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Abstract

Spatially explicit knowledge of recent and past soil organic carbon (SOC) stocks in forests will improve our understanding of the effect of human- and non-human-induced changes on forest C fluxes. For SOC accounting, a minimum detectable difference must be defined in order to adequately determine temporal changes and spatial differences in SOC. This requires sufficiently detailed data to predict SOC stocks at appropriate scales within the required accuracy so that only significant changes are accounted for. When de-signing sampling campaigns, taking into account factors influencing SOC spatial and temporal distribution (such as soil type, topography, climate and vegetation) are needed to optimise sampling depths and numbers of samples, thereby ensuring that samples accurately reflect the distribution of SOC at a site. Furthermore, the appropriate scales related to the research question need to be defined: profile, plot, forests, catchment, national or wider. Scaling up SOC stocks from point sample to landscape unit is challenging, and thus requires reliable baseline data. Knowledge of the associated uncertainties related to SOC measures at each particular scale and how to reduce them is crucial for assessing SOC stocks with the highest possible accuracy at each scale. This review identifies where potential sources of errors and uncertainties related to forest SOC stock estimation occur at five different scales—sample, profile, plot, landscape/regional and European. Recommendations are also provided on how to reduce forest SOC uncertainties and increase efficiency of SOC assessment at each scale.

Keywords Forest soils · Carbon stocks · Sampling · Plot · Soil profile · Landscape · National European

Introduction

Soil organic carbon (SOC) is the largest terrestrial car-bon (C) pool (Lal 2008) and plays an important role in the global carbon cycle. Small changes in the SOC pool may affect the carbon budget and the atmospheric CO_2 concentration dramatically (Smith 2008). Forests constitute an important carbon stock at the global scale (Grace 2004; IPCC 2003), with the largest part located in the soil. For temperate forests, the soil/plant C stock ratio may range from 1.2 to 3 (Lal 2005). In European forest ecosystems, soils store roughly 1.5 times more C than trees (De Vries et al. 2003) and the most recent European evaluation estimated up to 2.5 times more C in soils than in tree biomass (De Vos et al. 2015). The soil C stock is, however, an uncertain component in forest C budgets, due to the inherently large spatial variability of forest soils. Additionally, soil C pools are not routinely measured in inventories like stem volume.

Forest soils usually have a higher organic matter content, well developed organic layers, a greater spatial variability than agricultural soils and they typically show more marked variations of SOC with depth (IPCC 2000). These main differences need to be considered when evaluating the C stocks, balance and change of forest soil C (Conant et al. 2003).

The spatial variability of forest SOC content is clear-ly scale-dependent (Goidts et al. 2009). Small-scale spatial variation of SOC results from site-specific topography, drainage, erosion, biological activity, differential lithology and weathering intensities, temporal effects of soil moisture and soil management (Wilding et al. 2000; Ellert et al. 2001; Conen et al. 2004; Kirwan et al. 2005; Saby and Arrouays 2004; Yoo et al. 2006). For instance, litterfall (both aboveground and root litter) and its spatial distribution is one of the key factors responsible for small-scale spatial variability in organic layers and SOC in forest ecosystems (Liski 1995). Since both spatial and temporal variations in the organic layers are known to be high, it is important and challenging to design effective techniques for sampling this layer (Conant et al. 2003). Large-scale variability (e.g. at catchment level) is related to, e.g. topography (Seibert et al. 2007; Griffiths et al. 2009; Webster et al. 2011) and land use (Jian-Bing et al. 2006; Smith 2008; Bárcena et al. 2014; Fernández-Romero et al. 2014).

At regional or national scale, it is necessary to assess the effect of the number of observations and associated soil spatial variability on the detection of possible changes in SOC (Saby and Arrouays 2004; Bellamy et al. 2005, Chamberlain et al. 2010).

Due to the variability and diversity of forest ecosystems as well as the large span in environmental factors and forest management practices, the evaluation of their impacts on soil C quantity and quality is difficult with-out some knowledge on the inherent variability of forest soils. The evaluation of the confidence by which changes in SOC content can be detected is important for the implementation of EC Directives, national treaties, emissions trading schemes and a posteriori validation of predicted changes using models. A better understand-ing of the uncertainties associated with SOC stocks has been recommended in order to improve the forest C accounting and reporting (Cienciala et al. 2010).

According to the IPCC guidelines, countries may apply modelling to their SOC monitoring, but the modelled changes should be verified through repeated measurements of the stock size (IPCC 2003, 2006; Peltoniemi et al. 2007).

In order to improve SOC estimates, surveys are car-ried out per biome (Dixon et al. 1994), climatic zone, vegetation group (Jobbágy and Jackson 2000; Chamberlain et al. 2010), soil group (Batjes 1996) or at a national scale (Vanguelova et al. 2013). The established EU forest monitoring networks (level I and of ICP forests) represent the most detailed and harmonised forest soil surveys in Europe, and data from these have been used recently to estimate C stocks and their variability at European scale (Baritz et al. 2010; De Vos et al. 2015). However, the ability to measure and estimate SOC at different scales, SOC variability and uncertainties and how to control the sources of errors at different monitoring scales are underexposed but crucial for accurate forest soil C monitoring and accounting (Jandl et al. 2014). Further, measuring changes in forest SOC is generally a laborious and costly undertaking, because large numbers of samples are needed to detect relatively small changes in this large, heterogeneous soil C pool (Palmer et al. 2002; Conen et al. 2004). Thus, it is crucial to measure and monitor SOC in forest soils effectively and with sufficient accuracy.

This review evaluates potential sources of errors and uncertainty related to SOC stock estimates reported in the literature from sample to national and European scales (Fig. 1), and provides recommendations for reducing the SOC uncertainties and increasing the efficiency of assessing the SOC under forest at each given scale.

Soil sample scale

At the sample scale, uncertainties in C content include both sampling and analytical error: Field sampling en-compasses issues of (1) sample definition (organic layers, mineral soil horizons) and separation, (2) inclu-sion or exclusion of roots and/or coarse fragments and their diameter thresholds, (3) timing of sampling and (4) handling of samples between sample collection and analysis. Laboratory analysis includes uncertainties related to (1) pre-treatment of samples (e.g. mixing/ drying/sieving/milling/grinding) and (2) bias and preci-sion of different methods for SOC analysis, bulk density and fragment content measurements. Analytical uncer-tainties due to inter-laboratory differences are beyond the scope of this review. We assume the analyses are performed by laboratories with high proficiency that use appropriate laboratory procedures to obtain acceptable accuracy, including elimination of interfering com-pounds such as carbonates.

Sample definition and separation

For the forest floor, uncertainties are related to the sample definition, which should clearly define what is included (e.g. leaf litter, coarse or fine woody debris), and what is excluded (e.g. live roots). There is currently no internationally accepted definition for which dimensions of woody debris are to be included in forest floor samples. Woldendorp and Keenan (2005) suggested a common diameter threshold from 1 to 2.5 cm. Bastrup-Birk et al. (2007), on the other hand, suggested inclusion of woody debris that includes all fractions up to the minimum dimensions for inventories of coarse woody debris, i.e. often a minimum diameter of 5–10 cm.

Organic layers at the mineral soil surface are com-monly sampled separately from the underlying mineral soil, and incorrect separation of these layers is potential-ly a large source of error. Separation between L (fresh and almost undecomposed litter), F (recognisable, but fragmented) and H (humified) litter may be performed in the field, or alternatively in the laboratory by dry sieving where >8, 2–8 and <2 mm represent respectively L, F and H organic fractions (Hoosbeek and Scarascia-Mugnozza 2009). The separation of the different organ-ic layers supports the identification of different humus types, which contain distinctly different SOC qualities. The humus type has a strong relationship with C stocks, spanning from 1 to 2 t ha^{-1} in mull to 70 t ha^{-1} in peaty mor types (Fig. 2; Baritz et al. 2010; Bonifacio et al. 2011; De Vos et al. 2015). Ideally, the organic and mineral soil should be sampled at exactly the same location, in order to avoid double-accounting of the SOC content (Cools and De Vos 2010). When the target is to quantify changes in SOC, estimates should be based on the sums of the organic layers and the mineral horizons to avoid the error associated with the lack of accurate separation between horizons.

Coarse fragments, root volumes and biomass

The presence of coarse fragments (>2 mm) affects the calculation of SOC due to the decrease in the volume of the fine earth fraction. Based on estimates from a large European forest soil survey, the proportional volumetric content of coarse fragments in European forest soils is on average ~20 % (range 0–75 %) and increases with depth (De Vos et al. 2015).

Excavation (gravimetric method) is the only method that provides an appropriate evaluation of the >2 mm fraction. The core method tends to underestimate them because coring cannot sample larger stones and a sys-tematic bias is introduced which depends on the size of the corer (Harrison et al. 2003). Gravimetric methods are precise, but time consuming; therefore, alternative field methods have been developed. Among them, the rod penetration method (Viro 1952) for the estimation of the stone content is widely used in Finland, but the method must be tested and calibrated locally before it can be applied (Baritz and Van Ranst 2006, Cools and De Vos 2010).

Living roots are part of biomass pools, and except for the forest floor raw humus layer (see below), these are normally accounted for and separated from the sample during the sieving phases. Dead roots, on the other hand, are considered to be part of SOC (Soil Survey Staff 2010) and are excluded depending on its size, frequently above 2 mm. In practical terms it may not be possible to totally exclude live roots from SOC, even when spending much time and effort, and this is especially the case for very fine roots (<1 mm diameter) and mycor-rhizal hyphae. The effect of fine root mass on volume and bulk density (BD) has, however, been found to be minimal in forest soils of north-western Italy with root biomass between 0.03 and 2.21 % (n = 100). The influence of their mass introduced a variation in mean BD (core method, see below) from 1.142 ± 0.206 to 1.148 ± 0.206 g cm^{-3} (Bonifacio unpublished). Al-though the presence of coarse roots contributes to a decrease of the soil volume just as other coarse mate-rials, the root volume is difficult to assess and seldom investigated even in forest soils.

Time of sampling, transport and storage

Time of sampling can affect the SOC stocks as both gross primary production and ecosystem respiration, which govern the annual amount of organic C entering SOC stores, are influenced by temporal patterns of precipitation and temperature (Davidson and Janssens 2006; Jungkunst et al. 2008). Topsoil SOC is more sensitive to time of sampling compared to subsoil. For-est floor mass may vary substantially during the year, particularly in ecosystems containing deciduous tree species and conifers that have seasonal litterfall where the litter input is high in late autumn, winter and early spring, and organic matter decreases towards late sum-mer as decomposition proceeds (Vandecasteele et al. 2005). Such annual fluctuations are most pronounced in tree species or at soil types conducive to fast decom-position rates (Vesterdal et al. 2008, 2012). In order to reduce temporal variations especially in the organic layers, sampling is recommended just prior to the onset of litterfall (at minimum forest floor mass) as this en-ables assessment of decomposition constants when an-nual litterfall is known (Vesterdal et al. 2008). At sites with thick, slowly decomposing forest floors, the sam-pling time is of less importance (Hansen et al. 2009); the moisture content at the time of sample collection needs, however, to be taken into account as this may affect compression of the humus layer. For the sampling of mineral soil in soils conducive to fast decomposition rates, sampling activities should be confined to periods with low biological activity, e.g. winter or dry season, based on the aim of the soil C evaluation (Cools and De Vos 2010). Reassessments should be conducted during the same period.

Following the sample collection in the field, samples (in bags, boxes, metal rings, etc.) should not be exposed to open air or sun due to potential water evaporation and increase in biological activity. Short-term storage at 1 to 2 °C prior to analysis is recommended (Cools and De Vos 2010). In case of prolonged storage or transporta-tion time (> 2 weeks), where roots may start to disinte-grate (Vesterdal 2011), freezing of samples is recommended.

Sample pre-treatment

Pre-treatment procedures like sieving, by use of a stan-dard 2-mm sieve (ISO 1994), will most frequently remove roots from mineral soil. As mentioned above, in soil types that have a substantial forest floor where roots constitute a significant part, removal of fine roots from forest floor samples is not a common procedure due to its high cost. Fine root biomass can constitute around 3 t dry weight ha^{-1}, equivalent to about 1.5 t C ha^{-1} depending on tree species and site conditions (Finér et al. 2007). The way roots are handled will thus affect the soil C stocks, as well as the comparison of results between different studies/different countries where the root handling protocols differ. Further, it will affect the uncertainty that this inclusion or exclusion of fine roots represents. When comparing SOC stocks of different surveys, pre-treatment methodological differ-ences need to be identified and evaluated. Further, con-sistent methodologies need to be used in temporal SOC monitoring and studies to identify changes in SOC stocks. Air drying of the soil samples is part of the common pre-treatment procedure prior to analysis, and the pro-cedure does not significantly affect measurements of total carbon (TC) and total organic carbon (TOC) (Blake et al. 2000).

Soil organic C analyses

With the development of new instrumental equipment, common methods for the determination of C concentra-tion have changed from wet-oxidation (Walkley and Black 1934 and variants) to dry combustion (Matejovic 1993) by elemental analysers (TC). To date, the latter is considered as the reference method for SOC analysis. Due to the lack of external heating, Walkley and Black wet-oxidation (WB) typically yield a lower C content relative to TC analysis and a correction factor of 1.32 has been included as part of the method to account for incomplete oxidation. Several studies have shown that the results obtained by the two methods are closely related, with correlation coefficients up to 0.99 in forest soils (Wang et al. 1996; Lettens et al. 2007; Cools et al. 2008; Périé and Ouimet 2008), thus enabling the use of a posteriori correction. A wide range of correction fac-tors from 1.14 to 1.81 has been reported in the literature. A comprehensive analysis by De Vos et al. (2007) on more than 500 Belgian forest soils evidenced that an average correction factor of 1.58 should be applied in order to compare data obtained by the two methods. The highest agreement was found for sandy samples with low contents of organic C (<8 %). Lower agreement has often been reported in clay soils (Lettens et al. 2007; Velmurugan et al. 2009), which may be related to the protection of organic compounds through interactions with the mineral phases (Sollins et al. 1996, Six et al. 2002).

Soil C content has also been estimated from the amount of organic matter quantified directly through the mass Loss on Ignition method (LOI): the sample is heated to a high temperature until its mass ceases to change, and the difference in mass is determined. The correlation between LOI and TOC is similar to that found for WB and TOC, up to 0.99 (Jolivet et al. 1998; De Vos et al. 2005a); however, the ratio between the amounts obtained by the two methods is highly dependent on the LOI temperature range and on the quality of organic matter (e.g. Howard et al. 1998). Thus, the use of a common correction factor is difficult. A general agreement on the temperature is lacking, and LOI in forest soils has thus been measured both at 300 and at 600 °C (Abella and Zimmer 2007). Even if analysed at the same temperature, soils with different mineralogical composition will differ in their TOC/LOI relationship. Because of interferences by mineral com-ponents, the TOC/LOI ratio usually varies with soil depth (Cresser et al. 2007), soil type (Kasozi et al. 2009) and clay contents (Grewal et al. 1991; Komy 1995; De Vos et al. 2005a). In forest floors and peats, with little influence of minerals, the ratios between TOC and LOI has been found to vary between 0.50 and 0.56, with an average of 0.52 for more than 300 samples (Bhatti and Bauer 2002) and 0.57 for 66 forest floor samples (De Vos et al. 2005a). Overall, a conversion factor of 0.50–0.58 of LOI to TOC may be used (Nelson and Sommers 1996, Cools and De Vos 2010; Pribyl 2010). It is, however, important to keep in mind that TOC concentrations derived from LOI data may involve large errors depending on loss-on-ignition-temperature and sample clay content when these numbers are used for C stocks estimates.

Bulk density

Bulk density (BD) allows the transformation of mass-based data arising from laboratory to stock data expressed on a volume basis. Bulk density may refer to the whole soil, including coarse fragments (total BD) or the fine soil <2 mm fraction (fine earth BD). The volume of coarse fragments can either be measured (e.g. liquid displacement or other methods) or calculated (based on the weight and the particle density (2.65 g cm^{-3})). The calculation may not be appropriate for weathered fragments as they have a lower particle density (Corti et al. 1998).

Three classical methods are used to measure soil BD in mineral soil samples: 1) the core, 2) the clod and 3) the excavation method. In the core method, the volume of soil to be weighed is sampled by using a metal ring with a known volume. In the two others methods, the volume needs to be determined. Determinations of BD have relatively low precision, typically ±0.05 g cm^{-3}, which is due to sampling bias as well as natural variability (Skopp 2000). However, the methods differ in their sources of the error: the main source of uncertainty in the core method is an overestimation of the density that may occur if the sample is compressed (Blake and Hartge 1986). There are two types of core methods to determine fine earth BD: the most reliable involves the use of a 100-cm^{-3} volume steel core that is inserted at different depths /horizons within a soil profile. The less accurate is the use of a cylindrical corer to sample soil from the soil surface, due to a potentially larger compression of the soil during this sampling procedure. Vanguelova (2015) found an overestimation of between 1 and 24 % of total C stocks due to soil compaction by use of the latter core method. The compaction may be corrected by recording the depth of the sample in the core as well as the depth of the sampling hole; however, no information will usually be available on which part (top/middle/bottom) of the soil that harbour the largest compression. Both methods consider only fine earth BD. In the soil profile, determination of coarse fraction material (by weight) may be done to obtain total BD. Wirth et al. (2004) suggested, however, that sampling total bulk density with cylinders is only meaningful for soils <10 % stones. The excavation method is more time consuming as it involves determining the volume by filling an excavated area with sand, water, polyurethane foam or any other suitable material. The evaluation of the volume may be a large source of error on sloped surfaces and in the presence of roots and stones. On the other hand, if the excavated volume is large enough, the error will be small and barely affect final soil C stocks. Vincent and Chadwick (1994) recommended at least a 4-L volume of soil for soil with >34 % of coarse fragments and 5–50 L for soils with >54 %. Wirth et al. (2004) also concluded that application of the excavation method was useful for soils up to 50 % stones. In the clod method, the surface of a large ped (clod) is covered with a water-repellent substance (for instance by dipping in paraffin in a container kept at 60 °C) and the volume is determined through liquid displacement. Besides be-ing impossible in loose and coarse textured soils, this method should intrinsically give higher BD than the others as it does not consider the interped space (Blake and Hartge 1986, Van Remortel and Shields 1993).

In organic soil horizons, the soil mass is frequently measured on an area basis where the organic material is collected within a frame of known area (e.g. 25 × 25 cm), and weighed (Cools and De Vos 2010). The bulk density of peat is quite variable (e.g. up to 29 % CV, Vanguelova et al. 2013). As peat shrinks, its BD will increase, and peat bulk density is thus depen-dent on its initial water content. Strongly negative relationships have been found between peat dry bulk den-sity and field soil moisture content (Frogbrook et al. 2009; Vanguelova et al. 2013).

Bulk density is often calculated by Pedo Transfer Functions (PTF) as its measurement is time consuming and the data are not always reported in existing data-bases. PTFs are empirically determined by regression (Jalabert et al. 2010; Martin et al. 2009) and have been derived for a number of forest studies where BD gener-ally has been based on the concentration of organic C only (Callesen et al. 2003; Bonifacio et al. 2008; Périé and Ouimet 2008; Chamberlain et al. 2010; Kobal et al. 2011), and less frequently on additional variables, such as particle size distribution (Bernoux et al. 1998, De Vos et al. 2005b). The estimate of BD in organic soils through PTFs is particularly problematic, and some-times no relationship has been found between bulk density and soil C concentration (Frogbrook et al. 2009; Chamberlain et al. 2010; Vanguelova et al. 2013). In such cases, a better estimator may be the water content of the sample (Frogbrook et al. 2009; Vanguelova et al. 2013). Although the performance of the models may be good when applied to the original dataset or to comparable ones, the fitting often leads to systematic underestimation when used outside its orig-inal range, with mean prediction errors (MPEs) ranging between −0.01 and −0.51 g cm^{-3} (De Vos et al. 2005b). Kobal et al. (2011) showed that using different PTFs could result in stock differences as high as 160 t SOC ha^{-1} which amounted to more than 50 % of total SOC stock in organic-rich soils and up to 100 % of that in mineral soils.

Overall, the application of PTFs increases the variance and uncertainty of estimated SOC stocks if the error associated with the application of the function is not correctly accounted for. This may lead to a system-atic bias of calculated SOC (Smith et al. 2007; Hopkins et al. 2009; Schrumpf et al. 2011). The prediction of SOC stocks may be substantially improved by calibra-tion of the PTF model coefficients with data stratified according to each unique soil type, which was first recommended by Harrison and Bocock (1981) and sup-ported in recent evaluations (Callesen et al. 2003; De Vos et al. 2005b; Kobal et al. 2011). Thus, the verification of PTFs for local conditions/soil type needs to be part of the standard sampling and calculation procedures.

Soil profile scale

A soil profile is generally defined as the body of soil stretching from the soil surface down to bedrock or to a given soil depth. This body of soil may be sampled from the soil surface by use of various types of soil augers, as well as through the digging of soil pits. Uncertainties that may bias the evaluation of changes in C stocks at the soil profile level are mainly linked to the sampling strategy in relation to the vertical soil variability. This involves the total sampling depth that is included in a sampling regime, the variability in soil parameters relat-ed to soil depth and the choice of sampling approach related to genetic soil horizons versus fixed depths layers.

The most used soil augers for sampling soil profile samples are the Dutch augers where incremental soil samples are taken by depth, and core device (e.g. gouge auger) where a whole core is taken and samples are then split per depth. Both devices have their advantages and disadvantages. The Dutch auger may to some extent avoid soil compaction on certain soil types, but there may be soil contamination if care is not taken to clean the auger between each consecutive soil depth sampling. In addition, distinction between soil horizons may be inaccurate and augering depth is frequently more diffi-cult to assess. With the core sampling, soil compaction is likely and will depend on the length of the core and the soil type. There is also depth restriction of the sampling and the method may be unpractical in rocky and very compacted soils. However, if care is taken, both methods can produce similar results in all soil types (Shapiro and Kranz 1992).

Sampling by genetic horizons versus fixed depth layers

Since variability is an intrinsic soil property, it is impos-sible to define one unique depth (upper and lower boundary) per plot for each individual genetic horizon. Even with a fixed depth approach, to follow an ideal fixed boundary for sampling may be problematic: On sloping sites, layer borders can be easily identified on the profile, but in a three-dimensional space the layer border is not perpendicular to the exposed surface and care should be taken that the sample is collected in such a way that it corresponds to three-dimension boundaries. In such cases, augering may not be appropriate, and sampling in soil pits may be imperative.

In principle, the total SOC stocks obtained by sam-pling of soil horizons are identical to those found by the fixed depth approach. This, however, holds only if the total thickness of corresponding layers and horizons are being sampled, and the sample is fully representative of the total volume of soil. If a soil horizon is homoge-neous in terms of morphological, physical and chemical properties, SOC concentration and BD obtained by ge-netic horizons could be transformed into fixed depth value by weighted means.

No general agreement exists on which is the best method to detect changes in OC stocks. Temporal accumulation of soil C in the mineral soil were detected only when soil was sampled by horizon rather than depth in a site-specific long-term temporal monitoring of changes in forest soil C stocks in the UK (Benham et al. 2012). Grüneberg et al. (2010), however, demonstrated that changes in the complete soil profile may be detected much earlier by depth increments rather than by hori-zons. Palmer et al. (2002) found a significant difference between SOC stocks determined by horizons and by depth intervals for the same forest soil, with horizon-based stocks being 22 % lower (for the top 20 cm of mineral soil) than stocks calculated by fixed depth in-crements. According to Ellert et al. (2001), the differ-ences in the results obtained by the two sampling methods are linked to pedoturbation, either natural or anthropogenic.

The large differences (up to 29 %) in the forest floor stocks observed by horizon and fixed depth sampling by Cools et al. (2008) suggest that the ability to distinguish the different organic layers is very important. The same applies for mineral horizons, for example, underestimating the Ah-thickness with 1 cm results in a negative bias of 5.5 t C ha^{-1} on the 1-m SOC stock. The impact generally decreases in deeper horizons, al-though 1 cm delineation error of the Bh horizon in a Podzol, for instance, may affect the overall stock with 2 t C ha^{-1}. Moreover, under- or overestimating 1 cm of peat layer can affect the 1-m SOC stock with ~12.7 t C ha^{-1} (De Vos 2009).

Additional uncertainties arise when the objective is monitoring and assessing C stock changes. With time intervals of 10 years or more, the profile descriptions will most certainly be done on a different profile wall (or even pit) by another soil surveyor (Goidts et al. 2009). Thus, the spatial variability becomes a very important source of variation, whereas the differences due to the use of different laboratory methods might be relatively small in comparison (Cools et al. 2008).

Soil vertical variability

There is a distinct vertical distribution of C in soils. The vertical profile differences in SOC stocks comes primar-ily from the vertical variability in organic matter input to soils from aboveground litterfall as well as belowground turnover of roots. On average for Central and Eastern European soils, Batjes (2002) found that about 44 % of the total C pool down to 1 m soil depth was located within the top 0.3 m of the soil, whereas a corresponding ~55–65 % was measured by De Vos et al. (2015) for European forest soils. The vertical variability of the soil C stock depends on soil type, e.g. from 30 % in Histosols to 65 % in Gleysols (Table 1). The vertical distribution of SOC is controlled by various factors. In reviewing over 2700 soil profiles worldwide covering the global range of climatic zones and range of vegetation types, Jobbágy and Jackson (2000) conclud-ed that vegetation and climate were associated with the source of uncertainty in soil C monitoring and can be minimised only by careful fieldwork (Mäkipää et al. 2012). Defining appropriate sampling depths is essential for accounting purposes, and it has been proposed that a depth of at least 1 m is required to assess SOC stocks (e.g. Young et al. 2005). Kulmatiski et al. (2003) reported that the depth distribution of OC stocks could be well described by an exponential model, even when stones were present. De Vos et al. (2015) used both (1) a log-log depth distribu-tion function that performed best out of five functions tested by Jobbágy and Jackson (2000) and (2) mass-preserving smoothing splines described by Bishop et al. (1999) for SOC stock estimation over the soil profile from the EU forest soil survey large database and found good agreement between them. The spline approach was only found to estimate lower stocks in plots with SOC stocks below 100 t C ha^{-1} but higher stocks for more organic soils (De Vos et al. 2015). Soil bulk density across forest soil types and depths varied between 0.02 and 0.36 g cm^{-3} in the forest floor and between 0.5 and 1.7 g cm^{-3} in high clay content mineral soils in the EU BioSoil survey. No significant differences of mean BD were found with incremental peat depth but BD of mineral soil increased with depth due to decreasing bioturbation and reduced organic matter content (De Vos et al. 2015). In the UK BioSoil survey, the variability in bulk density in the soil profile was highest in peaty gleys/ podzols with averaged bulk density from 0.28 in the top organic soils to 0.71 g cm^{-3} in the mineral subsoil horizons (Vanguelova et al. 2013). The variability of bulk density measured in 75 forested mineral soil plots in Finland was highest in topsoil (0–5 cm; CV of 17–18 %), lower in deeper layers (30–35 cm; CV of 9–14 %) and almost halved in subsoil (60–65 cm; with CV of 8–11 %) (Tamminen and Starr 1994). The use of averaged bulk density for both top and subsoil of deep peats in Wales produced differences of around 40 % in total C stocks, compared to C stocks determined using the measured bulk density at each depth (Frogbrook et al. 2009) adding to the above evidence that depth-specific BD need to be measured for calculating SOC stocks accurately. Most PTFs perform differently when applied to topsoil or subsoil data. Prediction of topsoil bulk density showed the highest prediction error but separate calibration of topsoil and subsoil layers did not enhance the predictive capacity significantly (De Vos et al. 2005b). The distribution of the soil C stock is affected by the vertical distribution of fine root biomass. The root distribution commonly follow an exponentially declining curve with increasing soil depth; from 30 to almost 70 % of total fine root biomass and necromass is allocated in the organic layer and top mineral soil (Makkonen and Helmisaari 1999; Vanguelova et al. 2005). Broadleaved trees generally root deeper than coniferous tree species, and also their fine root biomass is higher than conifers (Finér et al. 2007). Jobbágy and Jackson (2000) reported an effect of vegetation type on vertical distribution of SOC stocks and attributed this to rooting patterns. As mentioned above, the mass of fine roots had minor influence on soil BD in mineral soils, but can be a significant part of the mass of organic matter in organic layers. Thus, SOC stocks reports need to clearly state whether live fine roots have been included or not in the estimated SOC stocks.

Soil plot scale

Plot-level SOC estimates are needed to evaluate the variability between plots, as well as to relate measured SOC stocks and changes to data on C stocks in trees and ground vegetation. Information on the variability is necessary for calculating the statistical confidence for the SOC estimates obtained and for the planning of an effective, cost-efficient and adequate repeated inventory in the future. The plot size is a key for appropriate soil SOC assessments. Generally, the size of a plot needs to be large enough to contain an adequate number of trees per plot, which again vary with forest type and manage-ment. For even-sized stands, the recommended size of a single plot for IPCC assessments may vary between 100 m^2 (for densely planted stands of 1000 trees/ha or more) and 600 m^2 (for sparsely planted stands of multi-purpose trees) (IPCC 2006). Important considerations regarding SOC uncer-tainties at a plot scale are the sampling design, the number of soil samples required to determine a mini-mum detectable difference of SOC between plots over time, analysis of separate or composite soil samples and the scaling up of point data to the plot level.

Soil sampling design

The landscape as well as the trees and the understorey vegetation determine the natural soil variability at the plot level. In most soil inventories, fixed sampling schemes are applied. Examples of plot-level sampling designs are grid model, randomised design, stratified randomised design and variogram-based designs. In soil C inventories, systematic sampling is most commonly applied, since it is effective and easy to implement. However, efficiency of the sampling can be improved and sampling errors reduced with stratification if a priori information on SOC is available. Using random or systematic, strat-ified or non-stratified sampling design, the sampling errors are only random and can be reduced by increasing the sample size. On the other hand, heterogeneous soils require a larger sample size to reach a degree of precision that is adequate for detection of a change by repeated measurements (Mäkipää et al. 2012). General rules for soil sampling in European forests are specified by the ICP Forest Soil Manual (Cools and De Vos 2010) and can be partly adapted for assessments of SOC. This involves soil grid sampling design with sampling points at least 1 m distant from tree stems and avoidance of animal holes and disturbances such as wind-thrown trees and trails. Saiz et al. (2006) intensively studied the spatial heterogeneity of afforested soils which had a high variability due to the mechanical site preparation (ridges and furrows). They concluded that a stratified soil sampling may be more efficient than a systematic approach which may be best suitable for almost all managed forest sites where a specific spatial structure is evident (pits and mounds after wind-throw; stumps after cutting; standing and laying dead logs after fire). The location of a given sampling approach (soil pit, borings, metal frames, collectors) needs to be carefully decided on the basis of the factors responsible for micro-spatial variability such as trees, decomposing logs and slash/woody debris, skidding/hiking trails, seed bed/ planting bed, peat cutting, mounds (tree falls), rock out-crops, drains, relief depressions, etc. The soil pit should be representative for the dominant soil type of the select-ed plot (FAO 2006 recommendations and EU Soil Manual; Cools and De Vos 2010). The sampling should be located where the typical site factors are as natural as possible. This also includes area covering artificial features such as furrows and dams produced after wind-throw or mechanical seed bed preparation. Such micro-topographic features need to be well-reflected by the inventory design (Baritz and Van Ranst 2006). Post et al. (2001) emphasised the importance to recognise spatial patterns in the field when designing a sampling scheme. Further, they found that a repeated inventory by use of a paired sampling approach, where a repeated inventory is conducted at exactly the same sampling locations (plots) as the first one, will help to reduce variability. This has been supported by Heim et al. (2009), who estimated that by replacing an un-paired sampling approach by a paired sampling ap-proach the detection limit of stock changes could be reduced approximately by a factor of four. Based on a detailed study on spatial variability in a forest site, however, Schöning et al. (2006) pointed out that some residual small-scale variability cannot be eliminated even in this way.

Minimum number of sampling points to represent SOC spatial variability at the plot scale

In soil C monitoring, the appropriate sample size is dependent on the sampling interval and the rate of change, as well as on the heterogeneity of the soil C stock (Conant et al. 2003; Smith 2004). A range of 4 to 36 sampling points to represent the spatial variability within a plot (commonly between 0.25 and 0.3 ha in size) have been reported in different studies. De Vries et al. (2000) and Wilding et al. (2000) propose that a set of at least four to six subsamples (mixed into one bulked sample) must be taken in order to represent a pedon. If the variability of the forest floor is considered, the number of required subsamples is even higher. For example, Kirwan et al. (2005), for UK Level II sites, estimated that the required sample density amounts to 25–36 pits (to represent the variability of a 0.3-ha forest plot) with the higher number of pits for topsoil and lower for subsoil due to less variability with soil depth. McNabb et al. (1986) reported 20 samples per 0.25-ha plot to be insufficient to determine SOC stocks in the 0– 15-cm layer within 10 % at the 95 % probability level in mountain forests. Tamminen and Starr (1990) have used 10–30 subsamples depending on organic layer thick-ness. A Flemish test study estimated that three bulk density measurements per layer was not sufficient to cover the within plot variability (0.3 ha), so that at least five core samples per layer were recommended in the EU BioSoil survey (Cools and De Vos 2013). The IPCC (2003, 2006) proposed that litter (forest floor) at plot level can be directly sampled using a small frame (either circular or square, usually about 0.5 m^2) from four subplots within the same plot. An alternative approach for systems where the forest floor is well-defined and deep (more than 5 cm) is to develop a local regression equation that relates depth of the litter to the mass per unit area with at least 10–15 data points collected to ensure that the full range of the litter depth is captured. With a sample size of over 20–30 samples per site, additional soil samples do not notably improve the precision of the mean estimate of organic layer SOC in study sites in Finland (core sampler; Ø = 58 mm) (Fig. 3; Muukkonen et al. 2009). Only a few studies have been successful in detecting changes in soil C in boreal forests on the basis of repeated measurements, and they have involved taking 20–40 samples of the organic layer per site (Berg et al. 2009; Tamminen and Derome 2005). The IPCC procedure recommends to test the soil variability based on nine soil points per plot, each con-taining three sampled depths (0–10, 10–20 and 20– 30 cm) (Baritz et al. 2008). The minimum number of samples needed for a required precision or minimum detectable difference (MDD) of SOC is determined by the use of the approximate formula:

$$n \geq 2\left(\frac{\mathrm{SD}(z_\alpha + z_\beta)}{\mathrm{MDD}}\right)^2$$

where n is the number of samples, SD the estimated standard deviation, z_α the two-sided critical value of the normal distribution at a given significance level α and z_β the one-sided quartile of the normal distribution corresponding to a probability of type II error β (Krebs 1999). The accuracy of the mean estimate increases with the number of samples per plot (Fig. 3; Muukkonen et al. 2009).

Separate or bulk soil samples

All soil samples that represent the same soil layer are often bulked on a plot level to reduce the costs of laboratory analyses, as suggested by the IPCC. These are then mixed and homogenised to make one bulked sample for each depth and plot. These bulked samples should always comprise the same number of subsamples and samples from different soil layers. However, the same number of samples or subsamples to bulk is not always possible if sampling is carried out by diagnostic soil horizon. SOC concentration of samples consisting of bulking from six replicates within each depth increment, sample time and plot were found to be very close to the average values of the six samples analysed individually, and in most cases SOC for the bulked samples fell within the 95 % confidence interval around the mean. SOC for bulked samples was within 5.4 % of the mean of the six replicates in less spatially variable plots, and up to 24.3 % of the mean values for the six replicates in the more spatially variable plots (Conant et al. 2003). Analysis of bulked samples (from 10 samples taken individually) showed a 5 % lower SOC value compared to mean SOC value calculated from the 10 analysed individual samples (Baritz and Van Ranst 2006; Fig. 4a), while comparison of bulked samples analysis (a) (after Baritz and Van Ranst 2006). Comparison of individual and composite measurements of SOC at Level I sites in Germany (Of horizon: n = 6; Oh horizon: n = 5) (after Baritz et al. 2006) (b) (from 5 to 6 samples taken individually) with their individual SOC measurements from organic soil horizons were almost identical (Baritz et al. 2006; Fig. 4b). Analysis of bulked and separate samples in the Italian Alps (Bonifacio unpublished) indicated small differences between bulked and the means of five replicates (e.g. 7.7 % on the average on 104 samples, with higher SOC in bulked samples when SOC concentration was high), but the large variability among replicates, hence the spatial variability of SOC, indicated that even small differences in sample location may hamper the correct evaluation of changes in stocks upon repeated surveys (Fig. 5). These results suggest that analysing bulked soil samples will not substantially impact the final SOC estimates of the plot, so cost efficiency in estimating SOC could be improved by bulking individual samples.

Plot-level SOC upscaling

Important factors for upscaling of SOC to plot level include rock outcrops, tree coarse roots and stumps and the topography of the plot under study. Estimates of rock outcrop in the field have commonly been done by visual assessment. These estimates are prone to er-rors, and in open forests the use of GPS-based tech-niques can yield better estimates. Under dense forest canopies, an alternative is to use intercept line lengths along transects in several subplots, recording the per-centage of total transect which is covered by rock out-crops. This method has been used successfully by O'Connell et al. (2000) in developing site descriptors for forest soil surveys. The volume of tree coarse roots is not commonly taken into account when scaling up soil C at plot scale. However, the spatial and vertical distribution of the vol-ume of stumps and coarse roots could be quantified and taken into account in upscaling of SOC to plot level if resources are available, or volumes could be estimated based on biomass equations for belowground tree bio-mass. Volume and biomass of dead coarse roots is usually estimated allometrically by using coarse root biomass equations based on diameter at breast height (dbh) or stump diameter measurements (Tobin et al. 2007), or more directly by estimating root necromass from stump diameter and time of decay (Melin et al. 2009). The micro-topography features, especially in man-aged forest, which includes artificial features such as furrows and dams, seed bed/planting bed, produced after site preparation, planting or tree windthrow, play an important role in the redistribution of aboveground litter but will also influence the SOC spatial variability due to disturbance. These plot features need to be well-reflected by the sampling plot design for the accurate upscaling of SOC from point to plot scale.

Landscape/regional/national scale

At landscape/regional scales, the interpretation of the analytical data and the way the dataset is stratified is crucial in order to define meaningful strata for which SOC stocks and changes can be estimated with minimal uncertainties, as well as to enable meaningful comparison and integration with other inventories. The scaling up of SOC stocks from plot level to landscape level is also a critical step, and uncertainties are especially re-lated to whether calculations are based on reliable spatial data, appropriate number of sampling plots to reduce strata variability and the application of adequate upscaling methodologies.

Stratification for soil C stocks estimates for national scaling up

Stratification by land use category, soil type, parent material and any distinct grouping where SOC stocks are similar will improve the efficiency of the sampling targeted for SOC monitoring (Post et al. 2001; Baritz and Van Ranst 2006; Häkkinen et al. 2011). Besides regional strata (e.g. climatic regions, clay/loam vs. sandy soils, parent material groups, lowland vs. moun-tainous sites, etc.), management factors may also pro-vide relevant information for stratification—especially in the light of the Kyoto Protocol reporting (Article 3.4, C sequestration from forest management). Factors such as tree species (proportion of conifers), stand age (young vs. old stands), regeneration method (natural regenera-tion vs. clear cutting and planting), disturbance type (fire, storm) as well as ownership (private vs. public) may introduce valuable strata to consider. Stratified sampling by parent material classes, which had a strong effect on SOC stocks in an inventory (27 plots covering an area of 77 ha) of a heterogeneous mountainous forest area in Switzerland, was found to reduce the uncertainty of SOC stock estimates by 45 % (Heim et al. 2009). Soil type is usually closely correlated with parent material, and is more often used for stratification than parent material. Soil type has been found to be the key factor and stratifier explaining the variability in mineral forest SOC stocks in national (Vanguelova et al. 2013) and wider EU BioSoil soil survey datasets (De Vos et al. 2015). For the forest floor, humus type and tree species explained SOC stocks best, whereas in peat soils, parent material was the factor that best ex-plained the SOC storage. In a Flemish study, soil texture and drainage class were found to be the best predictors for C stocks in forest soils (De Vos 2009), thus in this case texture classes in soil and hydrology maps were the most accurate tools for upscaling stocks to the national level. In mountain environments, the controlling param-eters are different: in NW Alps climate characteristics, such as rainfall and elevation, and vegetation (estimated by Normalised Difference Vegetation Index (NDVI)) were the most significant predictors of SOC stocks, but the best results were obtained through stratification by broad forest type and topographic parameters (aspect and slope) accounting for runoff (Oueslati et al. 2013).

Number of sampling plots to reduce strata variability in scaling to regional/national level

Due to the increase in CV% of SOC with increases in landscape variability (Fig. 6, Saby et al. 2008), the recommended number of sampling plots increases with the size of the area under investigation (Table 2, Saby and Arrouays 2004). The efficiency and precision of a survey to detect SOC may be improved by tailoring the number of sample plots for a given soil type to the expected variability in SOC stock for this soil type. For example, the minimum number of sampling plots needed to achieve 10 % CV on soil C stocks for peaty soils in the UK will require 3 to 5 times more plots compared to mineral soils, so a larger effort is needed in order to reduce errors and identify changes in such soil types (Table 3; Vanguelova et al. 2013).

Sampling approach at regional/national scales

The sampling approach for evaluating soil C stocks at national, regional and European level depends on the aim of the given study. Some of the European national forest soil monitoring networks coincide with the National Forest Inventories, which have systematic grid sizes that vary in density (e.g. from 1 × 1 km to 16 × 16 km). The European ICP Forests monitoring network such as Level I/BioSoil (http://icp-forests.net/) uses the systematic large-scale transnational grid of 16 × 16 km for soils and biomonitoring. The level II ICP soil monitoring network, on the other hand, is non-systematic but repre-sentative for the major national forest ecosystems. When randomised non-systematic sampling schemes are applied, this can avoid sampling points (plots) too close to each other and are more flexible than systematic sampling as the sample size in areas with an irregular shape can be adjusted (Stolbovoy et al. 2007). Such a sampling approach may thus be used as a cost-effective estimation method of SOC stocks and changes in areas where systematic sampling is not possible. In addition, schemes that avoid points too close to each other have been found to give a lower variance than simple random sampling (Bellhouse 1977; Bellhouse 1988). A study analysing the regional SOC stocks variabil-ity in the Hainich region in Thuringia/Germany with 89 sampling points distributed across a forested area of 160 km^2 showed that sampling by depth increment is favourable for the detection of regional SOC stocks changes (Baritz et al. 2006). Differences in SOC stocks among soil groups were, however, more pronounced if horizons were considered, which shows that the mixing of soil horizons by fixed depth increments may lead to the loss of important pedogenetic information. Howev-er, variability of regional SOC stocks was less controlled by SOC concentration and bulk density than by soil horizon thickness, which could have major implications for detection of changes in regional C stock. In addition, to detect differences smaller than 10 % of regional SOC stocks, one would need more than 300 A-horizon sam-ples, but if 0–10-cm increments were sampled, less than 100 samples would be sufficient to detect the same difference (Grüneberg et al. 2010). So sampling by depth is still the most cost-efficient, accurate and pre-ferred soil sampling method for estimating SOC stocks and changes. In addition to appropriate sampling design, a consis-tent soil sampling approach needs to be followed when estimating SOC stocks and potential changes at the regional level. As mentioned earlier, the sampling de-sign at the profile and plot level has implications for estimates of SOC stock and changes on a regional, national and European level. This includes the need for accurate measurements of soil thicknesses, the se-lection of a sampling approach by use of fixed depth or diagnostic horizon approach, as well as the design of repeated inventories which may follow a paired sam-pling approach for most accurate SOC change evaluations.

Soil C stocks—upscaling to regional/national level

Two main GIS-based matching procedures can be dis-tinguished which allow the regional assessment of SOC stocks from soil profile data obtained from inventory plots to be scaled up to regional or national level. These are based on soil mapping units and are called geomatching and classmatching (Baritz et al. 2006). The approaches have been applied in various national assessments (Belgium: Lettens et al. 2004, 2005; Germany: Baritz et al. (1999) and other EU countries in CarboInvent: Baritz et al. (2006) and more recent eval-uations (Chapman et al. 2009, Vanguelova et al. 2013)). SOC from geomatching is calculated on the basis of all plots matching a soil mapping unit, or other mapping units used as the regional area basis (Lettens et al. (2004). Classmatching assigns average values to a stra-tum, e.g. soil types. Values in a soil map are then based on all plots representing a certain soil type. While geomatching is very sensitive to plot density and representativeness, classmatching allows representation of large areas with few plots. Classmatching is also applied where the exact location of the sample plots is unknown. The uncertainty assessment for both approaches is difficult. Geomatching has an advantage because it quantifies the standard deviation for the respective soil mapping unit or landscape soil unit. Lettens et al. (2005) intensively investigated the region-al distribution of SOC in Belgium and after applying geo-/classmatching to 289 landscape soil units, 30 % of the landscape units had significantly different SOC stocks in 0–20 cm depth but only 11 % differed for 0– 100 cm. Such findings from upscaling exercises are rather typical. Zirlewagen (2003) found that the larger the soil map polygons were, the higher the coverage by inventory plots. Goidts et al. (2009) found that coeffi-cients of variation increased from 5 % to as much as 35 % in SOC stocks when upscaling from plot to land-scape scales in Belgian soils. Uncertainties in classmatching upscaling related to the precision of soil mapping were illustrated with case studies in Scotland (Morison et al. 2010, 2012) and in Wales (Vanguelova et al. 2012), which identified 11 and 14 %, respectively, landscape upscaling error by which forest soil C stocks differ due to different mapped proportions of soil types by lower resolution soil maps compared to higher reso-lution soil maps. On the other hand, the use of forest maps of different accuracy was the single factor that contributed most to uncertainties (up to 30 %) of the national soil C upscaling when comparing different soil surveys in the UK (Vanguelova et al. 2013). Another scaling up approach is regression-kriging, which is based on a combination of multiple regression analysis and geostatistics. The objective of regression-kriging is to utilise plot inventory and landscape (map) data in a multidimensional way which involves evaluation steps in order to efficiently detect and filter the drivers for SOC accumulation and loss (Zirlewagen 2003). This approach has been applied in many EU countries (Baritz et al. 2006). Relative to the other methods described above, regression-kriging offers the following advantages: (1) analysis of representativeness of the plot inventory, (2) analysis of uncertainties and (3) regional soil C assess-ment, allowing connection to other inventories and allowing the monitoring of management factors which relate to the predictors investigated such as tree species composition and stand age. The strengths of regression-kriging become best visible if high-resolution mapping data are available which reflect the landscape scale predic-tors from the SOC distribution model. If the landscape scale information is less accurate than performed by the regression model (e.g. coniferous and broadleaved forests in mapping data, tree species composition in modelled data), then additional error in the total stock assessment must be considered. Detailed steps in the regression-kriging are described by Baritz et al. (2006). The methodology used for upscaling

SOC at national level should be guided by the level and availability of information. Geomatching needs detailed soil maps and dense soil monitoring plots system, while classmatching needs detailed soil maps but a smaller number of soil monitoring plots, and regression-kriging needs higher resolution environmental datasets at landscape level in addition to soil maps and monitoring plots.

Scaling up to European forest soil C stocks

Although there are estimates of forest SOC stocks at national level and for specific sectorial activities at regional level (e.g. Howard et al. 1995; Liski and Westman 1997; Arrouays et al. 2001; Callesen et al. 2003, Vejre et al. 2003; Bradley et al. 2005; Lettens et al. 2005; Chapman et al. 2009; Chamberlain et al. 2010; Vanguelova et al. 2013), the SOC estimates given at national level are based on very diverse methodolo-gies, which apart from not being generally available with pan-European coverage, hamper any attempts at integrating the results into a harmonised dataset. The European upscaling of forest soil C stocks depends on the availability and quality of soil and forest cover maps and soil C stocks estimates (Fig. 7). EU forest soil estimates so far vary between 3 Pg C (Cannell et al. 1992) and 5 Pg C (Liski et al. 2002) for forest top soil, from 13.7 Pg C (Goodale et al. 2002) to 16.1 Pg C (Smith et al. 2006) for mineral forest soil, and from 22 to 25 Pg (De Vos et al. 2015) up to ~26 Pg C (Jones et al. 2005; Schils et al. 2008) for mineral forest soils plus organic layer. The EU BioSoil survey estimate of 22–25 Pg of SOC (to 1 m depth including forest floor material) reflects the most recent and probably the most accurate European estimate of SOC stock to date (De Vos et al. 2015). In this study, eight different schemes were applied for upscaling plot SOC stocks to the Eu-ropean level. When considering the total SOC stock (soil + forest floor), stratification by soil type led to the highest stock (~25 Pg C), significantly higher than strat-ification by humus form, forest type or tree species. Stratification by country led to the most uncertain esti-mate compared to the other schemes (De Vos et al. 2015). The use of unified EU forest cover map and standardised EU soil map for EU SOC upscaling may significantly reduce the uncertainties in SOC. A summary of the sources of errors and recommen-dations for reducing the uncertainties at sample, profile, plot, landscape/national and European SOC evaluations are summarised in Table 4 and Fig. 7.

Conclusions

This review highlights the importance of different scales for measuring, reporting and controlling the uncer-tainties of forest SOC stock assessments. The uncer-tainties in the data used for estimating SOC quantities depend on the sources of errors associated with the particular scale of evaluation. Common sources of errors which will produce considerable uncertainties in SOC at all scales are the inaccurate measurement and quantifi-cation of soil bulk density, fragment content and not accounting for the full depth of the soil profile. In addition, capturing sufficiently the within-site and between-sites SOC stock variability with adequate num-bers of soil sampling points and numbers of sampling plots is vital for upscaling estimates of SOC at both plot and landscape scales. Using high-resolution and accu-rate soil spatial and forest cover information, in addition to stratification per soil type, will substantially reduce the uncertainties of SOC upscaling to national and con-tinental scales. Variability of SOC could be larger than the expected change in SOC, thus accounting for the uncertainties at a given scale and attempting to reduce them will ensure a more powerful tool for detecting changes in soil SOC. A summary of sources of systematic errors and uncer-tainties in SOC evaluation and considerations/ recommendations for reducing such errors and uncer-tainties at the five scales investigated are summarised in Table 4 and Fig. 7.

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Table 1 Average carbon content and the coefficient of variation by major FAO85 soil grouping as estimated for Europe, the World, France and Central and Eastern Europe by De Vos et al. (2015), Batjes (1996), Arrouays et al. (2001) and Batjes (2002), respectively

FA085G	0–30 cm SOC (t C ha^{-1})				0–100 cm SOC (t C ha^{-1})		
Major	Europe	World	France	C. & E. Europe	Europe	World	C. & E. Europe
Soil group	De Vos et al. (2015)	Batjes (1996)	Arrouays et al. (2001)	Batjes (2002)	De Vos et al. (2015)	Batjes (1996)	Batjes (2002)
Cambisols	75 (0.57)	50 (0.91)	77 (0.57)	69 (0.73)	124 (0.76)	96 (0.77)	118 (0.51)
Regosols	58 (0.80)	31 (1.22)	50 (0.81)	69 (0.51)	89 (1.12)	50 (1.33)	104 (0.31)
Podzols	63 (0.96)	136 (1.01)	80 (0.60)	120 (1.87)	140 (1.35)	242 (0.94)	296 (1.46)
Arenosols	50 (0.77)	13 (1.08)	44 (0.73)	22 (0.62)	102 (1.54)	31 (0.77)	39 (0.71)
Luvisols	73 (0.89)	31 (1.03)	65 (0.64)	50 (0.57)	136 (1.60)	65 (0.78)	91 (0.46)
Leptosols	86 (0.64)	36 (1.28)	–	84 (0.92)	134 (0.84)	–	–
Histosols	181 (0.34)	283 (0.47)	267 (0.78)	221 (0.44)	607 (0.43)	776 (0.47)	729 (0.25)
Gleysols	94 (1.01)	77 (1.09)	–	114 (0.61)	163 (1.41)	97 (1.09)	173 (0.33)
Phaeozems	65 (0.62)	77 (0.53)	–	84 (0.33)	130 (0.59)	146 (0.47)	195 (0.36)
Planosols	45 (0.40)	39 (0.99)	–	58 (0.10)	67 (0.35)	77 (0.56)	108 (0.18)
Fluvisols	64 (0.58)	38 (1.14)	80 (0.61)	89 (1.00)	113 (0.81)	93 (1.36)	219 (0.98)
Andosols	150 (0.26)	114 (0.69)	93 (0.75)	–	310 (0.50)	254 (0.69)	–
Podzoluvisol	65 (0.43)	56 (0.65)	56 (0.75)	49 (0.78)	111 (0.63)	73 (0.43)	83 (0.74)

Table 2 Recommended number of sampling plots depending on the size of the investigated area (Saby and Arrouays 2004)

Size of the area	Number of sampling plots (n)
<5 ha	3
5–10 ha	4
10 25 ha	5
>25 ha	6

Soil type	Minimum number of plots
Surface water gley soils	7
Deep peats	10
Ground water gleys	15
Cambisol	16
Podzol	17
Peaty gleys/podzols	48

Table 3: minimum plots per soil type for 10% CV of the total C stocks per soil type estimated from the UK BioSoil plots (Vanguelova et al. 2013)

Table 4 Summary of sources of systematic errors in SOC evaluation at sample, profile, plot and landscape scales. The sources likely to produce high errors at each scale are highlighted in italics

Sample	• Samples are not homogenised • Different analytical procedures for C applied • *Bulk density is not assessed* • *Coarse fragment volume not assessed* • Separation of soil horizons and layers not done accurately • Inappropriate soil sampling time
Profile	• Sampling by horizon versus soil depth depending on the research aims • *Sampling at not full soil depth to account for vertical variability*
Plot	• *Micro-spatial variability not accounted for (not appropriate sampling strategy)* • Statistical sampling error due to different sampling schemes • Different inventory teams are not harmonised • Lacking quality of the geo-referencing (or the reported values) • *Not adequate numbers of sampling points* • *Bulk density and stone content not analysed* • Analytical (measurement) errors including sample preparation • Missing values, recording and truncation errors • Model errors (e.g. from the selection of inadequate pedo transfer rules or functions. inadequate model constants and conversion factors, etc. not site/soil specific calibrated
Landscape/ National/ European	• Lack of local and regional representativeness of sampling plots • *Important strata are underrepresented (e.g. wet mineral soils or peat soils)* • *Lack of tree species/forest cover maps* • *Lack of accurate soil/hydrology maps* • Landscape insufficient resolution of climatic data

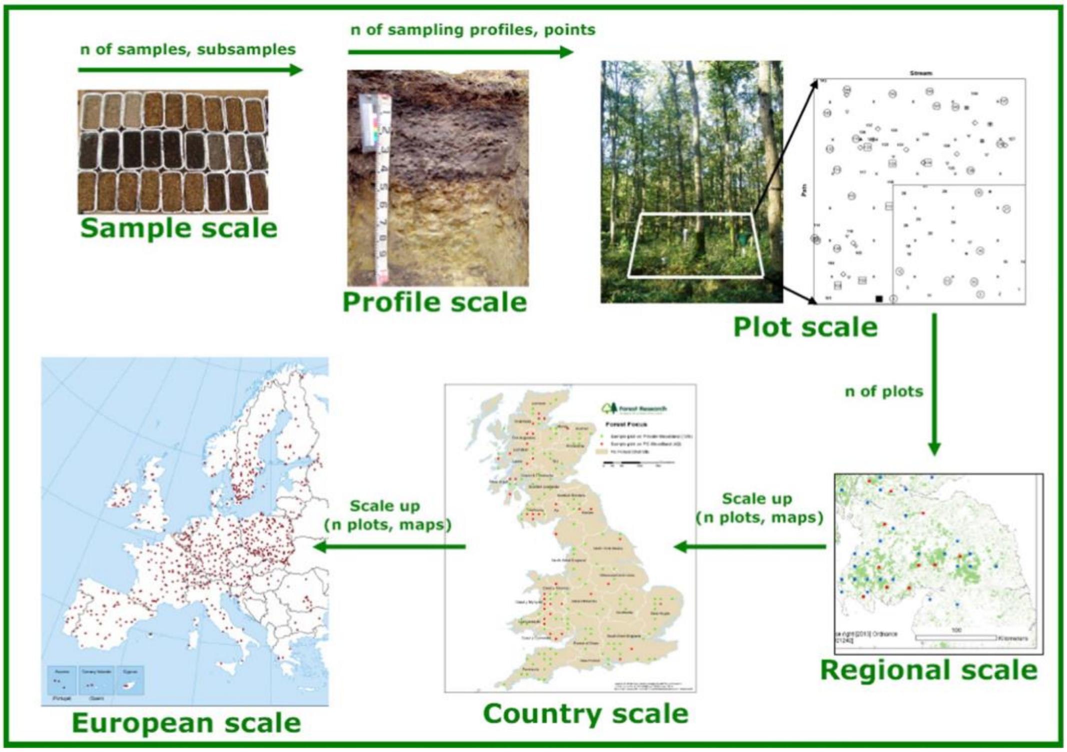
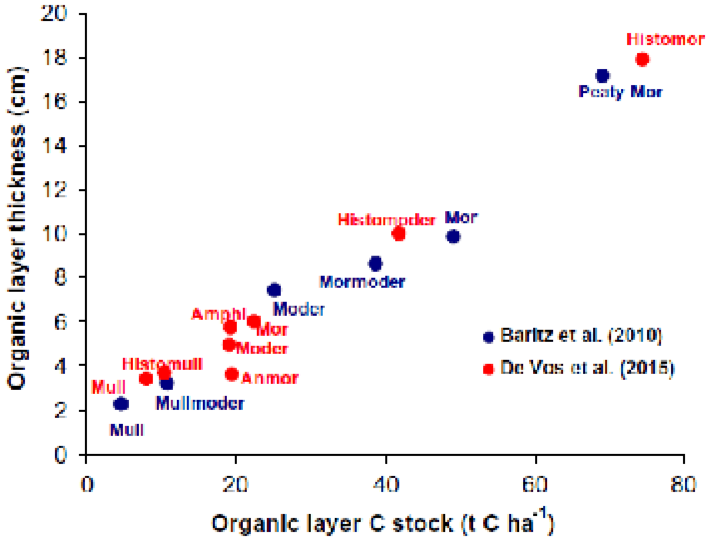


Fig. 1 Schematic overview of different scales used in soil survey work for forest soil carbon monitoring

Fig. 2 Relationship between C stock and thickness of the organic layer in different humus types from EU Level I forest plots evaluation (Baritz et al. 2010) and EU BioSoil survey evaluation (De Vos et al. 2015)



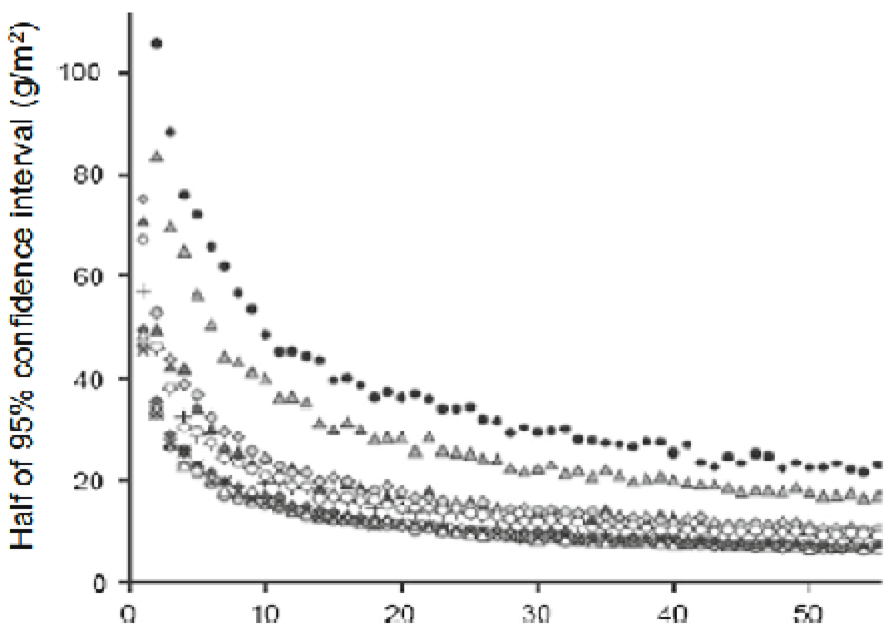


Fig. 3 Confidence intervals of the carbon stock of the organic layer according to sample size for 10 different study sites in Finland (Muukkonen et al. 2009). Different symbols represent the 10 study sites

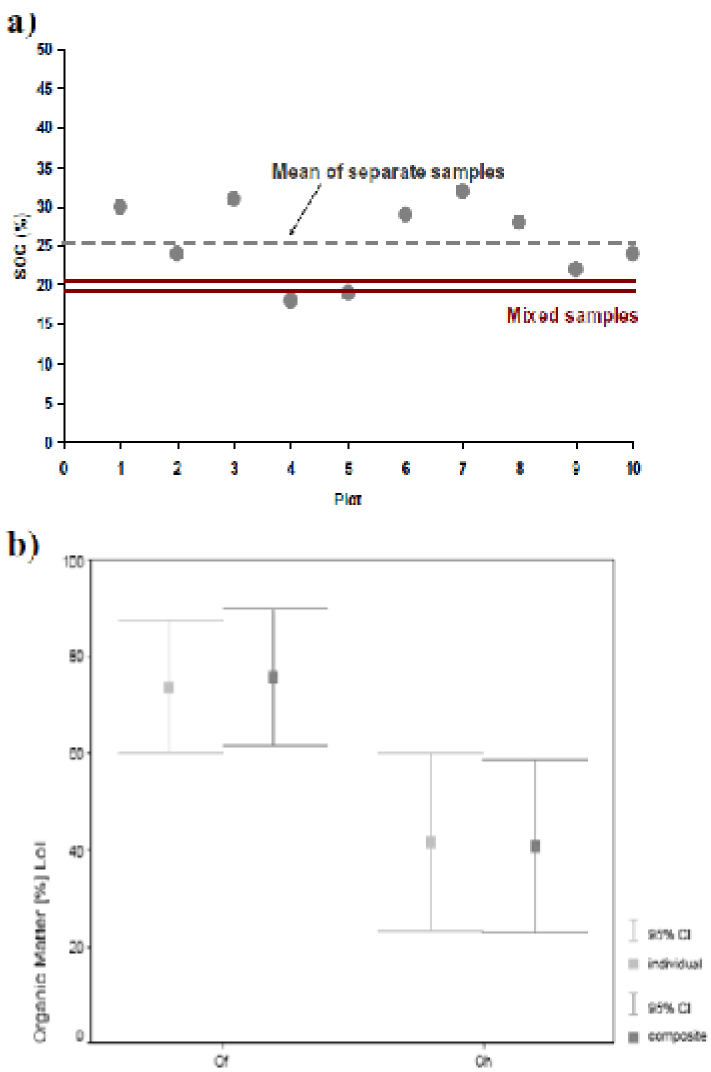


Fig. 4 Spatial variability in 10 m transect soil sampling with samples analysed separately and mean of 10 samples compared to mean of mixed samples

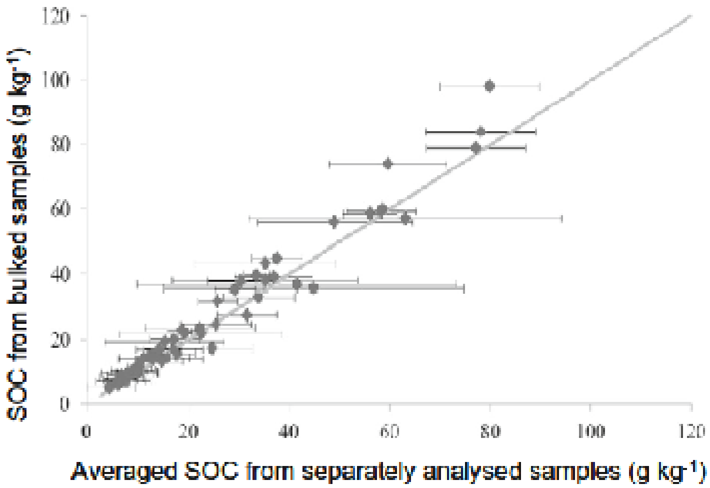


Fig. 5 Comparison of SOC from bulked and separately analysed soil samples from the Italian Alps. The bars represent the min-max range in SOC concentration of the separately analysed samples, the dots are the calculated average SOC values and the solid line shows the 1:1 relation (Bonifacio unpublished)

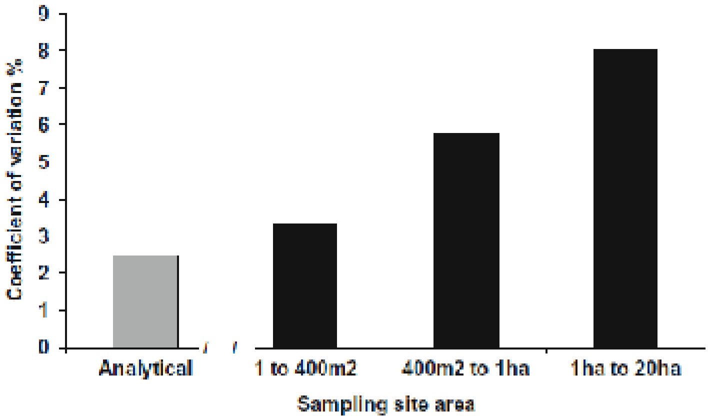


Fig. 6 Median coefficients of variation in SOC concentration according to site area. The analytical value corresponds to the coefficient of variation obtained by multiple analyses of the same sample (Saby et al. 2008)

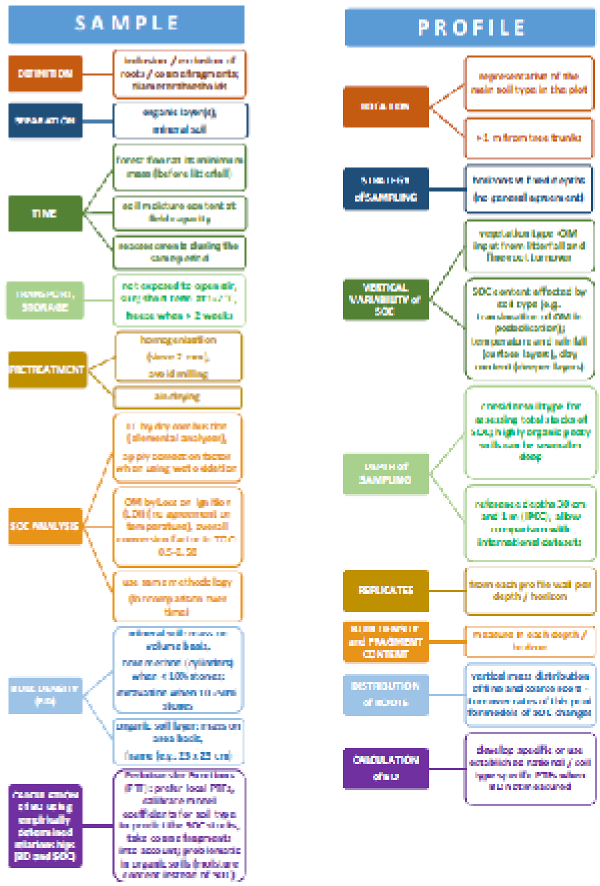

SAMPLE
organic layer(s),
mineral soil
TIME
air-drying
SOC ANALYSIS
PROFILE
REPLICATES

Figure 7: Decision tree to reduce errors and uncertainties in SOC evaluation at sample, profile, plot, regional and continental scales