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Soil organic carbon stocks and their determining factors in the Dano catchment (Southwest Burkina Faso)

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ABSTRACT

Although the evaluation of soil organic carbon (SOC) stocks across different types of land use and major reference soil groups is essential for mitigating climate change, there remains, to date, limited comprehensive understanding of whole tropical soil profiles. Therefore, this study aimed to explain the amount of SOC stocks in different land-use systems and across various soil groups, as well as its spatial pattern in the topsoil (0–30 cm) and subsoil (30–100 cm) within the savannah zone of Burkina Faso. Roughly 70 soil profiles were considered along with additional auger sampling to account for spatial variation in both cropland (CR) and savannah (SA). The machine learning technique random forest regression (RFR) and multiple linear regression (MLR) were used for modeling the surface and subsurface SOC stocks. For model calibration, covariates including land use, topographic, texture, and climatic data were considered as surrogate for soil forming factors. The prediction maps produced by the calibrated models were validated by an independent dataset. The results indicated that about 53% of the SOC stock over 1 m depth was held in the upper 30 cm. Only a marginal difference was recorded between the topsoil SOC stock in SA (41.4 t C ha⁻¹) and CR (39.1 t C ha⁻¹) soils. For the subsoil, a significant difference (p < 0.05) was observed between the SOC stock of CR soils recording about 40.2 t C ha⁻¹ and SA soils with 26.3 t C ha⁻¹. Among the reference soil groups, the Gleysols located at lower elevation positions revealed the highest SOC stocks over 0–30 cm $(44 t C h a^{-1})$ and 100 cm depth $(86.6 t C h a^{-1})$. The Stagnosols (45.2 t C ha⁻¹) followed by the Gleysols (42.7 t C ha⁻¹) recorded the highest SOC stocks over 30–100 cm. The variability of SOC stock in the topsoil was primarily related to site-specific elements, such as particle-size fraction and wetness index, while its distribution in the subsoil was mainly associated with the topographical orientation represented by the slope aspect. Compared to the MLR, RFR estimated mean top- and subsoil SOC stocks of the catchment fairly well, along with lower statistical error metrics, though extreme values were not covered. Nevertheless, the findings on SOC stocks reinforce the view that the semi-arid ecosystems of West Africa still offer a significant opportunity for carbon sequestration for both topsoil and subsoil, and these results represent a baseline for future modeling of SOC dynamics in the region.

1. Introduction

Globally, soils contain the largest terrestrial carbon pool on earth. Though subject to regular change, the global amount of carbon in soils is estimated at 2500 Gt, including 1550 Gt of soil organic carbon (SOC) and 950 Gt of soil inorganic carbon ([Batjes and Sombroek, 1997;](#page--1-0) [Lal,](#page--1-1) [2008\)](#page--1-1). As the SOC pool is 3.3 times the size of the atmospheric pool (760 Gt) and 4.5 times the size of the biotic pool (560 Gt) ([Lal, 2004](#page--1-2)), slight changes in soil C cycling may significantly impact the global C cycle. Nevertheless, little is known on the role of tropical soils in these changes.

The ecosystems in West Africa are facing severe degradation due to changes in land use from perennial vegetation to cropping, increased cultivation in marginal lands, soil erosion, and nutrient mining [\(Bationo](#page--1-3) [et al., 2007;](#page--1-3) [UNEP, 2006](#page--1-4)), as well as climate change [\(Brevik, 2013](#page--1-5)). Models have predicted that climate change will lead to the conversion of soils from carbon sinks to carbon sources [\(Cox et al., 2000](#page--1-6)). However, prediction uncertainty remains significant [\(Cox et al., 2000](#page--1-6); [Smith, 2008\)](#page--1-7), mainly due to the lack of adequate knowledge on SOC distribution across the landscape. Nowadays, different measures to conserve existing SOC stocks and trap the atmospheric carbon in the soil are being implemented in many areas in Africa, and comprise

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Fig. 1. The Dano catchment and sampling sites.

afforestation of degraded lands, agroforestry, and application of best agricultural practices and policies ([Batjes, 2008](#page--1-8)). Recent works have addressed the quantification of soil carbon stocks in African countries; such studies include those by [Akpa et al. \(2016\)](#page--1-9) for Nigeria and by [Minasny et al. \(2017\)](#page--1-10) for South Africa, Tanzania, Kenya, and Nigeria. However, comprehensive data is still lacking on SOC stock for different agrosystems [\(Anikwe, 2010\)](#page--1-11), especially for other countries in Western Africa. According to [Batjes \(2008\),](#page--1-8) an estimation of the current carbon stock should be carried out before considering the carbon change dynamics under land use and climate change.

To accurately address land degradation, spatial information on soil properties is required for land evaluation. Spatial soil information as represented in soil maps is beneficial for farmers, scientists, and policy makers in identifying priority areas and for a sound and objective decision making. However, maps from traditional surveys are mostly qualitative, labor intensive, time consuming, and costly [\(Taghizadeh-](#page--1-12)[Mehrjardi et al., 2015\)](#page--1-12), and thus in most cases also obsolete [\(Kilasara,](#page--1-13) [2010\)](#page--1-13). Recent advances in remote sensing and information systems have paved the way for digital soil mapping (DSM), which couples soil point data with statistically correlated auxiliary data ([McBratney et al.,](#page--1-14) [2003\)](#page--1-14). This coupling of point and auxiliary data is carried out by using (geo-) statistical classification or regression models. Multiple linear regression (MLR) has been widely used in many studies for the prediction of SOC ([Florinsky et al., 2002;](#page--1-15) [Guo et al., 2015](#page--1-16); [Meersmans](#page--1-17) [et al., 2008](#page--1-17)). However, soil–landscape relationships are often subject to nonlinear dynamics that might not be captured by MLR [\(Grimm et al.,](#page--1-18) [2008\)](#page--1-18). Many studies [\(Hengl et al., 2015;](#page--1-19) [Rad et al., 2014](#page--1-20); [Wiesmeier](#page--1-21) [et al., 2011\)](#page--1-21) have reported on the potential of random forest regression (RFR), an ensemble machine learning approach, to overcome this limitation.

Potential factors that affect SOC stocks and are used as covariates for DSM include climatic and topographic elements (for example, mean annual precipitation and temperature, slope, etc.), land use, physical soil characteristics (texture, parent material, etc.), and microbial biomass [\(Albaladejo et al., 2013](#page--1-22); [Jobbágy and Jackson, 2000](#page--1-23),; [Ladd et al.,](#page--1-9) [2013\)](#page--1-9). Many of these factors have been investigated in various studies conducted across the globe ([Albaladejo et al., 2013](#page--1-22); [Azlan et al., 2011](#page--1-24); [Bationo et al., 2007;](#page--1-3) [Burke et al., 1989;](#page--1-25) [Chaplot et al., 2010](#page--1-26); [Jobbágy](#page--1-23) [and Jackson, 2000;](#page--1-23) [Percival et al., 2000](#page--1-27)). However, these studies have mostly focused on surface soil horizons. Nevertheless, > 50% of SOC is usually allocated below 20 cm depth [\(Batjes, 1996](#page--1-28)). [Fontaine et al.](#page--1-29) [\(2007\)](#page--1-29) showed that this subsoil carbon is readily decomposable upon addition of a fresh C source, and [Fierer et al. \(2003\)](#page--1-30) concluded that it is even more sensitive to changes in temperature or nutrient availability than topsoil carbon is. However, these latter studies were not performed with tropical soils, which may have specific SOC storage conditions—for instance, due to their special oxide assembly [\(Feller and](#page--1-31) [Beare, 1997](#page--1-31); [Kögel-Knabner and Amelung, 2014](#page--1-32)).

The study detailed in this paper was performed in the Sudanian area of Burkina Faso, which is dominated by Plinthosols—that is, soils with high Fe oxide accrual—particularly in the subsoil. To the best of our knowledge, for such soils, neither (i) levels and distribution of SOC stocks nor (ii) the interactions between SOC stock and landscape properties have ever been investigated. Yet such quantitative data is Download English Version:

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