; negative) differed between the GSGs within or between land covers. The models were validated with independent datasets

Table 1
Initial verifications of the simulated values for soil organic carbon (SOC) and bulk density (ρ_d) with measured data up to 50 cm depth used to develop empirical models in terms of relative mean error (RME, %), root mean square error (RMSE, %) and coefficients of determination (R^2) with five as the number of sample (mean/single data point of a GSG under a land cover/use) population.

Soil depth (cm)	Gleys		Podzols		Brown Podzolics		Grey Brown Podzolics		Brown Earth		Lithosols		Peats	
	SOC	ρ_d	SOC	ρ_d	SOC	ρ_d	SOC	ρ_d	SOC	ρ_d	SOC	ρ_d	SOC	ρ_d
Grassland														
SE	0.06	0.06	0.09	0.04	0.10	0.04	0.05	0.02	0.04	0.05			0.03	0.13
RME	0.93	<-0.01	0.68	<-0.01	-0.62	-0.60	-0.38	<0.01	-0.15	0.31			<-0.01	-0.67
RMSE	15.02	3.61	9.49	1.64	27.51	3.24	22.94	2.24	11.20	2.15			0.18	6.67
R^{2*}	0.97	0.96	0.99	0.99	0.90	0.97	0.95	0.99	0.98	0.97			0.99	0.97
Rough grazing														
SE	0.11	0.06	0.13	0.14							0.06	0.07	0.04	0.19
RME	-0.41	<-0.01	-2.07	-6.07							-5.75	<-0.01	0.29	-13.04
RMSE	39.18	10.49	26.87	14.96							26.05	6.88	8.00	38.72
R^{2*}	0.94	0.98	0.95	0.93							0.99	0.98	0.99	0.76
Arable lands														
SE	0.13	0.09		–	0.07	0.03	0.10	0.08	0.07	0.06				–
RME	0.45	0.187			-0.75	<0.01	0.44	<-0.01	0.12	1.11				
RMSE	9.41	1.20			11.26	1.10	15.11	3.36	10.68	3.76				
R^{2*}	0.93	0.97			0.97	0.99	0.94	0.95	0.96	0.96				

SE = Standard error (50 cm average); * Significant at ≤0.05 level of probability

separately for both up to 50 and 100 cm, though limited but covering major soil types, and found to have equal statistical agreements and that extrapolation up to 100 cm soil depth were adopted. The validation resulted mainly for mineral and organo-mineral soil types with an RME of ≤44% (both positive and negative) and RMSE of ≤61%. An exception was for Gleys under rough grazing (the corresponding land use for validation was heath), showing larger bias and low accuracy of the predictions. However, the coefficient of determination was high,

Table 2
Parameters of depth distribution models derived from measured soil organic carbon (SOC) ratio functions to estimate SOC content (%) at lower depths based on its amount at the surface soil (0–10 cm) in the NSDB where SOC ($z \le 10$ cm) = SOC_{z10} and statistical evaluation of the depth distribution models for soil type specific estimates, which are adopted to calculate SOC stocks, using limited independent datasets.

Great Soil Group	Soil Type Specific (STS)		Statistical evaluation for STS			Land Cover Specific (LCS)	
	Equation ($\times SOC_{z10}$)	R^2	RME	RMSE	R^2	Mean	All data points
Grassland§							
Gleys	$1.2653 \cdot e^{(-0.031z)}$	0.99***	-14	53	0.88*	$1.4556 \cdot e^{(-0.037z)} \times SOC_{z10}$	$1.499 \cdot e^{(-0.040z)} \times SOC_{z10}$
Podzols	$1.0769 \cdot e^{(-0.029z)}$	0.87*	32	36	0.99*		
Brown Podzolics	$1.5477 \cdot e^{(-0.039z)}$	0.99***	6	26	0.97*	$R^2 = 0.99^{***}$	$R^2 = 0.76^{***}$
Grey Brown Podzolics	$1.6339 \cdot e^{(-0.045z)}$	0.99***	7	31	0.96*		
Brown Earth	$1.4895 \cdot e^{(-0.035z)}$	0.99***	4	26	0.96*		
Lithosols	$1.9668 \cdot e^{(-0.080z)\ a}$	0.99***					
Rendzinas	$1.2359 \cdot e^{(-0.023z)\ b}$	0.97***					
Peats	$1.4211 \cdot e^{(-0.038z)\ c}$	0.99*					
Sand	$1.3456 \cdot e^{(-0.051z)}$	0.95**					
Rough grazing§§							
Gleys	$1.6975 \cdot e^{(-0.042z)}$	0.98**	-78	128	0.87*	$1.1531 \cdot e^{(-0.020z)} \times SOC_{z10}$	$1.1531 \cdot e^{(-0.020z)} \times SOC^{c}_{z10}$
Podzols	$1.5357 \cdot e^{(-0.046z)}$	0.99***	-12	28	0.97*		
Brown Podzolics	$1.1054 \cdot e^{(-0.016z)\ a}$	0.96***				$R^2 = 0.98^{**}$	$R^2 = 0.98^{**}$
Grey Brown Podzolics	$1.1054 \cdot e^{(-0.016z)\ a}$	0.96***					
Brown Earth	NA						
Lithosols	$1.9668 \cdot e^{(-0.080z)}$	0.99***					
Rendzinas	$1.2359 \cdot e^{(-0.023z)\ b}$	0.97**					
Peats	$1.1457 \cdot e^{(-0.003z)}$	0.95***					
Sand	NA						
Arable lands							
Gleys	$1.2909 \cdot e^{(-0.016z)}$	0.91*				$1.3518 \cdot e^{(-0.021z)} \times SOC_{z10}$	$1.3535 \cdot e^{(-0.021z)} \times SOC_{z10}$
Podzols	NA						
Brown Podzolics	$1.3993 \cdot e^{(-0.023z)}$	0.93**				$R^2 = 0.95^{***}$	$R^2 = 0.83^{***}$
Grey Brown Podzolics	$1.4355 \cdot e^{(-0.025z)}$	0.96**	-44	61	0.94*		
Brown Earth	$1.3217 \cdot e^{(-0.021z)}$	0.98**					
Lithosols	NA						
Rendzinas	NA						
Peats	NA						
Sand	NA						

z = soil depth (0–100 cm); NA = not available; RME = relative mean error (%); RMSE = Root Mean Square Error (%); R^2 = Coefficient of determination; *, **, *** Significant at ≤0.05, 0.01 and 0.001 levels of probability.
§ For grassland: a = derived from rough; b = derived from IFS 12, 22 and 31, representing Brown Earth & peat mineral; c = derived from both grass and peat.
§§ For rough grazing: a = derived from Gleys (IFS 41); b = derived from grassland; c = mean taken due to huge variations.

explaining 87% of the variance, and was significantly correlated ($p<0.05$).

The land cover specific models also showed very high prediction power for SOC with depth ($R^2=0.83$–0.99; $p\leq0.01$–0.001). A comparative study between the soil type specific and land cover specific models demonstrated little variations in SOC within a land cover but some over- or under-estimations for a specific GSG under a land cover was observed (data not shown). Thus, soil type specific models were finally adopted to estimate the SOC concentration (%) to 100 cm using the 10-cm depth values available in the NSDB. Based on the SOC concentration of 0–10 cm depth available in the NSDB, the estimated concentrations (mean) using the depth distribution models (Soil Type Specific) for the acquired GSGs under a land cover varied significantly ($p\leq0.05$–0.001) with depths between soil types within a land cover as well as between land covers (Fig. 3a,b,c).

3.2.2. Bulk density estimates from pedotransfer function and validation

Table 3 shows the soil type specific and land cover specific empirical equations to estimate ρ_d from pedotransfer function (SOC) for individual GSGs within a land cover data (Eq. (2)). Regardless of land covers, the k values varied between the GSGs and the coefficients of determination were greater than 90% of the variance except for the Peats and Rendzinas under grassland/rough grazing ($p\leq0.05$–0.001). Statistical evaluation of the models for the predictions of bulk density from SOC was also performed using independent datasets (Diamond and Sills, 2011; Richards et al., 2009). Irrespective of land covers and soil types, the RME were ≤21% (both positive and negative) and RMSE were ≤22% except for Podzols under rough grazing (45%). The coefficients of determination were also high and significantly correlated ($p\leq0.05$), explaining ≥84% of the variance except for Brown Podzols and Brown Earth under grassland.

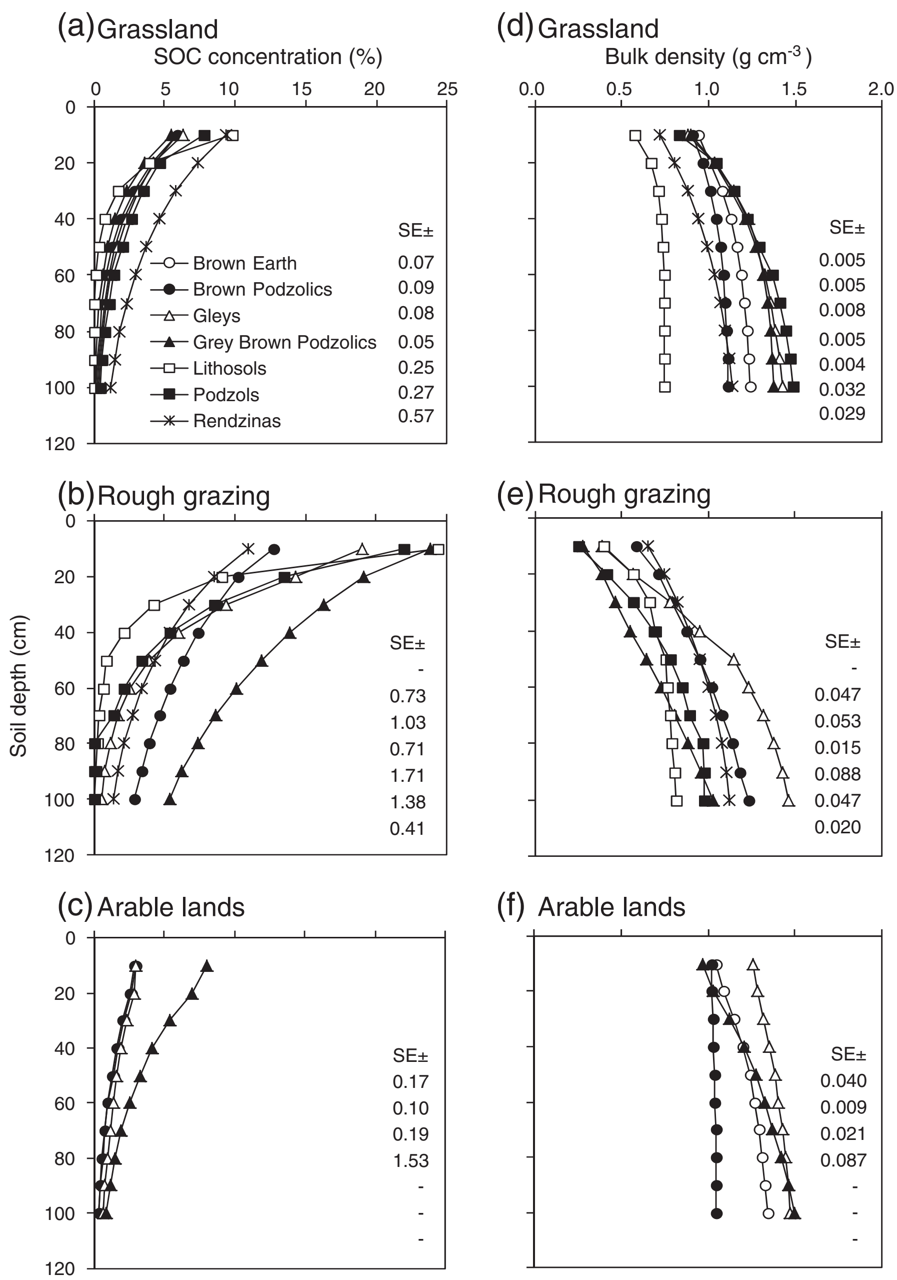

Fig. 3. Estimated (mean) soil organic carbon (SOC) concentration (%) and bulk density (g cm^{-3}) of the Great Soil Groups (GSG) except peats with soil depth under major agricultural land cover/use: (a, d) grassland, (b, e) rough grazing, and (c, f) arable lands. Within GSGs under a land cover/use, the standard error (SE) for SOC content and bulk density is the averaged SE of 0–100 cm profile.

Table 3
Estimate parameters for soil bulk density (ρ_d) derived from measured pedotransfer function [soil organic carbon content (SOC), %] across soil depths and statistical evaluation of the models for soil type specific estimates, which are adopted to calculate soil mass/ SOC stocks, using limited independent datasets.

Great Soil Group	Soil Type Specific (STS)		Statistical evaluation for STS			Land Cover Specific (LCS)	
	Equation	R^2	RME	RMSE	R^2	Mean	All data points
Grassland§							
Gleys	$1.466 \cdot e^{(-0.083 \cdot SOCz)}$	0.99**	10	14	0.87*	$1.3342 \cdot e^{(-0.071 \cdot SOCz)}$	$1.3699 \cdot e^{(-0.076 \cdot SOCz)}$
Podzols	$1.5091 \cdot e^{(-0.81 \cdot SOCz)}$	0.95*	4	6	0.98*	$R^2 = 0.99$***	$R^2 = 0.70$***
Brown Podzolics	$1.1272 \cdot e^{(-0.038 \cdot SOCz)}$	0.93**	4	9	0.68*		
Grey Brown Podzolics	$1.3828 \cdot e^{(-0.082 \cdot SOCz)}$	0.99***	12	14	0.81*		
Brown Earth	$1.2542 \cdot e^{(-0.050 \cdot SOCz)}$	0.99**	18	22	0.74*		
Lithosols	$0.7437 \cdot e^{(-0.027 \cdot SOCz)\ a}$	0.91*					
Rendzinas	$1.2177 \cdot e^{(-0.057 \cdot SOCz)\ b}$	0.85*					
Peats	$1.4045 \cdot e^{(-0.048 \cdot SOCz)\ c}$	0.86**					
Sand	$1.1701 \cdot e^{(-0.313 \cdot SOCz)}$	0.90**					
Rough grazing§§							
Gleys	$1.5232 \cdot e^{(-0.075 \cdot SOCz)}$	0.95**	3	18	0.85*	$1.624 \cdot e^{(-0.064 \cdot SOCz)}$	$1.624 \cdot e^{(-0.064 \cdot SOCz)\ d}$
Podzols	$0.9749 \cdot e^{(-0.067 \cdot SOCz)}$	0.97*	21	45	0.93*	$R^2 = 0.98$**	$R^2 = 0.98$**
Brown Podzolics	$1.5232 \cdot e^{(-0.075 \cdot SOCz)\ a}$	0.97**					
Grey Brown Podzolics	$1.5232 \cdot e^{(-0.075 \cdot SOCz)\ a}$	0.97**					
Brown Earth	NA						
Lithosols	$0.7437 \cdot e^{(-0.027 \cdot SOCz)}$	0.95*					
Rendzinas	$1.2177 \cdot e^{(-0.057 \cdot SOCz)\ b}$	0.85*					
Peats	$1.4045 \cdot e^{(-0.048 \cdot SOCz)\ c}$	0.86*					
Sand	NA						
Arable lands							
Gleys	$1.5257 \cdot e^{(-0.062 \cdot SOCz)}$	0.98*				$1.4018 \cdot e^{(-0.082 \cdot SOCz)}$	$1.6296 \cdot e^{(-0.157 \cdot SOCz)}$
Podzols	NA					$R^2 = 0.98$**	$R^2 = 0.73$***
Brown Podzolics	$1.0454 \cdot e^{(-0.016 \cdot SOCz)}$	0.93*					
Grey Brown Podzolics	$1.6925 \cdot e^{(-0.152 \cdot SOCz)}$	0.97**	−7	10	0.84*		
Brown Earth	$1.4289 \cdot e^{(-0.105 \cdot SOCz)}$	0.99***					
Lithosols	NA						
Rendzinas	NA						
Peats	NA						
Sand	NA						

z = soil depth (0–100 cm); NA = not available; RME = relative mean error (%); RMSE = Root Mean Square Error (%); R^2 = Coefficient of determination; *, **, *** Significant at ≤0.05, 0.01 and 0.001 levels of probability.
§ For grassland: a = derived from rough grazing; b = derived from IFS 12, 22 and 31, representing Brown Earth & peat mineral; c = derived from both grass and peats.
§§ For rough grazing: a = derived from Gleys (IFS 41); b = derived from grassland; c = derived from both grass and peat; d = mean taken due to huge variations.

The model developed by taking the mean values of all GSGs, herein land cover specific (Mean), under the land covers also explained >98% of the variance ($p \leq 0.01$–0.001). Whereas the entire data points under a land cover, herein land cover specific (All), led to a lower predictive power for ρ_d from SOC particularly for grassland and arable land ($R^2 = 0.70$ versus 0.73; $p \leq 0.001$) than by land cover specific (Mean). The estimated ρ_d (mean) using the soil type specific pedotransfer function for the corresponding soil depths of GSGs under a land cover/use varied significantly ($p \leq 0.05$–0.001) between soil types within a land cover as well as between land covers (Fig. 3d,e,f). Finally, the soil type specific empirical models were adopted to estimate soil mass for individual soil types and thereby SOC density for disaggregated agricultural land covers.

3.3. Soil organic carbon density in the Great Soil Groups and its variation

Under grassland, large differences in SOC density up to 60 cm soil depth between the GSGs were detected, being significantly ($p \leq 0.001$) greater in the Peats across soil depths and in the surface and bottom layers of the Rendzinas (Fig. 4a). The Lithosols had higher SOC density but decreased substantially at the deeper layers. There were mostly insignificant variations among the Gleys, Brown Podzolics, Grey Brown Podzolics and Brown Earth. Under rough grazing, the SOC density for the Peats was significantly ($p < 0.001$) higher than others except Lithosols in the surface. For the Lithosols it was higher in the surface soil only though it did not differ significantly with other soil groups (Fig. 4b). The Brown Podzolics and Rendzinas demonstrated higher SOC density in the surface only but varied insignificantly with the Grey Brown Podzolics and Gleys. The Podzols showed values significantly lower from 30 cm downwards than in the other soil types but were statistically identical particularly to Lithosols. Under arable lands, the overall SOC densities were smaller than that under rough grazing and grassland except for the Peats, which were significantly ($p \leq 0.001$) different than other soil groups (Fig. 4c). SOC densities across soil depths were estimated to be higher for the Gleys but did not significantly differ with the Grey Brown Podzolics, Brown Earth and Brown Podzolics.

3.4. Soil organic carbon density for Indicative Soil Type under major land covers

Under grassland, there were considerable variations of SOC densities among the ISTs under a GSG but mismatching of polygons between the two soil classification types, in terms of mineral versus organic soils, was detected (Fig. 5a). Under rough grazing, the organic soils within the ISTs did not contribute to increase SOC densities in mineral soils under GSGs (Fig. 5b). Similarly, the mineral soils falling within Peats represented mainly peaty soils by containing carbon more than it is used to be for the mineral soils. The SOC densities differed among the ISTs but were indistinguishable on an individual basis particularly in terms of organic, organo-mineral and mineral soils. Under arable lands, the number of total ISTs within a GSG was limited and the overlapping of organic versus mineral soil types was found to be small (Fig. 5c). Under arable lands, SOC densities were remarkably high in the Peats though containing a mineral soil but analogous to the amounts accounted for the Peats under the GSGs. Likewise, the cut (peat) falling under the Grey Brown Podzolics estimated similar amount as found for the mineral soils.

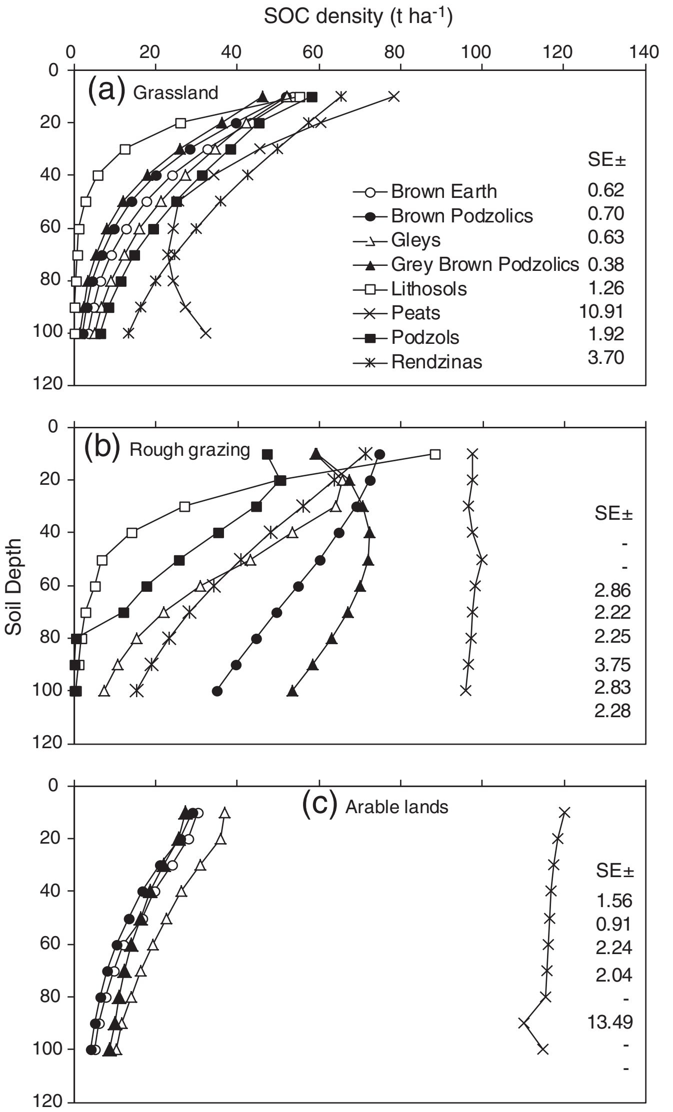

Fig. 4. Estimates of soil organic carbon (SOC) density (tonne per hectare) in the Great Soil Groups (GSG) with soil depth under major agricultural land cover/use: (a) grassland, (b) rough grazing, and (c) arable lands. Within GSGs under a land cover/use, the standard error (SE) for SOC density is the averaged SE of 0–100 cm profile.

3.5. Influence of Peats on SOC density in agricultural land covers

When the SOC values for the Peats were combined with the other soil groups, huge differences between the land covers were found, with coefficients of variation (CV) that ranged between 58 and 163% (Fig. 6a). Rough grazing had the highest SOC density up to 100 cm depth over the other two land covers (grassland and arable) and they varied significantly ($p<0.001$). When the Peat data were removed from the other soil groups, the CVs reduced to 46 and 67% (Fig. 6b). Under rough grazing, the SOC density was again significantly ($p<0.001$) higher throughout the profile than for the other two land cover classes. There was significant ($p<0.001$) variation between grassland and arable lands only at the surface soil. For arable lands, significant ($p<0.001$) increase in SOC density from 70 cm depth downwards over grassland was found. Considering the Peats only, the average of land covers reduced the huge variations to 65% but the SOC density mostly differed significantly ($p<0.001$) across soil depths between land covers (Fig. 6c).

The model-based estimates of SOC density varied significantly ($p<0.001$) and for grassland (on average includes rough grazing and without Peats) it was 52.2, 127.1, 170.9 and 213.8 t ha^{-1} at the 0–10, 0–30, 0–50 and 0–100 cm reference depths, respectively (Table 4). The corresponding amount for arable lands was significantly lower (29.9, 81.3, 117.6 and 167.5 t ha^{-1}). Relative to grassland (land use factor of 1), the SOC references at the 0–30 cm depth of mineral soils under arable are 0.67, corresponding to 40 t C ha^{-1} lower than grassland soils; and under rough grazing is 1.51, corresponding to 62 t C ha^{-1} higher than grassland soils.

3.6. Total SOC stocks in disaggregated agricultural land cover and national estimates

Being the dominant land use under grassland, pasture had a higher SOC stock of 139.4, 332.1, 441.3 and 537.1 Tg at 0–10, 0–30, 0–50 and 0–100 cm soil depths, respectively (Table 5). The nation total in the ROI (the sum of disaggregated grassland) SOC stocks (TOCS) for grassland was estimated to be 246.9, 608.1, 829.5 and 1079.3 Tg at the corresponding soil depth. Cereals being the dominant land use under arable lands had a SOC stock of 10.6 for the 0–10 cm, 28.7 for the 0–30 cm, 40.2 for the 0–50 cm and 52.2 Tg for the 0–100 cm soil depths, which was several times higher than the estimate for other crops (Table 5). The TOCS for arable lands was 13.5 for the 0–10 cm, 36.7 for the 0–30 cm, 50.2 for the 0–50 cm and 67.0 Tg for the 0–100 cm soil depth.

The TOCS for grassland and arable lands were summed with the other land cover classes from Eaton et al. (2008) to calculate national stocks. A TOCS of 888 for the 0–30 cm and 1832 Tg for the 0–100 cm soil depth was found (Table 5). For the complete soil profile that includes peats >100 cm depth (0–100+), using the values from Tomlinson (2005) and Eaton et al. (2008), our estimated TOCS is 2824 Tg. Grassland accounted 68.5% for the 0–30 cm, 58.9% for the 0–100 cm and 38.2% for the 0–100+ cm soil depth of the total national stocks. For arable lands, this amount was 4.1% for the 0–30 cm, 3.7% for the 0–100 and 2.4% for the 0–100+ cm soil depth, and the remaining accounted for other land cover classes.

4. Discussion

4.1. Models developed for the estimation of SOC stocks and their statistical evaluation

The Irish National Soils Database (NSDB) has a reasonably high spatial resolution dataset on Irish national grid-points, enabling the estimation of SOC stocks coupled with empirical and GIS approaches. Depth distribution models based on exponential functions developed using the data of Kiely et al. (2009) perform well, explaining 87 to 99% of the variance. The *k* values (Eq. (1)) can be used to differentiate between the GSGs and between the various land covers. The total difference and bias between measured and simulated values were mostly <61% and highly significantly correlated. This indicates that the models can reliably estimate SOC across soil depths particularly for mineral and organo-mineral soils. Despite the high R^2 (>87%), the large SOC variability for the Gleys under rough grazing specifies that the amount of independent datasets should be land use-specific and large enough to validate a model for this soil type/land cover. The Land Cover Specific models show little variation for SOC within a land cover type compared to the Soil Type Specific models. It is possible to use a single empirical equation to describe SOC. However, this approach does not capture the importance of land cover and soil type, which is in line with observations of Xu and Kiely (2009).

The empirical models developed in this study to estimate ρ_d from the pedotransfer function (SOC) are applicable for the each GSG within a land cover. This is in accordance with the statistical evaluation of the model's predictability that was validated using independent datasets, showing total difference and bias between measured and simulated values were reasonably small (<45%) and highly significantly correlated. It was found that exponential functions provided the best fit to the

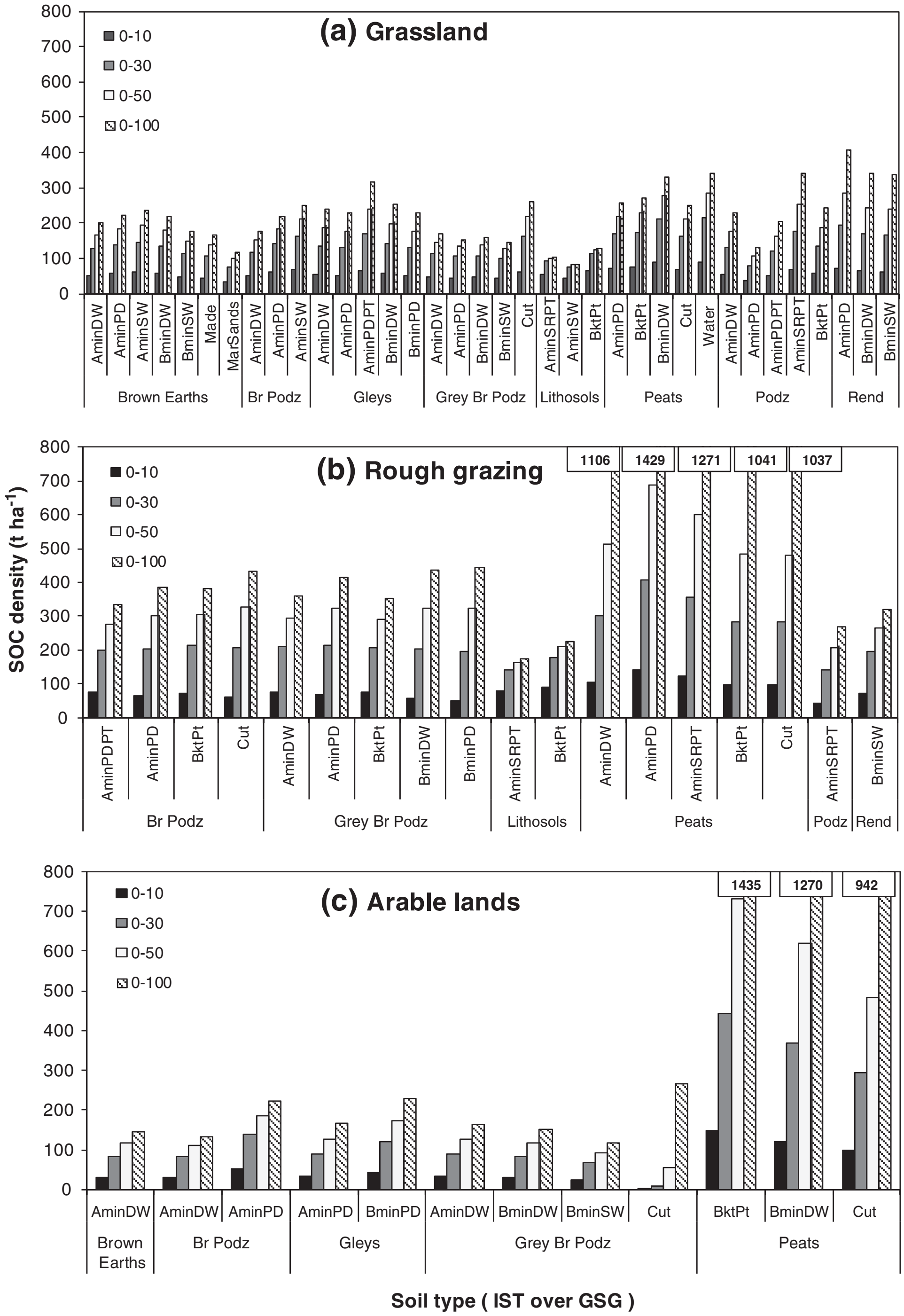

Fig. 5. Comparative estimates of soil organic carbon (SOC) density (tonne per hectare) for the Great Soil Groups (GSG, refers to Table 4) and Indicative Soil Type (IST) with soil depth under major agricultural land cover/use: grassland (a), rough grazing (b) and arable land (c). Br = Brown, Podz = Podzols/Podzolics, Rend = Rendzinas. IST legends (Fay et al., 2007): A = Acidic, B = Basic, min = Mineral, D = Deep, W = Well drained, S = Shallow, P = Poorly, PT = Peaty top, SP = Shallow parent materials, SR = Shallow, rock or gravels, Alluv = Alluvium, MRL = Marl type, Lac = Lacustrine type, Rs = Raised bog, Pt = Peat, Bkt = Blanket, Cut = Cutaway/cutover, Fen = Fen, Scree = Scree, AeoUND = Wind-blown sand undifferentiated, MarSands = Beach sand and gravels, MarSed = Marine/Estuarine sediments, Swamp = Reed swamp/Marsh, Made = Made/built land, Water = Water (including lakes, reservoirs and larger rivers), Unclass = Unclassified).

measurement data. Similar methodological approaches, using either linear or non-linear empirical equations developed using pedon parameters, were implemented elsewhere (e.g. Meersmans et al., 2009; Xu and Kiely, 2009). To minimize uncertainty occurring within a soil type (both GSGs and ISTs) and to better represent a soil type under a land cover/use, the Soil Type Specific models explained more than 86% of the variance, and were adopted to estimate SOC below the surface layers and ρ_s from SOC across soil depths.

4.2. Soil organic carbon density variations across soil types

Analysis based on the GSGs shows that SOC densities in mineral soils (Gleys, Brown Podzolics, Grey Brown Podzolics, Brown Earth and somewhat Podzols) particularly under grassland and arable lands are similar but vary with the amount across soil depths. In a few instances, there is evidence of the existence of organo-mineral soil layers, particularly within Lithosols and Rendzinas. However,

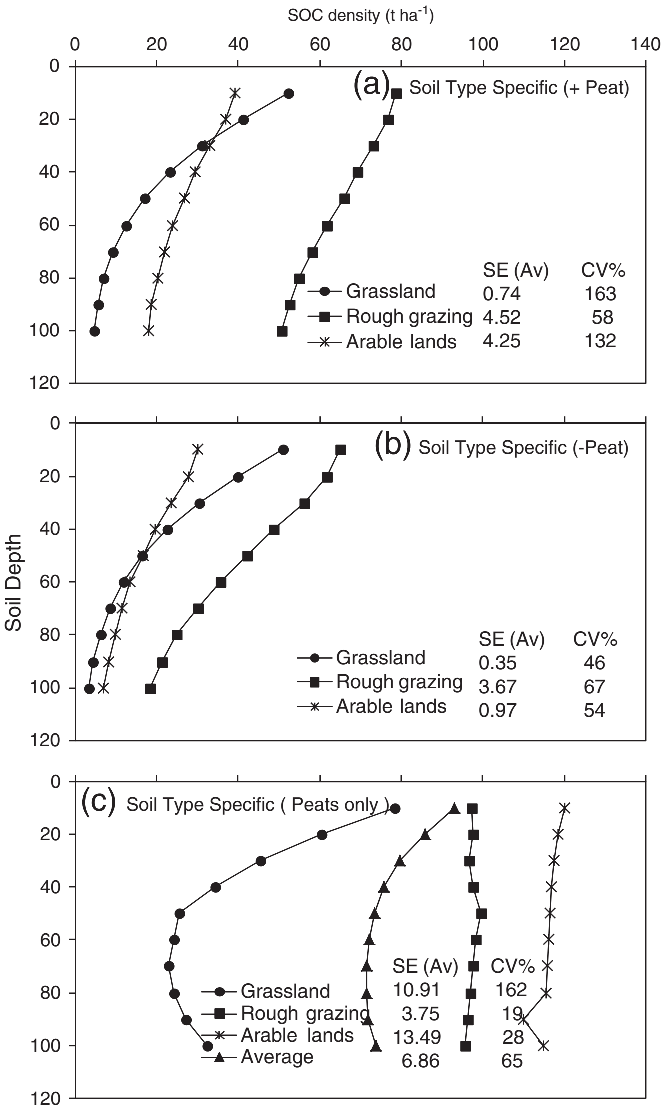

Fig. 6. Estimates of soil organic carbon (SOC) density (tonne per hectare, t ha^{-1}) across soil depths of the major land cover/use containing the respective GSGs with (a) and without peats (b) as well as for peats only (c). Within a land cover/use, the standard error (SE) for SOC density is the averaged (Av) SE of 0–100 cm profile, and the coefficient of variation (CV%) is derived from its density in the GSGs.

influences of particle size distribution, bulk density, elevation and climatic conditions, including rainfall distribution which regulate the degree of decomposition and thereby organic C accumulation in soils, are thought to be important factors for long-term SOC stocks (Meersmans et al., 2009; Smith et al., 2000). Unlike under grassland, the SOC density for the Peats under rough grazing and arable lands is a reasonable estimate. Arable crops are generally not grown on peat soils and that the errors associated with General Soil Map should be corrected through reinvestigation. Despite some variations within the organo-mineral soils under all land covers near the surface layers, most evident in the analysis of rough grazing, the models provide a good estimate of the SOC concentration and thereby density across the soil depths, in line with calculated values for the mineral soils.

The overlay of the high spatial resolution Indicative Soil Map onto the General Soil Map reveals a high degree of variation in SOC content and density. This highlights the importance of the data used for the estimation of the Indicative Soil Map for a particular soil type. However, the mismatching of polygons/grid-points between the two soil classification types, in terms of mineral versus organic soils (particularly peats as cut, Bkpt) associated with mineral soils of a GSG and vice-versa, triggers accounting/representation errors in the SOC densities. By omitting organic soils (cut, Bkpt) and water from the ISTs falling within the GSGs, a higher level of agricultural disaggregation for SOC density across soil depths is found. In general, the SOC density is significantly higher under rough grazing up to 100 cm soil depth than under grassland and arable lands.

A high spatial variability (CV of 50%) for SOC density in grassland compared to arable lands has been reported by Cannell et al. (1999) where soil samplings with depths had a large contribution (Chevallier et al., 2000). In our study, Peats played a major role in uncertainty and that the separate analysis of Peats reduced the CV in analysis of the other soil groups to 28%. The average estimate of three land covers for the Peats, with CV of 65%, may be used for a realistic estimate under the agricultural land covers. The large SOC variability for the Peats under both land covers suggested that it is useful to separate the analysis of peats from other soil types. For best estimates of SOC for the Peats, a large number of sampling sites are required, which to date are limited. However, it would be rational to explicitly consider soil specific estimation so as to reduce the uncertainty due to soil heterogeneity and the impacts of climate and vegetation on it. Our estimate is consistent with the IPCC default values (IPCC, 1996) for the SOC references at 0–30 cm depth of the mineral soils under arable lands relative to grassland (considering land use factor of 1). The factor for rough grazing is higher (1.51) than the "IPCC natural reference = 1" but probably reflects the poor quality high peat content of these low productivity soils.

On average, the SOC density for all soils (excluding peats) under grassland (includes rough grazing) is greater for the 0–10 cm and 0–30 cm (11 versus 4%) but lower for the 0–50 cm (−4%) than the estimates of Xu and Kiely (2009). Considering the 0–30 cm versus 0–100 cm depths, it is 27 and 7% greater than estimates of others (Bradley et al., 2005; Eaton et al., 2008). In this study, the estimated

Table 4
Estimates of soil organic carbon (SOC) density (tonne per hectare) derived from the respective GSGs under grassland, rough grazing and arable lands with and without peats, with standard error (SE) of mean and coefficient of variation (%) in the parenthesis.

Reference soil depth (cm)	SOC density ± SE (t C ha^{-1})			
	Grassland	Rough grazing	Grassland + rough grazing (average)	Arable lands
With peat				
0–10	52.3 ± 0.9c (26)	78.6 ± 2.3a (29)	56.0 ± 0.9b (32)	39.1 ± 2.3d (78)
0–30	124.7 ± 2.7c (29)	228.3 ± 6.7a (28)	139.1 ± 2.5b (39)	109.2 ± 6.7c (84)
0–50	164.5 ± 4.7c (32)	363.4 ± 11.6a (35)	192.5 ± 4.3b (50)	165.6 ± 11.7bc (94)
0–100	204.1 ± 10.9c (60)	641.3 ± 27.0a (52)	265.0 ± 10.1b (85)	268.6 ± 27.3bc (120)
Without peat				
0–10	50.9 ± 0.6b (22)	95.1 ± 2.0a (18)	52.2 ± 0.6b (24)	29.9 ± 1.6c (33)
0–30	121.5 ± 1.7b (25)	183.2 ± 5.5a (17)	127.1 ± 1.7b (28)	81.3 ± 4.5c (34)
0–50	160.6 ± 2.8c (28)	274.0 ± 8.8a (37)	170.9 ± 2.7b (34)	117.6 ± 7.2d (33)
0–100	194.9 ± 4.7c (47)	404.1 ± 15.0a (44)	213.8 ± 4.5b (47)	167.5 ± 12.2c (33)

The mean values followed by the same letter are not significantly different between the land uses.

Table 5
Areas (hectare, ha) and soil organic carbon (SOC) stocks (Tg, Terragram) for disaggregated land use classes under grassland and arable lands derived from Land Parcel Information System (LPIS, 2004) and their total estimates at four reference depths.

Land cover	Disaggregated, grouped land cover/use	Area (ha)		SOC stocks (Tg) at a reference depth (cm)			
		LPIS (2004)	CSO (2004)	0–10	0–30	0–50	0–100
Grassland							
	Pasture	2,476,435	2,218,100	139.4	332.1	441.3	537.1
	Rough	506,318	453,500	33.6	97.9	150.5	240.4
	Hay	211,012	189,000	11.2	27.5	37.4	47.1
	Silage	1,139,243	1,020,400	62.7	150.6	200.3	254.6
Total[a]		4,333,008	3,881,000	246.9	608.1	829.5	1079.3
Arable lands							
	Cereals	319,955	310,100	10.6	28.7	40.2	52.2
	Roots + Tubers	41,054	49,700	1.3	3.6	4.3	6.6
	Oilseed + Foliage + Fodder	30,103	36,900	1.0	2.7	3.6	5.1
	Horticulture + Fruit + Other	18,496	26,100	0.6	1.7	2.1	3.2
Total		409,608	422,800	13.5	36.7	50.2	67.0
Grand total		4,742,616	4,303,800	260.5	644.8	879.8	1146.2

National estimates	SOC stocks (Tg) at a reference depth (cm)		
	0–30	0–100	0–100 + (>100 for peats)
This study[b]	888	1832	2824
Eaton et al. (2008)	728	1469	2437
Tomlinson (2005)	–	–	2021

[a] The proportions of CSO are taken for best estimation of land use classes in the LPIS (2004). For disaggregated CSO under arable, fodder beet is included under Roots and Tubers.
[b] For comparison, land use areas under CORINE 2000 used by Eaton et al. (2008) and Tomlinson (2005) were taken.

amount of arable lands is 34 and 24% lower compared to reference depths estimated by Xu and Kiely (2009) but higher by 8 and 25% compared to the amounts estimated by Bradley et al. (2005). The main reasons of the SOC density differences with ours are most likely the use of a common equation, variable data sources, absence of land cover/use as variables and inclusion of peats/peaty soils in their calculations.

Considering the 0–100 cm depth values, our estimate for grassland (without Peats) is 16% greater than for arable lands, which is similar to the estimated (16%) in Great Britain by Cruickshank et al. (1998) and inclusion of rough grazing raises to 28%. However, our estimate is lower (except for the latter conditions) than the estimates (24–43%) made by others (Lettens et al., 2004; Liebens and Van Molle, 2003; Meersmans et al., 2009, 2011). When peats are included, the estimate for grassland SOC density increased by 14% only at the 0–30 cm but decreased by 1% at the 0–50 cm and by 24% at the 0–100 cm reference depths over arable lands. This again implies that peats must be accounted separately for reliable estimates of SOC density across land covers/use.

4.3. Total SOC stocks in disaggregated agricultural land covers and national estimates

Grassland is the dominant land cover in the ROI and pasture SOC stocks account for 50% of the total grassland stocks, silage (24%), rough grazing (22%) and hay (4%). In comparison with Eaton et al. (2008), our estimates for the 0–30 cm and 0–100 cm depth are 61 and 79% higher. Moreover, our estimates are 38% at the 0–10 cm, 32% at the 0–30 cm and 24% at the 0–50 cm higher than the estimates of Xu and Kiely (2009). A question arises with regard to the placement of land cover ‘Heterogeneous Agricultural Areas/Other’, which is considered as a separate entity derived from CORINE (Eaton et al., 2008). It seems reasonable to place the areas either under grassland considering the amount of stocks provided for arable lands or split it for placement into both the land cover classes. Despite cattle grazing and silage under grassland being the dominant land use, the high amount of SOC in rough grazing was taken into account separately in this study unlike others (Eaton et al., 2008; Xu and Kiely (2009).

In this study, for the first time for Ireland, the higher spatial resolution data (LPIS and ISM) are used to estimate the total SOC stocks for the selected soil depths under disaggregated agricultural land covers. The total areas for grassland and arable lands are representative of the reported data of the Central Statistics Office (CSO). Moreover, the high spatial resolution data for land use areas and soil types to some extent adopted here have advantages over the CORINE map. The estimated national SOC stocks of 888 and 1832 Tg at the 0–30 and 0–100 cm soil depth is considerably higher (22 versus 25%) than previous estimates (Eaton et al., 2008). For the 0–30 cm soil depth, our estimate is slightly lower (2%) than that of Xu and Kiely (2009). Considering the complete soil profile, taking values for other sectors from Eaton et al. (2008), the total SOC stock is 2824 Tg, which is 16 and 40% higher than the estimates of Eaton et al. (2008) and Tomlinson (2005), respectively. The findings of Xu and Kiely (2009) would have advantages mainly in terms of using the measured data over the previous studies. Compared to ours, they have reported similar estimates of the national SOC stocks, lacking information for the 0–100 cm depth. However, the SOC density differences found by Xu and Kiely (2009) between the land cover classes seem unrealistic and might be narrowing future implications of its use in carbon accountings for agricultural soils. In this study, the employed methodological approaches take into account the SOC variations across soil depths, and the estimates of its stocks are consistent with but larger than previous estimates. Thus, the empirical models developed have potential to estimate SOC stocks for disaggregated land use classes and can be adopted to account SOC stock changes in the LULUCF. However, it is worth noting that many variables, soil samplings through interpolation/extrapolation across land use, soil type and climatic conditions, trigger large uncertainty in their estimates and that consistent standard approaches to see the changes over years are critically important.

5. Conclusions

The exponential relationships derived from the measured SOC concentration and bulk density data could provide the best estimates of SOC and ρ_d for mineral and most of the organo-mineral soils. This is supported by the statistical results of RSME. The large variability of

SOC content for the Peats across land covers made it necessary to analyse peat separately from other soil types to minimize the uncertainty. Soil Type Specific models can estimate SOC at depths below the surface layers. Bulk density can then be estimated from the estimated SOC across soil depths with less ambiguity within a soil type and also under a land use. The higher spatial resolution data for land use areas used in this study, providing disaggregated agricultural land covers, have advantages over the CORINE map. Soil disturbances associated with arable lands leads to a lower total SOC stocks than for grassland, having huge potential to offset greenhouse gases from other sectors and/or opportunities to claim carbon credits. The estimated baseline SOC stocks for disaggregated agricultural land covers could be useful for the LULUCF accounting, including the supply of stratified input data for use in any ecosystem models and their verification. Results imply that the methodological approaches of the present study can provide robust estimates of SOC stocks for the development of Tier 2 and thereby for associated land use changes. Further studies should aim to: (i) include soils topography affecting the SOC stocks, and estimate spatial distribution of SOC and develop maps with depth functions; and (ii) quantify land transition factors with data available in the ROI and elsewhere, leading to further refinement of Tier 2 for LULUCF.

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