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Soil organic carbon increases under intensive agriculture in the Central Sands, Wisconsin, USA

Kabindra Adhikari[a,*], Alfred E. Hartemink[b,*]

[a] University of Arkansas, Department of Crop, Soil, and Environmental Sciences, Fayetteville, AR 72701, USA
[b] University of Wisconsin-Madison, Department of Soil Science, FD Hole Soils Lab, Madison, WI 53706, USA

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ABSTRACT

Soil organic carbon (SOC) plays a crucial role in maintaining fertility and productivity in sandy soils. This study mapped the spatial variability of SOC concentration, A-horizon thickness, and SOC stocks from the Central Sands in Wisconsin. Soil samples were collected from three different areas (area A, B, and C) that were sampled through grid sampling (GS, $n = 100$), conditioned latin hypercube sampling (cLHS, $n = 100$), and random sampling (RS, $n = 150$) schemes. Average SOC concentration of the A-horizon from soil sampling area A, B, and C were 6.1, 7.1, 8.3 g kg^{-1}, respectively. The mean A-horizon thickness for agricultural soils was 28 cm compared to 15 cm under adjacent grassland. Regression kriging was selected as prediction model where EC_a and local topographic information (i.e., slope gradient, slope aspect, elevation, wetness index, altitude above channel network etc.) were used as predictors. We observed an increased SOC content, SOC stock, and A-horizon thickness with EC_a and wetness index. SOC from area B had the strongest spatial dependency (NSR = 0.64) followed by area A (NSR = 0.72), whereas that from area C was the weakest (NSR = 0.78). Compared to SOC content and A-horizon thickness prediction, SOC stocks prediction had the maximum uncertainty. Predicted SOC stock (t ha^{-1}) ranged from 28 for sampling area A to 40 for B, and 59 for area C. These high SOC stocks are the result of decade long intensive agriculture with high amount of nitrogen input and irrigation. It has resulted in deep A-horizon and high SOC stocks. This study found that SOC stocks in the Central Sands could be estimated from A-horizon thickness ($R^2 \sim 0.5$).

1. Introduction

Soil spatial variation is a well-known phenomenon and has been studied extensively. Variation occurs at a range of scales, from kilometers to few meters, between or within fields, and at microscales (Beckett and Webster, 1971; Trangmar et al., 1986). Understanding the variation in soil properties at field scales is important to improve soil management practices and to evaluate agricultural impact on the environment. It also helps to design soil-sampling strategies (Nielsen and Wendroth, 2003) that reduce the cost of sampling and ensure data quality in geographical and feature space. Soil organic carbon (SOC) is a key component of soil quality (Herrick and Wander, 1997), and a determinant of atmospheric carbon dioxide (CO_2) concentration (Lal, 2004). Carbon inputs in soils are influenced by climate, landuse, soil management, and soil physical characteristics all of which vary spatially leading to substantial variability in SOC (Robertson et al., 1997). Assessment and monitoring of SOC variability is a research priority (Hartemink et al., 2014). Among several controlling factors, carbon storage in well and moderately well drained soils is influenced by soil texture. If all other factors mentioned above are equal, fine textured soils tend to have a higher SOC sequestration potential as the carbon is protected against decomposition. SOC levels in sandy soils are often low and it is generally perceived that sandy soils have a low SOC sequestration potential. Studies show that the amount of SOC associated with sand particles is lower than with clay (Christensen, 1992) because the later has larger specific surface area (Kennedy et al., 2002), and is, in general, higher in microbial biomass (Sørensen, 1983). Given the widespread areas of sandy soils in the world (Bramao, 1962; Driessen et al., 2000; Papadakis, 1965) and their ease of use for crop production, assessment of SOC levels and stocks is needed. Sandy soils are easy to till and show a quick response to management. Continuous farming of these soils for decades lead to changes in physical-chemical and biological properties including increase in A-horizon thickness (Watson and Hartemink, 2015).

There is a growing body of knowledge on SOC prediction and mapping (Hartemink and McSweeney, 2014). Digital soil mapping technique (DSM, McBratney et al., 2003) is used to map SOC variability at different spatial scales. Multiple linear regression (MLR), Regression

* Corresponding authors.
E-mail addresses: ka017@uark.edu (K. Adhikari), hartemink@wisc.edu (A.E. Hartemink).

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kriging (RK), Regression trees (RT), Random Forest (RF), rule-based RK etc., are commonly used techniques in the prediction and mapping of SOC at different spatial scales (Adhikari et al., 2014; Grimm et al., 2008; Martin et al., 2011; Mueller and Pierce, 2003; Odeh et al., 1995). Minasny et al. (2013) reviewed a wide range of DSM techniques for SOC mapping. Most techniques consider SOC variability as a function of soil forming factors (Jenny, 1941), where topographic information has successfully been used to predict SOC distribution (Adhikari and Hartemink, 2015; Minasny et al., 2013; Moore et al., 1993).

The present study applied RK techniques to predict and map field-scale SOC variation from sandy soils under intensive agriculture in the Central Sands of Wisconsin (WI). The study was based on the data collected from three different areas using three soil sampling schemes: grid sampling (GS), conditioned latin hypercube sampling (cLHS), and transect plus random sampling (RS). The main objectives of this study were to: (i) predict and map SOC concentration, topsoil depth, and SOC stock using DSM techniques, (ii) assess the effect of intensive farming on SOC stocks and establish its relation to A-horizon thickness.

2. Materials and methods

2.1. Study site

The study site is located in the Central Sands in Wisconsin (43° 53″ 30′ to 43° 56″ 0′ N; 89° 39″ 0′ to 89° 42″ 0′ W) where the soils are developed on a glacial outwash and are relatively young in age (< 15,000–17,000 yrs.). The sandy deposits are residuals from Glacial Lake Wisconsin and are distinguished by a blanket of sandy Pleistocene sediment, overlying Cambrian sandstone bedrock. In the study area, topography is relatively flat with micro-relief (mean slope gradient 1.3%), and an elevation of 311 m asl. The climate in the area is characterized by long cold snowy winters, warm summers, and spring and fall that are relatively short. Average annual temperature in the winter is − 7 °C, and average summer temperature is 21 °C. The total average annual rainfall is about 833 mm, and snowfall of 1143 mm.

The soils are coarse grained, deep and excessively drained, with low nutrient status and water holding capacity. Common soils are Entisols (Plainfield Series) and classified as Mixed, mesic Typic Udipsamments (Soil Survey Staff, 1999). The soils are under intensive agriculture with corn, soybean, and potato as main crops, and are irrigated with underground water at a rate of 200–300 mm yr^{-1}. The soils are limed and receive inorganic fertilizers; average application rates are 225 kg N ha^{-1}, 336 kg K ha^{-1}, and 56 kg P ha^{-1}, in addition to 1250 kg of dolomitic lime every three years (personnel communication with farmers). Since 2012, the farmers applied liquid cow manure to most of their fields. During the past 75 yrs., the Central Sands has witnessed extensive changes in land cover (conversion of forest and prairie to cropland) and increased groundwater pumping for irrigation (Watson and Hartemink, 2015).

2.2. Soil sampling and laboratory analysis

Soil samples were collected from three different areas, namely A, B, and C, following three sampling schemes: Grid Sampling (GS, $n = 100$), conditioned Latin Hypercube Sampling (cLHS, $n = 100$), and Random Sampling (RS, $n = 150$) with total number of 350 sample locations (Fig. 1). Table 1 combines sampling area and sampling scheme applied in the study area. Sampling area A employed a GS scheme, area B a cLHS scheme, and area C was based on RS scheme. The spatial extent of sampling area C covered area B, and A whereas the latter two did not overlap. This restricted the prediction comparison studies among sampling areas as well as sampling schemes. For GS scheme, a grid size of 40 × 40 m was selected and soils were sampled from the grid nodes. The total area for GS scheme was 15 ha with a density of 7 sampled per hectare. The cLHS scheme employed elevation, and surface apparent electrical conductivity (EC_a) data as auxiliary information to identify sampling locations from two selected pivots. The main goal of cLHS is to cover the diversity of auxiliary variables as completely as possible with the defined number of samples such that variability in the feature space can be accurately represented. Details on the procedure and algorithm of cLHS can be found in Minasny and McBratney (2006). At each sampling location in sampling area A, and B, a 45–50 cm deep mini-pit was dug and soil samples were collected from the middle of the A-horizon. The area B covered about 60-hectare area with a sampling density of 2 A-horizon samples per hectare. Sampling scheme in area C is a combination of a random sampling for A-horizon, and a random-transect sampling of soil profiles, and it covered an area of about 1111 ha. The density was < 1 sample per hectare. Profile samples in area C consisted of soil samples from all genetic horizons up to 1.5 m, but this study only considered the data from the A-horizon. Soils were also sampled from the adjacent grassland (8 observations) where the sampling locations were identified randomly. Soil samples were analyzed for bulk density and SOC content. At each soil sampling location, the depth of the A-horizon was measured.

Samples were air-dried, crushed and passed through a 2-mm sieve. Soil organic carbon content (%) was determined by dry combustion and the value was multiplied by 10 to get SOC (g kg^{-1}). Soils were sampled for bulk density (BD) using 100 cm^3-rings at 15 randomly selected locations covering the entire study area. Bulk density (g cm^{-3}) of the samples was calculated after oven-drying the ring samples.

2.3. SOC stock calculation

The BD from 15 locations was interpolated using Inverse Distance Weighting (IDW) method, as the data were not spatially auto-correlated. The BD values for all SOC observation locations were derived through point intersection. The SOC stock was calculated according to Eq. (1) that considers it as a function of SOC concentration, bulk density, and soil thickness and it represents the SOC stock of the A-horizon. Calculated SOC stock was not corrected for gravel content, as the soils from A-horizon were gravel free. Both SOC concentration and SOC stock were log-transformed for predictions and were back − -transformed to original units for final outputs.

$$SOC_{stk}\,(t\ \ ha^{-1}) = [\{SOC\ \ (g\ \ kg^{-1}) \times BD\ \ (g\ \ cm^{-3}) \times D\ \ (cm)\}/10] \qquad (1)$$

where, SOC_{stk} is soil organic carbon stock of A-horizon, SOC soil organic carbon concentration, BD bulk density, and D the A-horizon thickness.

2.4. Terrain parameters and electrical conductivity measurement

Digital elevation model (DEM) was the primary source of terrain information used in this study as predictors of SOC and A-horizon thickness. A processed DEM at a spatial resolution of 1.52-m was acquired from a Light Detection and Ranging (LiDAR) flight in 2010 and re-projected to North American Datum 1983 (NAD83 UTM Zone 16N). Elevation ranges between 303 and 321 m with a mean of 311 m asl. The following terrain derivatives were used: slope aspect, catchment slope, mid-slope position, multi-resolution valley bottom flatness index, normalized height, slope gradient, slope height, slope-length factor, topographic wetness index, and vertical distance to channel network. All the digital terrain analysis including the extraction of terrain derivatives were done in ArcGIS (ESRI, 2012), and SAGA GIS (Conrad et al., 2015).

Data on apparent electrical conductivity were collected by scanning the field with Veris Sensor and continuous EC_a maps were generated using empirical bayesian kriging in ArcGIS. The Veris Sensor Cart was pulled through the field at speeds of up to 10 mph acquiring geo-referenced EC_a measurements (mS/m) every second intervals. The distance between the two adjacent drive path was about 18 m.