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Spatially-explicit regional-scale prediction of soil organic carbon stocks in cropland using environmental variables and mixed model approaches

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ABSTRACT

The effects of soil redistribution on the carbon (C) cycle and the need for spatially and depth-explicit C estimates at large scales have recently been receiving growing attention. In eroding agricultural landscapes, C gets transported from erosional to depositional landscape elements forming a heterogeneous pattern in quantity and quality of the distributed carbon. At present, methods and research to characterize this horizontal and vertical variability are either limited to local slope scales or, if applied to larger scales, to surface soil horizons with large uncertainties when extrapolated to deeper layers. In this study, we used soil profile data collected in two zones of differing soil texture (loam and clay-rich soils) in Luxembourg, to calibrate a linear mixed-effect model to predict the 3D soil C stock distribution on a regional scale for cropping systems using a set of spatially-explicit hydrologic, climatic, pedologic and geomorphologic variables. We demonstrate that due to a high spatial variability of C stocks it is mandatory to consider various environmental processes to predict C accurately on a regional scale, especially in deeper soil layers, and to avoid simple depth extrapolation of topsoil C data as has been done earlier in flat landscapes. Using estimates of topsoil C contents derived from hyperspectral remote sensing, we predict spatial patterns of C stocks for cropland on a regional scale and provide new insights into the spatial heterogeneity of soil C storage covering a large area. The variability of C stocks in the two texture zones expressed as values larger or smaller than the mean ± standard deviation is hereby lower in the loam zone (26.2%) than in the clay zone (38.7%). We estimate a mean C stock (to 100 cm soil depth) of 9.4 ± 3.1 kg/m^2 for the clay-rich soils and 11.3 ± 2.4 kg/m^2 for loamy soils. This represents the first regional estimate for C stocks for the research area using continuous spatial explicit datasets.

1. Introduction

At large spatial scales (i.e. watersheds, regions and up to continents) the main controls on C stock variability are considered to be climate driven variables such as soil temperature (Davidson and Janssens, 2006; Rustad et al., 2001; Smith et al., 2008) and soil moisture regime (McHale et al., 2005; Thomsen et al., 2003), vegetation and land use (Guo and Gifford, 2002; Li et al., 2012; Rees et al. 2005), land management (Lal et al., 2007; Paustian et al., 1998; Van Wesemael et al., 2010) as well as mineralogical and pedological factors (Guo et al., 2006; Torn et al., 1997). At these scales, the effect of topography on C storage variability is usually not considered (e.g. Batlle-Aguilar et al., 2011; Goidts et al., 2007, 2009; Lettens et al., 2005). The representation of the horizontal and vertical patterns of soil C in current assessments is typically informed by data from stable, non-eroding landforms. Nevertheless, topography can have a strong influence on the local microclimate and -hydrology (Burt and Butcher, 1985; Kang et al., 2000, 2003; Schwanghart and Jarmer, 2011). It has further been demonstrated that through control on erosion processes, topography is a key control on the vertical and spatial distribution of soil organic carbon (C). In sloping landscapes, erosion and deposition processes lead to temporally and spatially dynamic patterns of C stocks and also alter the quality of soil C. In environments with high soil redistribution rates such as agro-eco systems, soils can then (i) exhibit a large variability in C quantity due to the burial of C rich topsoil material at colluvial foothill sites and C depletion at eroding slope positions due to the removal of C rich soil layers (De Gryze et al., 2008; Gregorich et al., 1998; Heckrath et al., 2006; Nadeu et al., 2012; Quine and Zhang, 2002; Schwanghart and Jarmer, 2011; Van Oost et al., 2005; Vandenbygaart et al., 2012; Wang et al., 2010) and (ii) affect C quality and C turnover in soils (e.g. Berhe, 2012; Berhe et al., 2008, 2012; Doetterl et al., 2012; Rumpel and Kögel-Knabner, 2011). However, the relationship between topography and patterns of C storage has

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generally been investigated at the scale of individual slopes, and the interaction of biogeochemical soil and C properties (von Lutzow et al., 2006) and environmental controls for C stability are complex and highly variable (Dungait et al., 2012). As a result, the importance of this small-scale variability induced by topography-related processes for a larger-scale C storage assessment is unclear.

Recent advances in remote sensing make it possible to acquire large amounts of spatially explicit information on soil properties including C concentration covering large areas at a relatively low cost (Cécillon et al., 2009; Mulder et al., 2011; Viscarra Rossel and Chen, 2011). Using hyperspectral airborne sensors and a set of local field calibration data, large areas of bare land (such as recently seeded croplands) can be measured resulting in maps of soil C contents across various soil types and landforms (e.g. Gomez et al., 2008; Stevens et al., 2010). However, when data are acquired using air or space-borne platforms, the signal represents surface properties alone at lower accuracy (RMSE ~3–4 g C kg^{-1}) than lab-based reference methods. Such applications cannot provide information on C contents below this layer and observations of soil C depth distributions are generally sparse on a regional scale. These limitations lead to high uncertainties (±30%; Meersmans et al., 2009a,b) associated with the estimation of regional *three-dimensional* C distributions. Recent studies have shown the potential of mapping approaches for subsoil C predictions, where sparse C depth profiles are complemented by more dense secondary attributes that can be derived from available DEM data or soil maps to extrapolate topsoil C information for C predictions at greater depths (e.g. McKenzie and Ryan, 1999; Meersmans et al., 2009b; Mishra et al., 2010; Schwanghart and Jarmer, 2011; Zhang et al., 2012). In many cases, the mapping of C stocks is the main objective and it remains unclear (i) how explanatory variables are linked to environmental processes affecting the C distribution, (ii) what is the specific importance of these variables for the prediction of C and (iii) at what spatial scale these variables have to be considered.

In this study, we address this gap between spatially explicit C stock assessments and process understanding at larger scales. We present a pilot-study that aims to identify variables that can be linked to environmental processes controlling the 3D C distribution in cropland at a regional scale. These variables are then ranked according to their explicative power and used for the prediction of spatially explicit C stocks. First, we collected field samples for a region of 500 km^2 in Luxembourg which we used to construct a vertically explicit C database. We then use this dataset in combination with climatic, pedologic, topographic and hydrologic data that we derive from existing DEM and climate data for the region in order to identify the key environmental controls on the spatial and vertical patterns of C storage and to build a 3D C prediction using linear mixed effect models. Finally, we use our model in combination with continuous topsoil C data from airborne hyperspectral remote sensing (HRS) to present a regional C stock estimate. For this estimate, we discuss the spatial variability as well as caveats and potential pitfalls of our approach. We further show how estimates using our approach differ from stable landscape approaches that usually work with depth extrapolation of C contents (e.g. Meersmans et al., 2009b) and discuss the implications of our findings for the application of C models at the landscape/regional scale.

2. Material and methods

2.1. Study area

The study area is a c. 500 km^2 north–south transect in the Great Duchy of Luxembourg (NW corner: 50°03′N 6°03′E; SE corner: 49°33′N 6°12′E). This research stripe has been chosen based on (i) the availability of HRS derived C concentrations for the cropland surface layer (0–5 cm) from Stevens et al. (2010), (ii) the abundant coverage with cropland, (iii) the large variability in soil types and (iv) its sloping topography. The climate of Luxembourg is temperate semi-oceanic with c. 863 mm yearly precipitation and a mean annual temperature of 8.8 °C (Climatedata, 2012). The northern part of the country belongs to the Ardennes massif with a mean altitude of 450 m and has slightly lower mean temperatures then the southern part with a mean altitude of 244 m. The transect covers the major agricultural soil types of temperate Europe including Cambisols, Arenosols and Luvisols (IUSS Working group, 2006). The soil map of Luxembourg classifies colluvial and alluvial areas as a separate class and these areas have been manually assigned to a soil texture class according to the surrounding texture zone (which provides the input material to these depositional settings) taking into account local topography and flow patterns (Fig. 1).

The majority of the cropland in our study area (>75%; EEA, 2012) is situated in two texture zones, i.e. a loam (68.5 km^2) and clay (79.1 km^2) zone. All further analysis was performed separately for these two dominant classes. Notably, the two texture zones covered in our study differ in terms of landforms. The northern part of the study area, dominated by loamy soils, is characterized by a hilly topography with steep slopes (Slope: 8.1 ± 4.8%) and most of the cropland is located on either plateaus or slopes. The southern part, dominated by clay-rich soils has a much lower relief intensity (Slope: 5.9 ± 3.6%) and is less undulating with cropland ranging from plateau over slopes to positions in the valley bottom (Table 1).

2.2. Field sampling

In the loamy and clay-rich texture zones within the study area, we sampled 100 soil cores from cropland up to 1 m depth. The profiles (further called LUX profiles) have been sampled at 15 slope transects along geomorphic gradients: profiles on flat or less sloping plateaus at the hilltop, slope positions with differing steepness and curvature and positions on the footslope and in the valley bottom (Fig. 1). We sampled undisturbed cores using a closed sampler (Ø 4.5 cm) (Eijkelkamp, The Netherlands). The cores were stored in sealed PVC-tubes at −18 °C until preparation for analysis. In order to increase the number of available soil profiles, we added data from 35 soil profiles to the database (further called SDP profiles), provided by the pedologic soil survey service of Luxembourg. This data originate from soil surveys conducted in the 1960's and (BDSOL LU, 1969) were used to create the pedologic map of Luxembourg.

2.3. Soil analysis

Soil bulk density (BD) was analyzed according to Blake and Hartge (1986) and stone content (as percent mass) was assessed by dry sieving at 2 mm. The fine soil C content of the LUX profiles was measured by depth intervals of 10 cm to a depth of 1 m for each profile using a VarioMax CN dry combustion Analyzer (Elementar GmbH, Germany) and analyzed in duplicate. Samples containing inorganic C were pre-treated before the combustion by adding 3% HCl to remove inorganic C (Elementar GmbH, 2009). Carbon in the SDP dataset has been estimated with bichromate wet combustion (Walkley and Black, 1934), including a factor correcting for the incomplete combustion using this method of 1.33 (Meersmans et al., 2009a,b). Several studies have identified the conversion factor between wet combustion and total combustion derived SOC values as a source of uncertainty, i.e., as the conversion factor can change for different soil texture classes (Brown et al., 2006; Goidts et al., 2009). No direct comparison between dichromate wet combustion and total combustion derived SOC values has been done for the SDP dataset so that this issue remains unchecked in this assessment here. However, this factor has been proven to be fairly constant for a wide range of loamy soils under cropland in Belgium and for soils with varying carbon contents (Lettens et al., 2005; Meersmans et al., 2009a,b; Sleutel et al., 2007) and converted C values in the SDP dataset were in a similar range as the C values in the LUX dataset (SDP: 0. 4–36.7 g C kg^{-1} SOC; LUX: 0. 2–36.4 g C kg^{-1} SOC). As bulk density information is not provided for SDP profiles, we used