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Landscape scale estimation of soil carbon stock using 3D modelling

F. Veronesi, R. Corstanje *, T. Mayr

Cranfield University, Bldg. 37, School of Applied Sciences, MK43 0AL Bedfordshire, United Kingdom

HIGHLIGHTS

- Effective regional mapping of soil C must consider its behaviour over the soil profile.
- Regional estimates of C stock must consider the profile behaviour of soil bulk density.
- Depth functions combined with interpolation can successfully map stock in 3D.
- Spatial interpretation of performance identifies soil strata.

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ABSTRACT

Soil C is the largest pool of carbon in the terrestrial biosphere, and yet the processes of C accumulation, transformation and loss are poorly accounted for. This, in part, is due to the fact that soil C is not uniformly distributed through the soil depth profile and most current landscape level predictions of C do not adequately account the vertical distribution of soil C. In this study, we apply a method based on simple soil specific depth functions to map the soil C stock in three-dimensions at landscape scale. We used soil C and bulk density data from the Soil Survey for England and Wales to map an area in the West Midlands region of approximately 13,948 km^2. We applied a method which describes the variation through the soil profile and interpolates this across the landscape using well established soil drivers such as relief, land cover and geology. The results indicate that this mapping method can effectively reproduce the observed variation in the soil profiles samples. The mapping results were validated using cross validation and an independent validation. The cross-validation resulted in an R^2 of 36% for soil C and 44% for BULKD. These results are generally in line with previous validated studies. In addition, an independent validation was undertaken, comparing the predictions against the National Soil Inventory (NSI) dataset. The majority of the residuals of this validation are between $\pm$5% of soil C. This indicates high level of accuracy in replicating topsoil values. In addition, the results were compared to a previous study estimating the carbon stock of the UK. We discuss the implications of our results within the context of soil C loss factors such as erosion and the impact on regional C process models.

1. Introduction

Soil C is the largest pool of carbon in the terrestrial biosphere (Schlesinger and Bernhardt, 1997), it accounts for three times as much carbon compared to that available in the vegetation and twice that in the atmosphere (Schils et al., 2008). The capacity to predict the consequences of climate change on the soil C pool and act accordingly, depends upon our understanding of C distribution in the soil volume (Jobbagy and Jackson, 2000). These consequences are explained in the IPCC report (2007) which suggests a change in the precipitation pattern, with an increase of around 2–10% in the annual runoff. This means an increase in the frequency of exceptional weather events coupled with dry soils, giving rise to potential increase in the risk of soil erosion. For this reason an increasing percentage of soil C stocked in the very top part of the soil profile can be at risk of being lost, impacting the fertility of the soils which are already highly stressed by years of intensive agriculture practices.

In order to assess which areas will be most affected by these future climate pattern changes, there is a need for precisely predicting soil C stocks through the depth profile and at fine spatial resolution. However, most of the available soil C stock maps, including the UK map (Bradley et al., 2005, provide only average estimates of C available in topsoil (from 0 to 30 cm) and subsoil (from 30 to 100 cm). The spatial changes in vertical distribution of soil C is an aspect still poorly represented (Jobbagy and Jackson, 2000; Gifford and Roderick, 2003)).

There have been various technical advances in estimating spatial C stocks in the soil profile. For instance, Ellert and Bettany (1995) developed the use of genetic horizons as reference levels by using an 'equivalent soil mass' concept. The sampling for soil C (and other elements) was carried out by depth increments corresponding to soil horizons. Zan et al. (2001) modified the approach of Ellert and Bettany (1995), replacing genetic horizons with depth segments

* Corresponding author.

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such an s 15 cm layers. Both suffer from the problem that both bulk density and soil C continuously vary down the profile rather being uniform within the genetic horizon or each 15 cm segment. Grimm et al. (2008) developed a 3D model for predicting soil organic carbon a fixed depth intervals using digital soil mapping techniques and soil units as the basis for spatialisation. Minasny et al. (2013) provided a comprehensive review of modelling organic carbon and demonstrated their various approaches with case studies. For the Edgeroi area of Australia they used ta combination of equal-area splines and a spatial prediction model to map the whole are for bulk density and organic carbon.

In a typical soil profile, the first centimetres can have a very high organic matter content (Batjes, 1996), derived from plant and animal residues. With depth the percentage in volume of organic carbon decreases non-linearly with a pattern that is frequently modelled with exponential functions (Russell and Moore, 1968; Hilinski, 2001). There are also other equations proposed to describe the decrease of soil carbon with depth, but they are just a variance of the exponential model (Arrouays and Pelissier, 1994; Bernoux et al., 1998). Minasny et al. (2013) used a generalized negative exponential depth function. However, in very wet soils decay is inhibited, causing the accumulation of organic matter and the formation of peat, which can be found either continuously throughout the soil profile, or as a buried horizon. In either case, C in these soils exhibits a different behaviour by depth than the previously described typical soil. For this reason, considering only volume averages cannot be sufficient to accurately assess the potential changes driven by climate change.

There are broadly three pathways through which C is lost from soil; through erosion, leaching (hydrological) and respiration (Dawson and Smith, 2007). Each of these is sensitive or depends on the vertical distribution of soil C. Soil C loss through water erosion can occur in two ways, through sheet flow over the surface of the soil or through channel erosion. Overland flow removes top soil and changes the distribution of soil C through the profile. The amount lost through erosion also directly depends on the vertical distribution of soil C. Hydrological loss of C from soil is a function of the movement of C from soil OM to the soil water, which is then lost through leaching as discharge from soil to the surface water. Dawson and Smith (2007) describe numerous studies in which significant correlations between soil C and dissolved organic C in UK catchments are observed; movement and loss of C through this pathway depends on the spatial and vertical distribution of soil C (Grieve, 1990; Hinton et al., 1998). Peak C loss tends to coincide with peak discharge events, in which the 15–20 cm surface layer dominates flow characteristics (Worrall et al., 2003). This would suggest that the vertical and horizontal distribution of soil C determines both the concentration and also flow characteristics of C loss from soil.

The largest amount of C is lost through organic matter mineralization. These losses are typically modelled using spatially distributed, integrated land–atmosphere process models such as JULES (Harrison et al., 2008). Improvements to the vertical distribution of soil C component in these types of models increases their response-sensitivity to changes in soil stocks and processes. Jones et al. (2005) compared the outputs from a generic Soil C model with measurements of topsoil (organic) C aggregated spatially according to both soil mapping and administration units. In a comprehensive review by Minasny et al. (2013), the outcome of various studies are tabulated and where, in general, R^2 for prediction accuracy range from 0.21 to 0.98 for soil C prediction from areal imagery, the statistics obtained by cross-validation, internal or external validation. There is only one study in this list in which the C stock predictions are independently validated (R^2 of 0.41).

In this paper we consider a method developed previously (Veronesi et al., 2012) for in field mapping of soil compaction, and we consider this now for regional scale C stocks. The method is developed and applied within an area of the UK with a high density of soil profile observations, but validated using an independent topsoil dataset sampled on a 5 km grid. The method creates a fine vertical resolution 3D map of the soil C stock, describing its behaviour both vertically and spatially.

2. Materials and methods

2.1. Study area

The study area is located in the West Midlands region, extending approximately 13,948 km^2 (Fig. 1). Within the pilot area, there are 118

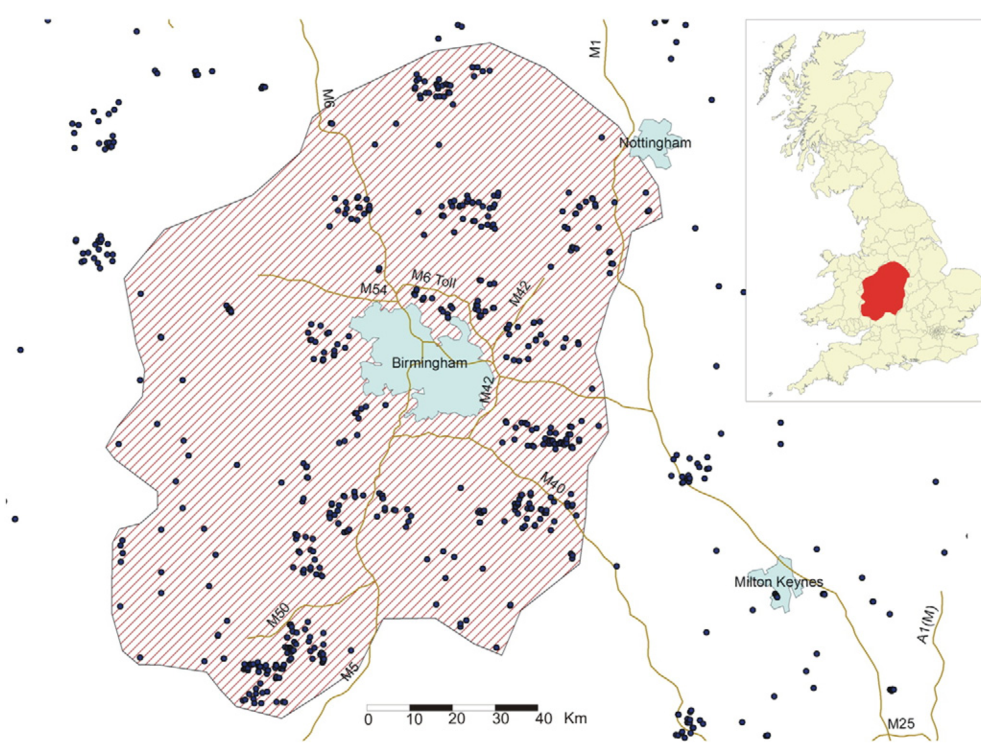

Fig. 1. Map of the area under study. The area extends for 13,948 km^2 over the West Midlands region and on the Welsh border.