



Detecting and quantifying field-related spatial variation of soil organic carbon using mixed-effect models and airborne imagery



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ABSTRACT

Evidences exist that the spatial variability of soil organic carbon (SOC) in cropland is partially controlled by environmental or human factors acting on a field basis (e.g., agricultural management, landuse history, landscape structure). However, few studies have quantified the relative importance of the fields-related variability at the regional scale. Recent airborne hyperspectral imagery methods provide SOC estimates at high resolution and over large surfaces. They may be used to quantify and explain the spatial variation of SOC. In this study we used a SOC hyperspectral image over Luxembourg to separate SOC variation in three components: the effect of the texture class (as defined by a texture map), the effect of fields (as defined by a cadastral map) and spatially dependent residuals. The relative variance of these components and the spatial structure of the residuals were rigorously assessed by restricted maximum likelihood (REML). Results indicated that $65.7 \pm 0.3\%$ of the variance of SOC in the study area was explained by texture classes. The intensity of the field effect was largely dependent on the location. In some sub-areas of homogeneous texture class, no significant effect could be observed while in others, field explained up to $68.8 \pm 12.0\%$ of the variance. In contrast with other methods like ANOVA, the method developed here measures the variation related to spatial units (soil map units or fields) while taking explicitly into account spatial dependencies. As soon as the boundaries of these spatial units and a spatially extensive (or at least very dense) knowledge of a soil property over a region of interest are available, it allows rigorously determining if the soil property depends on these spatial units. In the present application, findings pointed out the importance of considering fields-related variability in SOC modeling and mapping studies.

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1. Introduction

Soil organic carbon is a property that plays a role in multiple soil functions, like nutrient cycling, water control, physical stability, biodiversity and climate change mitigation. It is itself influenced by multiple factors acting at various spatial scales, like climate, soil type, land use, land management and topography (Minasny et al., 2013).

Studies that characterize the spatial variations of SOC at regional scale for cropland demonstrate an important role of the soil type. Kempen et al. (2010) show for example large and significant differences between the mean topsoil SOC content for different soil types in a province in the Netherlands, with the most SOC-enriched soil type (thick peat soil) containing on average 5.7 times more SOC than the least enriched type (sandy soil). Soil type (or related properties such as texture class, drainage class or parent material) is also selected as predictor in many regional SOC prediction models (Zhang et al., 2012; Meersmans et al., 2012).

If we focus on cropland with relatively homogeneous soil type, the variation of SOC observed at short range (i.e., in a radius of a few hundreds of meters) reaches generally the same order of magnitude as the variations over the whole region (Goidts et al., 2009). Short range variation is complex because of the large number of possible processes that are involved. Although interactions between them may exist, there is a clear distinction between processes that act almost continuously in space and processes that are rather constant over an entire field. Continuous processes are basically the effect of water and tillage erosion (Van Oost et al., 2005; VandenBygaert et al., 2012) or differences in moisture and temperature conditions related to the topography and affecting SOC equilibrium (Florinsky et al., 2002). Factors affecting SOC on a field basis are rather linked to agricultural management or landuse history (tillage practices, manure and amendments applications, crop rotations, residue management, former presence of grassland or forest, etc.). Landscape features may also affect SOC in a way that is in some cases spatially related to the field structure like hedges or buffer zones (Viaud et al., 2010).

Processes acting at the field scale have been demonstrated in specific cases or in field experiments and they are widely implemented in SOC modeling tools. A field divided into multiple plots undergoing different treatments may display large and significant differences in the SOC

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content after several years (VandenBygaert et al., 2003). The long-term effect of land use/land management changes has been studied in many geographical contexts and SOC dynamics models have been coupled to land use evolution models to understand past changes or estimate future changes in SOC carbon stocks (van Wesemael et al., 2010; Smith et al., 2005). However, evidence of spatially explicit and systematic differences in SOC content between fields for a given landscape is sparse in the literature. Large scale SOC dynamics studies are extrapolations based on field experiments and local surveys (Meersmans et al., 2012). Digital soil mapping studies, for their part, are mainly divided between precision agriculture studies and regional mapping studies. The first ones generally focus on individual fields (Casa et al., 2012) while the second ones do not generally aim at mapping SOC at such a fine resolution. Moreover, observations in the landscape are not always sufficient to assess the presence of field-related variation in a landscape and sound statistical methods are often needed for consolidation.

Nevertheless, differences between the mean SOC content of contiguous fields have been mentioned in SOC images from soil or airborne spectroscopy (Stevens et al., 2006). Hyperspectral imagery from remote sensing is a recent (and still evolving) method in soil science which has tremendously increased the extent of the area over which soil properties can be mapped at high resolution and at relatively low cost, and has been used for SOC estimation in different contexts (Gomez et al., 2008; Uno et al., 2005; Hbirkou et al., 2012). Typically, airborne imagery techniques produce maps of soil properties at a resolution of a few meters and over a region of several hundreds of square kilometers. As observed by Gomez et al. (2012), the map of a soil property, if the value of each pixel is predicted only from the spectral information of this pixel (i.e., no interpolation), may be used to describe in detail its short range variation. In our case, a SOC image could be exploited (in totality or after sub-sampling) to better explain the role of the various controlling factors on the spatial distribution of SOC at different scales.

The main objective of this study was to quantify the relative influence of field-related processes on the topsoil organic carbon variation in the cropland of a 420 km² region in Luxembourg. To achieve this, a SOC image derived from hyperspectral imagery was used along with spatial mixed linear models fitted by restricted maximum likelihood estimation method (REML). After a preliminary exploratory analysis, the effect of texture was first isolated and quantified using texture units from a soil map as fixed effect. Then, spatial clusters composed of neighboring fields of the same texture class were selected and, for each of them, the field indices derived from a cadastral map were used as fixed effect in order to separate field-related variation from spatially correlated residuals. The model was then applied on randomly transformed data to test if the retrieved results were significant. The influence of the field effect in each cluster was estimated as the part of the variance explained by the field component.

2. Material and methods

2.1. Study area

The study area is a stripe of approximately 60 km × 7 km that crosses the Grand-Duchy of Luxembourg in north–south direction (see Fig. 1). The two geological regions of the country are represented (Marx, 2013). The northern third of the study area is part of the Oesling region and the Ardennes massif. It is a relatively homogeneous region with an average altitude of 450 m and a substrate of Devonian slate underlying shallow loamy cambisols and regosols. The most common crop rotation is a 6 to 8 years rotation where cereals alternate with forage crops by 3 or 4 year periods. In the south, the Gutland region lays on Secondary sandstone, marl and limestone substrates and presents a more varied topography with an average altitude of 244 m. It is covered by (sometimes gleyic) cambisols and luvisols mainly displaying clay or



Fig. 1. Study area and texture zones. Fields cover 42% of the area while prediction of the surface SOC content from hyperspectral measurement is available for 9% of the total surface of these fields. The red square in the South indicates the position of cluster 12 for which SOC predictions are displayed in Figs. 6 & 7.

sandy textures. The most common crop rotation is a three years rotation of winter wheat, winter barley and silage maize. Overall, the region has a temperate oceanic climate with mean monthly average temperatures ranging from 0 °C to 17 °C and 863 mm of average annual rainfall. Fields cover 42% of the area.

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