Geoderma Regional 7 (2016) 167–176

Contents lists available at ScienceDirect

Geoderma Regional

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

Digital soil mapping of organic carbon concentration in paddy growing soils of Northern Sri Lanka

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ARTICLE INFO

Article history:
Received 9 November 2015
Received in revised form 17 March 2016
Accepted 23 March 2016
Available online 25 March 2016

Keywords:
Soil organic carbon
Digital soil mapping
Spatial modeling
Tropical paddy fields

ABSTRACT

In this study we explore the environmental covariates that are useful in mapping SOC contents in tropical paddy growing soils in Northern Sri Lanka. We carried out digital mapping of SOC contents across the study area using a spatial soil prediction function with auto correlated errors *via* linear mixed models (LMMs). Two separate LMMs were fitted considering two depth intervals, 0 to 0.15 m and 0.15 to 0.30 m respectively. Results revealed that environmental covariates of SOC content for the two depth intervals considered in this study were different despite being situated within a zone typically considered as the top soil (0 to 0.3 m). Landsat 8 bands and its products derived from those bands (namely Landsat 8 band 2, band ratios 4/3 and 4/7) were identified as significant environmental covariates for both depth intervals. In terms of spatially auto correlated residuals, optimum spatial models for both depth intervals were identified as a spherical model. Residuals were found to be spatially auto correlated up to 10,000 m and 5000 m for 0 to 0.15 m and 0.15 to 0.30 m depth intervals respectively. Cross validation results suggest that fitted LMMs are adequate to carry out mapping across the study area with little difference between estimated bias (−0.006% for 0 to 0.15 m and −0.004% for 0.15 to 0.30 m depth intervals) and accuracy (0.441% for 0 to 0.15 m and 0.367% for 0.15–0.30 m depth intervals) for fitted LMMs considering two depth intervals. However, in case of Lin's concordance correlation value, 0 to 0.15 m depth interval reported higher value (0.81) compared to 0.15 to 0.30 m depth interval (0.60) suggesting upper depth interval model is much superior to the lower one. In conclusion, this study provides; a) firsthand information on current status of SOC contents in northern paddy growing soils in Sri Lanka, b) generated information that are useful to optimize spatial sampling of SOC in future applications and c) provided firsthand information vital to establishment of a national carbon accounting system in future.

1. Introduction

SOC is continuously subjected to decomposition and other biologically mediated transformations that generate or consume greenhouse gases (Baldock et al., 2012). In the global context, soils and their management have the potential to either increase or reduce atmospheric concentrations of greenhouse gases and the magnitude of any associated climate change (Baldock et al., 2012). Additionally, SOC plays a vital role in maintaining different biological, chemical and physical properties and processes that exist in soils and are important in sustaining the ecosystem services (Baldock and Broos, 2011). Therefore, a decline in SOC will have negative consequences in relation to soil health and productivity.

Due to the importance of SOC, much attention has been given to the digital mapping of SOC and its fractions or conceptual pools in space (*e.g.* Karunaratne et al., 2014a), space and depth (3D) (*e.g.* Poggio and Gimona, 2014) and, space and time (*e.g.* Karunaratne et al., 2014b). Digital soil mapping (DSM) techniques are used to estimate SOC contents/concentration and stock/density (Minasny et al., 2013). Methods of mapping soil properties including SOC using the DSM approach can be broadly categorized under three main approaches *i.e.* geostatistical; deterministic and hybrid geostatistical approaches. Out of these three approaches, the most common approach practiced is the hybrid geostatistical approach. Among the different hybrid geostatistical approaches, such as co-kriging, universal kriging and regression-kriging, latter described by Odeh et al. (1995) is the most commonly applied method. In this study we adopted a similar approach to regression-kriging approach in terms of linear mixed model (LMM) as described by Lark et al. (2006). The application of LMMs for DSM of carbon stocks

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http://dx.doi.org/10.1016/j.geodrs.2016.03.002

and the associated measureable fractions were successfully demonstrated by Karunaratne et al. (2014b) and Karunaratne et al. (2014a).

As with many countries in South and South East Asia, rice is the staple food of Sri Lanka. It has been reported that paddy fields have higher SOC storage and sequestration capacity compared to dry land cropping systems (Pan et al., 2004). Rice cropping under waterlogged conditions enhances the soil organic matter (SOM) accumulation (Lal, 2002). The decomposition rates of SOM are considered to be smaller under anaerobic conditions than under aerobic conditions (Sahrawat, 2003), resulting in SOM accumulation and ensuring the carbon remains sequestered in the soils. Wu (2011) reported that SOC accumulation in paddy ecosystems was faster and more pronounced than in other arable ecosystems. Additionally, higher content of silt and clay in paddy soils compared with upland soils contributes to the larger SOC accumulation (Lal, 2002). Therefore, the maintenance of SOC in paddy fields is important not only for improving agricultural productivity but also for the reduction of greenhouse gas emission. However, little information is available on the SOC contents/stocks in tropical and sub-tropical paddy soils. It has been reported that SOC in China's paddy growing top soils contributes approximately 1.3 Pg, which is about 2% of the total SOC storage in the topsoil (Pan et al., 2004). A study conducted in Indo Gangetic Plains of India reported the total organic carbon (TOC) concentration is 6.8 g kg^{-1} in the surface 0 to 0.15 m soil layer (Nayak et al., 2012). Few studies have mapped the SOC contents and stocks in paddy growing soils (Sumfleth and Duttmann, 2008; Minasny et al., 2012). So far, no studies have investigated the spatial distribution of SOC in paddy growing soils at a regional scale within Sri Lanka.

In Sri Lanka, land cultivated under paddy covers approximately 34% of the total cultivated lands (Central Bank of Sri Lanka, 2014). Rice is cultivated mainly using two cropping systems *i.e.* mono crop and crop rotation using either irrigated or rainfed. Rain is received from two major monsoons namely: South West monsoons (*Yala season*) [May to September] and North West monsoons (*Maha season*) [October to February]. In northern dry zone of Sri Lanka, rice is cultivated mainly in the *Maha* season and in the *Yala* season those lands either kept as fallow lands or crop with other field crops.

Currently the Sri Lankan rice sector is facing numerous issues such as low yield, increasing fertilizer cost, adverse weather conditions and insufficient supply of irrigation (Central Bank of Sri Lanka, 2014). Therefore, firsthand information vital for regional scale land resource planning will be provided through DSM of SOC which includes current status and information on soil health in the paddy growing regions.

In this study we have applied DSM techniques to quantify the SOC content across the paddy growing soils covering the Northern Province of Sri Lanka. We have concentrated on mapping SOC contents due to the absence of bulk density data, which prevented the calculation of SOC stocks/densities. Significantly this is the first detailed study on digital mapping of any soil property covering a large area of extent using DSM approach in Sri Lanka. Specific aims of this study were to; (a) develop an appropriate spatial soil prediction function with an auto correlated error (SSPF) model for the identification of environmental drivers and to carry out prediction of SOC contents across the study area; (b) validate the developed SSPF and finally (c) discuss the possible use of derived DSM products in regional and national level planning related to soil and land resources.

2. Methods

2.1. Study area

This study was carried out in paddy growing soils in the Northern Dry Zone of Sri Lanka. Samples were selected from the following districts (administrative units) namely: Jaffna, Kilinochchi, Vavuniya, Mannar and Mullaitivu. Major soil types in the study area that grow rice includes; Low Humic Gley Soils (USDA soil taxonomy order: Alfisols; Word reference base Major group: Gleysols), Calcic Red Yellow Latosol (USDA Soil taxonomy order: Oxisols; Word reference based Major group: Ferralsols), Solodized solonetz (USDA Soil taxonomy order: Alfisols; Word reference base Major group: Solonetz) and Alluvials (USDA Soil taxonomy order: Entisols; Word reference base Major group: Fluvisols) (Panabokke, 1996). The average mean temperature of the study area varies in between 25.0 to 27.5 °C while annual cumulative rainfall is reported in between 1000 to 1500 mm (Survey Department of Sri Lanka, 2007). Rainfall of the study area is seasonal and mainly governed by the North East Monsoon. Terrain of the study is characterized with undulating terrain which is common in the defined dry zone catena of Sri Lanka.

2.2. Soil sampling collation design

A purposive sampling design was adopted in this study considering the limited budget and accessibility. A brief description on the sampling design adopted in this study is described as follows. Twenty one (n = 21) main sampling sites were selected considering the percentages of land area under paddy in each administrative district (Table 1). These 21 main sites were selected depending on accessibility for the paddy sites. In order to determine the local variation of SOC, additional sampling site was selected for each main sampling site. This is similar to approach adopted by Dorji et al. (2014) where paired sampling was carried out for main sampling locations at approximate distance of 1 km which resulted to a total of 42 sampling sites. Finally, considering those resulted 42 sampling sites, another close range sample was taken at approximate distance of 100 m away similar to approach described by Karunaratne et al. (2014b) except in one location. In total, 83 samples were selected to represent the paddy growing soils of northern Sri Lanka (Table 1). Soil samples were collected at two depth intervals namely 0 to 0.15 m and 0.15 to 0.30 m respectively targeting SOC content of top soils. Sampling was carried out in January 2015. Fig. 1 depicts the distribution of sampling locations and paddy fields within the study area.

2.3. Preparation of soil sample and analysis

All visible organic debris, stones and plant roots were removed and large soil aggregates were crushed prior to sieving of samples. Then samples were sieved using a 2 mm mesh sieve. Prepared samples were analyzed for SOC, soil moisture content, soil pH (1:2.5 soil: water suspension) and conductivity. For the current study we concentrated on the analytical values of SOC contents. For the SOC analysis, samples were air dried and ground to a powder to less than 0.15 mm and determination of TOC was carried out using 'wet' oxidation by acidified dichromate of organic carbon (Baker, 1976). In this study TOC is considered as equal to SOC.

2.4. Preparation of environmental covariates

Table 2 summarizes different environmental covariates used in the development of SOC spatial models in this study. These environmental covariates can be grouped into four main categories; topographic, climatic, biological, and spatial which represent some elements of the

Table 1
Distribution of main sampling sites and close range sampling sites.

District	Number of main sampling sites	Number of samples at approximately 1 km distance	Number of samples at approximately 100 m distance
Jaffna	2	4	8
Kilinochchi	6	12	24
Vavuniya	5	10	20
Mannar	4	8	15
Mullaitivu	4	8	16