Science of the Total Environment xxx (2017) xxx–xxx

Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

Assessing top- and subsoil organic carbon stocks of Low-Input High-Diversity systems using soil and vegetation characteristics

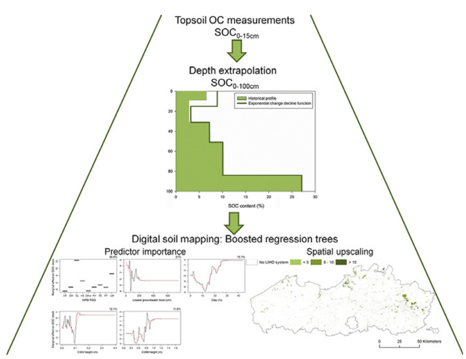
Sam Ottoy [a,*], Koenraad Van Meerbeek [a], Anicet Sindayihebura [a,b], Martin Hermy [a], Jos Van Orshoven [a]

[a] Department of Earth and Environmental Sciences, KU Leuven, Celestijnenlaan 200E Box 2411, 3001 Leuven, Belgium
[b] Department of Earth Sciences, Burundi University, P.O. Box 1550, Bujumbura, Burundi

HIGHLIGHTS

- Limitations in depth and spatial density of soil inventories hamper environmental mapping.
- By combining depth extrapolation with digital soil mapping we estimated top- and subsoil organic carbon stocks.
- Soil and vegetation characteristics were identified as key predictors of both top- and subsoil stocks.
- Subsoil stocks should not be neglected in ecosystem service assessments.

GRAPHICAL ABSTRACT



ARTICLE INFO

Article history:
Received 28 November 2016
Received in revised form 18 January 2017
Accepted 14 February 2017
Available online xxxx

Keywords:
Ecosystem services
Depth extrapolation
Digital soil mapping
Regional assessment

ABSTRACT

The soil organic carbon (SOC) stock is an important indicator in ecosystem service assessments. Even though a considerable fraction of the total stock is stored in the subsoil, current assessments often consider the topsoil only. Furthermore, mapping efforts are hampered by the limited spatial density of these topsoil measurements. The aim of this study was to assess the SOC stock in the upper 100 cm of soil in 30,556 ha of Low-Input High-Diversity systems, such as nature reserves, in Flanders (Belgium) and compare this estimate with the stock found in the topsoil (upper 15 cm). To this end, we combined depth extrapolation of 139 measurements limited to the topsoil with four digital soil mapping techniques: multiple linear regression, boosted regression trees, artificial neural networks and least-squares support vector machines. Particular attention was given to vegetation characteristics as predictors. For both the stock in the upper 15 cm and 100 cm, a boosted regression trees approach was most informative as it resulted in the lowest cross-validation errors and provided insights in the relative importance of predictors. The predictors of the stock in the upper 100 cm were soil type, groundwater level, clay fraction and community weighted mean (CWM) and variance (CWV) of plant height. These predictors, together with the CWM of specific leaf area, aboveground biomass production, CWV and CWM of rooting depth, terrain slope, CWM of mycorrhizal associations and species diversity also explained the topsoil stock. Our total stock estimates show that focusing on the topsoil (1.63 Tg OC) only considers 36% of the stock in the upper 100 cm (4.53 Tg OC). Given the magnitude of subsoil OC and its dependency on typical ecosystem characteristics, it should not be neglected in regional ecosystem service assessments.

* Corresponding author.
E-mail address: sam.ottoy@kuleuven.be (S. Ottoy).

http://dx.doi.org/10.1016/j.scitotenv.2017.02.116
0048-9697/© 2017 Elsevier B.V. All rights reserved.

1. Introduction

The effective and potential level of services that ecosystems provide is increasingly inspiring land use planning (Goldstein et al., 2012; Broekx et al., 2013; Galati et al., 2016). For such mapping and assessments, the soil organic carbon (SOC) stock is an important indicator (Maes et al., 2016). Whereas a considerable fraction of the total SOC stock is known to be stored in the subsoil (Batjes, 1996; Jobbágy and Jackson, 2000) and should not be neglected in an ecosystem service context (Jandl et al., 2014), routinely available measurement data and hence stock estimates are often limited to the topsoil, e.g. see Minasny et al. (2013). To include the subsoil stock, vertical extrapolation of the topsoil measurement is often necessary. However, the commonly used exponential decline function is not capable to accurately model the stock in soil types characterised by SOC-rich subsurface horizons, such as spodic and peat horizons (Sleutel et al., 2003; Aldana Jague et al., 2016). To take these 'anomalies' into account, we have developed an exponential change decline function in earlier research, assuming that not the OC content but rather the difference between the target (2009–2011) and the historical (1947–1974) reference topsoil measurement value declines exponentially with depth (Ottoy et al., 2016).

Another shortcoming of routine soil sampling is its limited and heterogeneous spatial density which is a weak basis for regional SOC stock assessments (Carré et al., 2007; Ottoy et al., 2015). In many cases, soil profiles have been sampled for the major land units (LUs), but are lacking for the many minor LUs. To cope with this lack of data, digital soil mapping or 'SCORPAN' approaches have been proposed which exploit the covariance of a soil variable (s) with predictors representing Jenny's (1941) soil forming factors (climate (c), organisms (o), topography (r), parent material (p), age (a)) extended with geographic position (n) (McBratney et al., 2003). For the case of SOC stock modelling, numerous techniques have been proposed, ranging from multiple linear regression (Meersmans et al., 2008) to more recently developed machine-learning methods like Boosted Regression Trees, Artificial Neural Networks and Support Vector Machines (Martin et al., 2014; Were et al., 2015; Taghizadeh-Mehrjardi et al., 2016).

These SCORPAN-methods do not only contribute to more reliable SOC stock assessments, but also provide insights in the relative importance of the candidate predictors of the SOC stock and hence in the functioning of the soil system. At the biome level, climate variables such as mean annual precipitation and temperature and their interaction with vegetation are important controls of the SOC storage capacity of soils (Jobbágy and Jackson, 2000; O'Rourke et al., 2015). At the regional scale, physical and chemical soil variables like the texture fraction, moisture content, pH and soil profile development are typically identified as variables explaining SOC storage (Meersmans et al., 2008; Wiesmeier et al., 2011; Were et al., 2015). In addition, land use intensity including manure application was found to explain regional variations in the SOC stock (van Wesemael et al., 2010; Parras-Alcántara et al., 2015a; Manning et al., 2015). Another important representative of SCORPAN's 'organism' factor is the vegetation, which can contribute to controlling both soil carbon input and loss (Chapin, 2003; De Deyn et al., 2008) and hence the resulting SOC stock (Grigulis et al., 2013; Manning et al., 2015). Similarly, diversity of plant species (Tilman et al., 2006) and functional groups (Steinbeiss et al., 2008) were found to affect SOC storage.

The aim of this study was to assess the SOC stock in the upper 100 cm of soil of Low-Input High-Diversity (LIHD) systems in Flanders (Belgium) using available topsoil (upper 15 cm) measurements. Managed nature reserves are typical LIHD systems characterised by low levels of inputs (e.g. manure application) and high species diversity. Recently, these systems have come into the picture due to their high potential to mitigate climate change through the production of bioenergy (Tilman et al., 2006; Van Meerbeek et al., 2016), but their SOC storage capacity remained relatively underexplored. To include the subsoil in our regional assessment and spatially densify the available measurements, we combined depth extrapolation of topsoil measurements with digital soil mapping. Additionally, this estimate was compared with the stock found in the topsoil only. Through this process, we aimed at identifying the main predictors of top- and subsoil stocks, considering various soil properties, plant functional traits and trait diversity measures.

2. Material and methods

2.1. Study area

We assessed the SOC stocks in the upper 15 and 100 cm of mineral soil of LIHD systems in the region of Flanders, N. Belgium. This region of 13,522 km^2 is characterised by a maritime temperate climate, with a mean annual temperature of 9.8–10.5 °C (mean minimum of 6.7 °C and maximum of 13.8 °C) and a mean annual precipitation of 733–832 mm (Peel et al., 2007). A pronounced gradient of decreasing sand and increasing silt fractions is present from north to south.

2.2. Soil and environmental data

2.2.1. Soil and vegetation sampling

From 2009 to 2011, 139 sites in nature reserves across different ecoregions were visited and sampled following the procedure described in Van Meerbeek et al. (2014). At each site, a plot of 10 × 10 m was positioned in a homogeneous vegetation patch. Therein three subplots of 0.5 × 0.5 m were randomly selected, forming a composite sample. In each subplot, the topsoil was sampled to a depth of 15 cm. The SOC content (%) was determined using a modified version of the Walkley and Black (1934) method. A correction factor of 1.14 was applied to account for incomplete oxidation (Lettens et al., 2005). Also the aboveground biomass was harvested in each subplot. The SOC content and the dry weight of the harvested biomass were averaged over the three subplots to obtain one value per plot. Furthermore, the cover (%) of each plant species was visually estimated for the subplots.

2.2.2. Plant functional traits and trait diversity

Trait-based diversity indices were chosen to represent the two main classes of effects of biodiversity on ecosystem processes, namely the complementarity effect and the selection effect (Loreau and Hector, 2001). First, the community weighted mean value (CWM) was calculated for each trait in each plot. Weighting was done by the relative abundance (cover, %) of the plant species. CWM corresponds to the selection effect in which dominance by species with particular traits affects ecosystem processes (Loreau and Hector, 2001). Next, the functional dispersion (FDis) index is the weighted mean distance of the species to their centroid in a multivariate trait space (Laliberté and Legendre, 2010), and is an indicator of variability of the trait values in a community. The third trait-based index considered was the community weighted variance (CWV) (Sonnier et al., 2010). It is the weighted variance of trait values with respect to the CWM. Both FDis and CWV are used as proxies for the complementarity effects, in which niche complementarity leads to higher resource use and ecosystem functioning (Loreau and Hector, 2001).

To compute the three selected trait-based diversity indices, we selected twelve functional traits based on their assumed relevance for belowground carbon sequestration (De Deyn et al., 2008; Pérez-Harguindeguy et al., 2013) and extracted corresponding trait values from the TRY database (Kattge et al., 2011). Because of the high percentage of missing values in the trait matrix (41%), we estimated the missing values using a phylogeny with the 'Rphylopars' package of R-software (Goolsby et al., 2016). This package can perform missing data imputation on an estimated evolutionary model, in our case a brownian motion model. The phylogenetic tree used in this analysis was constructed from the dated phylogeny for higher plants of Western Europe (Durka and Michalski, 2012) with the 'Picante' package of