Journal of Environmental Management 286 (2021) 112191

Contents lists available at ScienceDirect

Journal of Environmental Management

journal homepage: http://www.elsevier.com/locate/jenvman

Research article

Estimating spatially distributed SOC sequestration potentials of sustainable land management practices in Ethiopia

Wuletawu Abera[a,*], Lulseged Tamene[a], Assefa Abegaz[b], Habtamu Hailu[c], Kristin Piikki[d,e], Mats Söderström[d], Evan Girvetz[e], Rolf Sommer[f]

[a] International Center for Tropical Agriculture (CIAT), Addis Ababa, Ethiopia
[b] Department of Geography and Environmental Studies, Addis Ababa University, Ethiopia
[c] Ministry of Agriculture (MOA), Sustainable Land Management Program (SLMP), Ethiopia
[d] Swedish University of Agricultural Sciences (SLU), Skara, Sweden
[e] International Center for Tropical Agriculture (CIAT), Nairobi, Kenya
[f] WWF Deutschland, Agriculture & Land Use Change, Berlin, Germany

ARTICLE INFO

Keywords:
Climate change
Ethiopia
Random forest
Resilience
Sustainable land management
SOC sequestration

ABSTRACT

The sustainable land management program (SLMP) of Ethiopia aims to improve livelihoods and create resilient communities and landscape to climate change. Soil organic carbon (SOC) sequestration is one of the key co-benefits of the SLMP. The objective of this study was to estimate the spatial dynamics of SOC in 2010 and 2018 (before and after SLMP) and identify the SOC sequestration hotspots at landscape scale in four selected SLMP watersheds in the Ethiopian highlands. The specific objectives were to: 1) comparatively evaluate SOC sequestration estimation model building strategies using either a single watershed, a combined dataset from all watersheds, and leave-one-watershed-out using Random Forest (RF) model; 2) map SOC stock of 2010 and 2018 to estimate amount of SOC sequestration and potential; 3) evaluate the impacts of SLM practices on SOC in four SLMP watersheds. A total of 397 auger composite samples from the topsoil (0–20 cm depth) were collected in 2010, and the same number of samples were collected from the same locations in 2018. We used simple statistics to assess the SOC change between the two periods, and machine learning models to predict SOC stock spatially. The study showed that statistically significant variation ($P < 0.05$) of SOC was observed between the two years in two watersheds (Gafera and Adi Tsegora) whereas the differences were not significant in the other two watersheds (Yesir and Azugashuba). Comparative analysis of model-setups shows that a combined dataset from all the four watersheds to train and test RF outperform the other two strategies (a single watershed alone and a leave-one-watershed-out to train and test RF) during the testing dataset. Thus, this approach was used to predict SOC stock before (2010) and after (2018) land management interventions and to derive the SOC sequestration maps. We estimated the sequestrated, achievable and target level of SOC stock spatially in the four watersheds. We assessed the impact of SLM practices, specifically bunds, terraces, biological and various forms of tillage practices on SOC using partial dependency algorithms of prediction models. No tillage (NT) increased SOC in all watersheds. The combination of physical and biological interventions ("bunds + vegetations" or "terraces + vegetations") resulted in the highest SOC stock, followed by the biological intervention. The achievable SOC stock analysis showed that further SOC stock sequestration of up to 13.7 Mg C ha–1 may be possible in the Adi Tsegora, 15.8 Mg C ha-1 in Gafera, 33.2 Mg C ha-1 in Azuga suba and 34.7 Mg C ha-1 in Yesir watersheds.

1. Introduction

Ethiopia is investing a huge amount of resources to tackle land degradation through land restoration under its various initiatives such as Food for work, Managing Environmental Resources to Enable Transitions (MERET), and the sustainable land management program (SLMP). In the last decade, Ethiopia has invested more than US$1.2 billion annually in restoring landscapes in its major regions (Adimassu et al., 2018). Some of the Sustainable Land Management (SLM) practices implemented include physical measures (soil/stone terraces, trenches,

* Corresponding author. Bole sub-city, Gurd shola area, P.O. Box 5689, Addis Ababa, Ethiopia.
E-mail address: wuletawu.abera@cgiar.org (W. Abera).

https://doi.org/10.1016/j.jenvman.2021.112191
Received 13 July 2020; Received in revised form 11 February 2021; Accepted 11 February 2021
Available online 2 March 2021

micro basins, percolation bonds, and gully treatments); biological measures (area closure, tree/forage planting on terraces, bamboos); or a combination of the two. The full list of SLM practices implemented in Ethiopia are detailed in Nedessa et al. (2015). SLM interventions have been implemented across the country to achieve multiple aims such as (i) reducing soil erosion and surface water sediment loads (Tamene and Vlek, 2007), (ii) reducing surface water runoff and enhancing groundwater recharge (Woldearegay et al., 2018), and (iii) promoting revegetation and soil fertility, thereby increase agricultural productivity (Abera et al., 2020). In addition to improving livelihoods, the land restoration efforts also support the government of Ethiopia to achieve its regional and international commitments such as the “4 per 1000” initiative and the Land Degradation Neutrality programme (Chabbi et al., 2017). It is also expected to contribute to the achievement of both the national REDD + programme and the Climate Resilient Green Economy (CRGE) strategy.

Land management practices implemented in many parts of Ethiopia showed positive impacts on restoring degraded landscapes and enhanced soil fertilities (Abdalla et al., 2018). Abera et al. (2020) conducted a meta-analysis to summarize how different land restoration practices and interventions affect ecosystem services. Other studies also investigated the effect of land restoration on various ecosystem and livelihood benefits in Ethiopia (Balehegn et al., 2019; Adimassu et al., 2018; Araya et al., 2011). Despite these efforts, there is however a knowledge gap about the impacts of land management practices on sequestration of soil organic carbon (SOC; see e.g. Namirembe et al., 2020). SOC plays a key role in various agricultural and ecological processes related to soil fertility (Abdalla et al., 2018), carbon cycle and soil-atmosphere interactions including CO2 sequestration (Ramesh et al., 2019; Xu et al., 2019; Murty et al., 2002). As SOC is the largest pool of carbon in the terrestrial ecosystems (Schlesinger and Bernhardt, 2013), any effort to sequester SOC is a key mechanism to reduce CO2 in the atmosphere due to humans and contribute to mitigate climate change (Paustian et al., 2016; Smith et al., 2016; Zomer et al., 2017). Thus, our knowledge about the relationship between land management practices and SOC will be crucial to facilitate informed decision making and also contributes to the global and regional knowledge pool.

The scientific community has spent considerable efforts in mapping SOC, modelling its spatiotemporal variation and confirming its primary role in shaping ecosystems functioning (Grinand et al., 2017; Ajami et al., 2016; Ratnayake et al., 2014). Accurate estimation of SOC and its dynamics are necessary to support improved carbon management and climate change mitigation, and to identify land management practices with higher SOC sequestration benefits. Good understanding of the spatiotemporal dynamics of SOC in relation to land management practices can also enable us to understand what options placed where can sequester the most carbon, making our interventions more effective and efficient. This can ultimately enable governments to achieve their Nationally Determined Contributions (NDCs) within their planning horizons. In CRGE, the contribution of soil as potential for carbon sequestration through land restoration and climate smart agriculture practices is stated.

At a local scale, SOC concentrations are largely governed by soil physical and chemical properties, which determine the SOC stabilization (Cotrufo et al., 2019), environmental conditions and land use changes (Martin et al., 2010; Fantappiè et al., 2010; Abegaz et al., 2016), intensive agricultural practices (Yan et al., 2012), and shifts in soil management practices (Powlson et al., 2011; West and Post, 2002). Conservation tillage practices such as reduced tillage and no-tillage have been proposed, as an alternative to conventional tillage, for their advantages in preserving SOC (Beare et al., 1994; Liu et al., 2014) and improve soil physicochemical properties (Blanco-Canqui and Ruis, 2018; Johnson and Hoyt, 1999). The relationship between environmental variables, land management factors and SOC is complex and non-linear. Recently, the use of machine learning (ML) techniques to unravel patterns and identify complex relationships is suggested to improve the SOC prediction (Khaledian and Miller, 2020; Lamichhane et al., 2019). In most cases, random forest (RF) as an ensemble ML method has often outperformed other ML models (Keskin et al., 2019; Mahmoudzadeh et al., 2020; Tajik et al., 2020; Forkuor et al., 2017). In this study, we used RF to estimate the impacts of SLMP interventions on SOC in four selected watersheds in Ethiopia. The specific objectives were to: (i) comparatively evaluate RF model calibration strategies; (ii) estimate and map the impacts of SLMP on SOC sequestration and; (iii) estimate and map the achievable SOC sequestration hotspots due to existing land management practices such as conservation tillage and physical soil managements.

2. Materials and methods

2.1. Study area description

The study was conducted in four watersheds (Adi tsegora, Yesir, Gafera and Azuga shuba) where the SLMP has been implemented. The watersheds are systematically selected from different agro-ecological zones (Fig. 1 and Table 1). The watershed areas are 88.7 ha (Azuga shuba), 99.8 ha (Gafera), 116 ha (Yesir) and 129 ha (Adi Tsegora). In all watersheds, implementation of the SLM program started in 2010. Each watershed has distinct characteristics in terms of land use and topography (Table 1).

2.2. Soil sampling and laboratory analysis

Soil samples were collected in 2010, before SLMP interventions, and in 2018, after 8 years of interventions. The former were collected by the SLMP project as baseline data while in 2018 the research team collected samples from corresponding locations of 2010. The soil samples were collected from a 1 km grid in both years. This sampling design was chosen to give an unbiased estimate of SOC contents and SOC stocks in the areas. The sampling approach was the same in all the four watersheds. A total number of 397 soil sample locations were surveyed both in 2010 (before scenario) and in 2018 (after scenario), constituting 794 soil samples in the four watersheds. The distributions of number of soil samples across the four watersheds is presented in Table 1. The sampling depth is the topsoil (0–20 cm). The same laboratory analyses procedures and methods were used for both years (2010 and 2018). During the field survey, the land uses/covers types corresponding to each sampling point of each site were recorded. Within each individual sampling plot, four sub-plots were established, one in the center and three on a radial arm with 120° angles between them (Vågen et al., 2013; Abegaz et al., 2016) and four equal subsamples were used for a composite sample. Composite samples were produced by hand-mixing after removing unwanted materials like dead plants, roots, and organic piles. The soil samples were air-dried, crushed, and passed through a 2-mm sieve for laboratory analysis. SOC content was determined using the Walkley-Black oxidation method (Schnitzer, 1982), and SOC stock ha-1 was quantified for the 0–20 cm soil depth according to Eq. (1) (Aynekulu et al., 2011):

$$SOC_{st} = SOC^{*}BD^{*}D \tag{1}$$

where SOCst is the soil organic carbon stock (Mg C ha−1), SOC is the soil organic carbon concentration (g C g−1 soil), BD is the bulk density (g cm−3), D is soil sampling depth (cm), in this case 20.

2.3. Statistical analysis

One of the key objectives of this study was to evaluate if the SOCst varied between before and after the SLM interventions in the four watersheds covering different agro-ecological zones (Table 1). Tests of inferential statistics (paired samples *t*-test and one-way analysis of variance (ANOVA)) were done and results were tested at the 0.05 significance level. The paired-samples *t*-test was used to test whether the

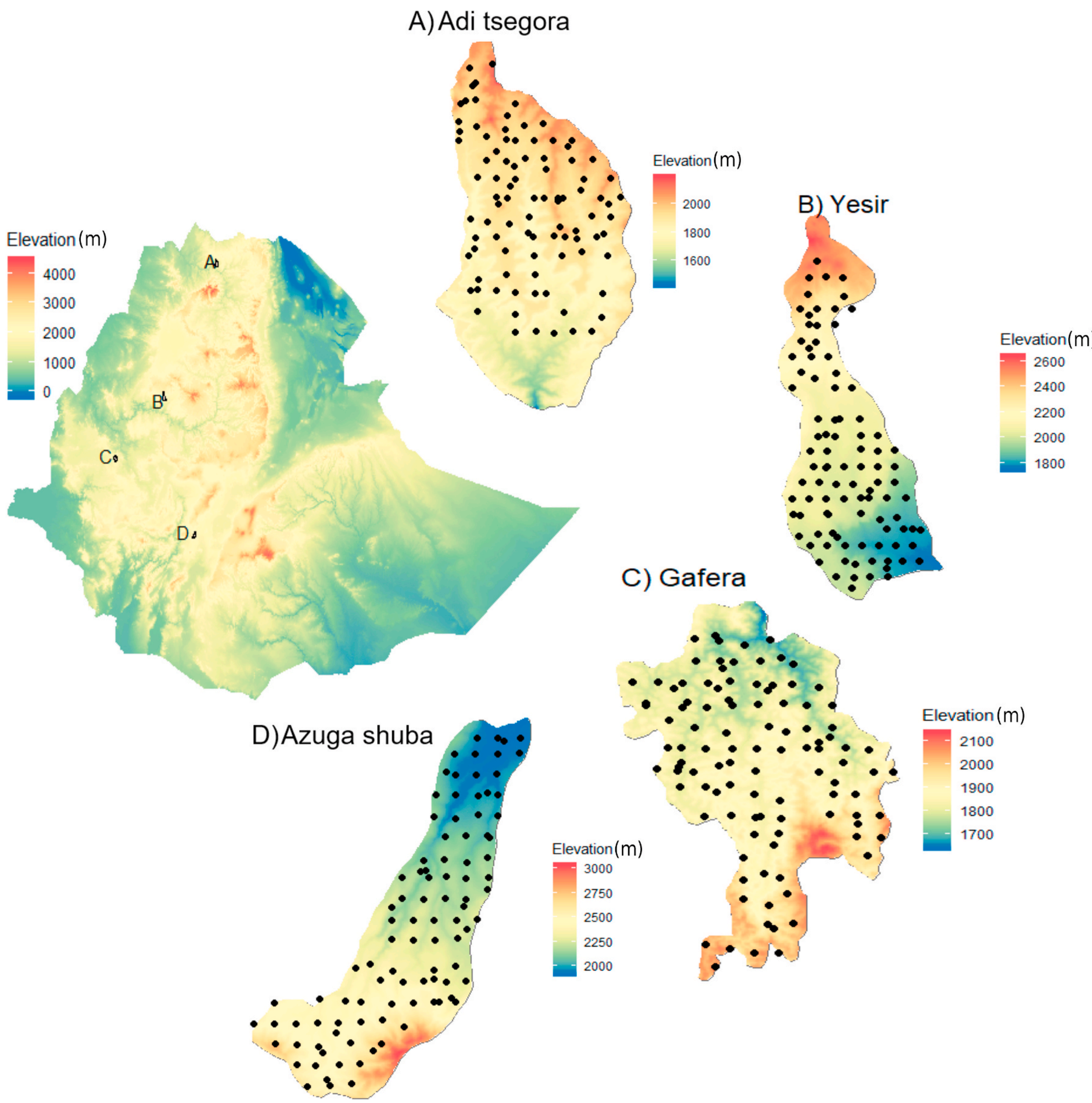

Fig. 1. The four watersheds and soil sampling point locations where SOC sequestration assessment is conducted in Ethiopia a) Adi Tsegora, b) Yesir, c) Gafera, d) Azuga shuba (elevation data from SRTM (Jarvis et al., 2008)). The four soil composites at each sampling site are not plotted here as they are really close each other (20 m-50 m).

Table 1
Studied watersheds, their regional locations and selected physical characteristics.

Watersheds	Region	Area (ha)	# of sample locations	Dominant topography	Mean altitude (m.a.s.l)	Mean temp (°C)	Mean precip (mm)	Agroecological zone
Adi tsegora	Tigray	129	95	Mountainous	1818	20	921	Sub-moist
Yesir	Amhara	116	98	Flat	2044	18	1269	Moist
Gafera	Oromia	99.8	106	Mountainous	1816	20	1791	Sub-humid
Azuga shuba	SNNP[a]	88.7	98	Undulating slope	2242	17	1203	Sub-humid

[a] Southern Nations Nationalities and Peoples.

mean SOCst between the before and after of each of the studied watersheds was significantly different or not. The one-way ANOVA was conducted to examine whether the mean SOCst among the studied watersheds were significantly different or not.

2.4. Selection of environmental variables for modelling

It has been well-established that factors such as topography, vegetation, climatic conditions, farming practices, and soil properties affect the SOCst variability to different extents (Jobbágy and Jackson, 2000; Miller et al., 2004; Kemmitt et al., 2006; Fantappiè et al., 2010). Included topographic variables are: elevation, slope, topographic position index (TPI), and topographic wetness index (TWI). These are derived from the digital elevation model (DEM). DEM of 90-m resolution was obtained from the Shuttle Radar Topography Mission terrain (STRM). Climate variables of various seasons, in addition to the long-term mean, were considered as important covariates to enable us to consider if the seasonal climate variables have influence on SOCst dynamics. Climate data particularly precipitation and temperature, at 4-km and monthly temporal resolution, were acquired from the Ethiopia Institute of Agricultural research (EIAR) (Dinku et al., 2018). Long term average (2010–2018) Moderate Resolution Imaging Spectroradiometer (MODIS) derived normalized difference vegetation index (NDVI) data product (MOD13Q1) were used to infer the spatial variability of greenness. The complete list of covariates used to develop predictive models are detailed in Table 2. The selection of those variables is guided by previous literature (Mahmoudzadeh et al., 2020; Were et al., 2015; Minasny et al., 2013). All covariates were resampled using nearest neighbor approach to a common grid of 90 × 90 m resolution.

2.5. SOC stock and sequestration hotspot mapping

The RF is a classical, powerful and efficient machine learning method which is commonly used in the research of environmental modelling (Mahmoudzadeh et al., 2020; Tajik et al., 2020). RF models are relatively robust with respect to collinearity among predictor variables and noisy covariate data (Svetnik et al., 2003; Wang et al., 2018). As a result, we chose an RF model to estimate soil carbon stock and its spatial dynamics in our study sites. In the RF model, the data is divided into training and testing components for building the model and model validation/testing, respectively (Svetnik et al., 2003). In order to assess the effect of model building strategies on the model performances and identify the best model that can be used for prediction, we evaluated three modelling strategies. These are (1) the use of a single watershed data for calibration, validation and prediction of SOCst spatially, 2) the use of all the four watersheds' combined dataset for calibration, validation and prediction of SOCst, and 3) the use of three watersheds' dataset to train the model and use this model to test and predict at the fourth watershed. This is important to know where the machine learning model can be extrapolated spatially. Specifically, we used three modelling and validation strategies conducted based on: i) each watershed individually, ii) four watershed datasets combined, and iii) leave-one-watershed-out. To assess goodness-of-fitness of the modelling/training strategy, we used R^2 between predicted and observed SOCst in both the training and testing datasets. Among the three modelling/training strategies, we selected the one with higher R2 for testing dataset because a good model performance for testing dataset is an indication of a good predictive capacity of a model as it indicates the model performance in places with no in-situ measurements. In addition to R^2, we used root mean square error (RMSE), to diagnostic the model performance. Then, the selected model is used for predicting SOCst spatially.

To build an optimal predictive model we tuned the Random forest, in ranger package (Wright and Ziegler, 2015), hyper parameters: we varied mtry (i.e. number of variables randomly sampled as candidates at each split) from 2 to 20; and min. node.size (i.e. minimum node size) varied from 2 to 15, in R caret package (Kuhn, 2008). Finally, an optimized ensemble of regression trees (in this case 100) and their parameters were constructed at the training stage and then for the model prediction. We used repeated 30-fold cross validation (CV) to search the hyper-parameter space. Approximately 25% of data in the overall dataset were randomly selected for validation, and the other 75% were used for model training. Based on the final model, important covariates that are responsible for predicting SOCst were selected based on variable of importance analysis. The difference between the predicted SOCst in 2018 and SOCst in 2010 is used to map the actual SOCst sequestration due to the SLM implementation in this period:

$$SOCst\ seq = SOCst_{2018} - SOCst_{2010} \quad (2)$$

Map areas with positive SOCst seq indicate good performance of SLM practices in sequestering SOC in 8 years while areas with low and negative SOCst seq depict poor sequestration or even further depletion of soil carbon loss. To obtain target SOCst, which is the practically obtainable SOC level by implementing existing available SLM practices in the area (Piikki et al., 2019), we estimated the 95% quantile of the scenario based model considering a combination of SLM practices. We have developed spatial layer of managements, for instance, one layer for SLM practice 1 (all same value for the whole area e.g. bunds), another layer for SLM practice 2 (terrace), SLM practice 3 (reduced tillage), etc. For each management scenario, we calculated SOCst based on all covariates used in SOCst2018 and $SOCst_{2010}$ model and these management layers. The target SOCst is then estimated as the maximum SOCst values of all the scenarios and the $SOCst_{2018}$, as in the following:

Table 2
List of covariates considered in building the RF model for prediction of SOC sequestration in the four SLMP watersheds of Ethiopia. TPI = topographic position index; TWI = topographic wetness index.

Variable	Derived element	Acronyms	Source	Native resolution	References to data or method
Climate	Annual precipitation	Annual Precip	EIAR	4 km	Dinku et al. (2018)
	Kiremt (Summer) Precipitation	Kiremt Precip			
	Bega (Winter) Precipitation	Bega Precip			
	Belg (Autumn) Precipitation	Belg Precip			
	Annual Temperature	Annual Temp			
	Kiremt (Summer) Temperature	Kiremt Temp			
	Bega (Winter) Temperature	Bega Temp			
	Belg (Autumn) Temperature	Belg Temp			
Topography	Elevation	Elevation	SRTM	90 m	Jarvis et al. (2008); Zhu et al. (2019); She et al. (2014); Patton et al. (2019)
	Slope	Slope	SRTM-derived	90 m	
	TWI	TWI	SRTM-derived	90 m	
	TPI	TPI	SRTM-derived	90 m	
Soil	pH	Soil pH	ISRIC	250 m	Liang et al. (2019); Novara et al. (2020)
	clay	Clay			
	Silt	Silt			
	CEC	CEC			
Land use	Land use	Land use	Ethiopia Sentinel 2 Land Use Land Cover 2016	20 m	Fusaro et al., (2019); Nyawira et al. (2016)
Vegetation	NDVI	NDVI	MODIS (MOD13Q1)	250 m	Hunt et al. (2002);
Socio-economic	Population density	Pop density	www.worldpop.org	100 m	Linard et al. (2012);
SLM practices	Tillage practice (conventional tillage, reduced tillage, and No tillage)	CT, RT, and NT respectively	Survey	At each soil sample point	
	Physical and biological measures		Survey	At each soil sample point	

ISRIC = International Soil Reference and Information Center

$$targetSOC_{st} = argmax(SOCst_{2018}, SOCst_{Practice1}, SOCst_{Practice2}, \ldots SOCst_{Practicen}) \quad (3)$$

The target SOCst status (what could be reached in eight years) is what we can potentially achieve by implementing SLM technologies that are appropriate to a specific location. We conducted a survey on which land management (physical, biological) and what kind of conservation agriculture practices have been implemented on each sampling plot and to fit relevant management options for each site. The list of SLM practices used to generate spatial model scenarios are described in section 2.5. Based on the partial dependence plot, we showed the effect of the different SLM practices on the SOCst level. In cases where the targeted SOCst was not achieved at the current condition, we calculated the achievable SOCst sequestration potential as the difference between the $SOCst_{2018}$ and target SOCst, as follows (Piikki et al., 2019):

$$Achievable\ SOCst\ seq = target\ SOC_{st} - SOCst_{2018} \quad (4)$$

Model uncertainty due to many factors affect SOC estimations at watershed scale. The source of uncertainty in the current approach is the quality of input covariates. The availability of Ethiopia national soil information system (ETHIOSIS), produced some years back, for researchers would have improved the model quality and model results. In our approach, we have limited ourselves to those covariates with spatially coverage at national scale and freely accessible by anyone so that we can use the model to predict SOC at any location in the country. In addition, there is a lack of detailed, geolocated, land management practice data, which also affect the model performances.

2.6. *The impact of selected SLM practice on SOCst*

We have collected the list of SLM technologies implemented at each sampling location. Bunds, terraces, biological (such as grasses and trees) are the most common interventions at the landscape level. A combination of physical (Bund, or terraces) and biological is also found in some sites. At farmland, there are some conservation tillage practices such as reduced tillage (RT) and no-tillage (NT) which have been implemented as an alternative to conventional tillage (CT).

In this study, we evaluated the impacts of two categories of SLM practices: i) the impacts of biophysical intervention existed at the landscape level particularly bunds, terraces, biological and a combination of physical (bunds and terraces) and biological; and ii) the impacts of conservational tillage practices particularly conventional tillage (CT), reduced tillage (RT) and no-tillage (NT) on the SOCst sequestration, and recommend optimal practice that optimize SOC stock in the four SLMP watersheds. We used the partial dependence plot (Álvarez-Cabria et al., 2017), which illustrates the effect of a predictor variable on the SOCst level after considering the mean effects of all the other predictor variables (Elith et al., 2008), of 2018 RF prediction model to evaluate the relationships between these SLM practices and the SOCst level.

3. Results and discussion

3.1. *SOC stocks in the studied watersheds*

The mean statistics for SOCst for each watershed in the two years (before and after SLM interventions) have been presented in Fig. 2. The general level of SOCst varied between the highest 57.9 (±18.5) Mg C ha-1 in Gafera, followed by 52.2 (±20.7) Mg C ha-1 in Yesir, 40.5 (±15.9) in Azuga shuba, and 25.3 (±11.2) Mg C ha-1 in Adi Tsegora watersheds. The standard error values are estimated from spatial distribution of SOCst at the watershed level. The highest mean of SOCst in the Gafera watershed is because the area is dominated by forest land use while the lowest in Adi Tsegora watershed is because the site is dominated by relatively degraded landscape. The relatively high SOCst level at Yesir watershed could be due to better agricultural land management options such as cover crops being implemented compared to the other watersheds. In addition, the initial soil fertility of the site was better than the others. The range of SOCst reported here (25.3 ± 11.2 to 57.9 ± 18.5 Mg C ha−1) is similar to the ranges previously reported in the highlands of Ethiopia. For example, Abegaz et al. (2020) reported a mean surface (0–20 cm depth) SOC stock of 31.4 Mg C ha−1 for intensive grazing lands, 50.4 Mg C ha−1 for intensive croplands, 49.8 Mg C ha−1 for controlled grazing lands, 108.3 Mg C ha−1 for managed cropland, and 69.4 Mg C ha−1 for enclosures based on survey collected from different part of the country. Many case studies confirmed that the implementation of SLMP improved SOCst in different part of the country (Woolf et al., 2018; Hishe et al., 2017; Aynekulu et al., 2017). The carbon sequestration values observed in the four watersheds are relatively lower than the values report by Akpa et al. (2016) which is in the ranges

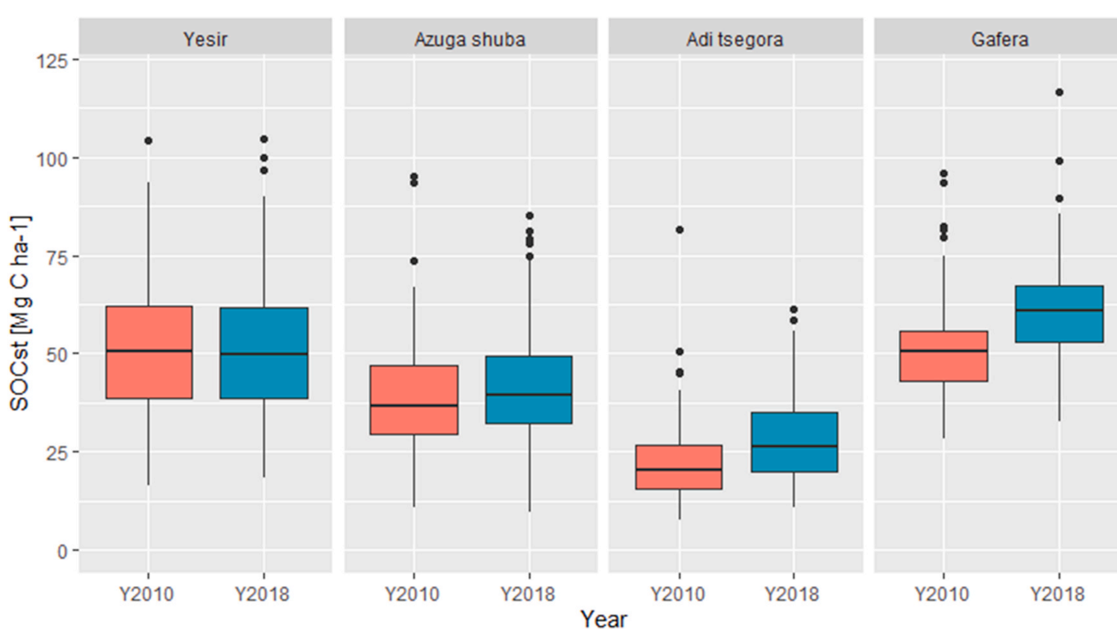

Fig. 2. Distribution of soil organic carbon stock (SOCst) in the four SLMP watersheds. The mid horizontal lines of the boxes show the mean, the boxes show the 25-75-interpercentile range, the whiskers represent the non-outlier range and the points represent outlier observations.

of 17–30 Mg C ha− 1 for Nigeria using a similar approach. The ANOVA result revealed that the mean SOC stocks (for both before and after) spatial variation among the four watersheds was significant ($P < 0.05$; Fig. 2), and generally increasing from the north (Adi Tsegora) to southwest (Gefera) (Figs. 1 and 2). The paired samples *t*-test revealed a significant statistical difference in SOCst between the two years in Gafera watershed in southwest Ethiopia and Adi Tsegora watershed in Northern Ethiopia (Fig. 2), but the differences in Azuga shuba and Yesir watersheds were not significant. This indicates that significant SOCst can be achieved in a short period (in this case in 8 years) in high potential areas whereas an increase in SOCst could take a longer period in some other areas. The observed differences could be attributed to different factors – on the proper application of SLM, the specific SLM technologies implemented and their potential differences in SOC sequestration, agroecological and other environmental variables that influence the performances of SLM options. These results are in agreement with a recent meta-analysis study conducted by Abera et al. (2020) which shows that agroecological zone and the specific technology implemented affect the performances of SLM technologies.

3.2. SOC stock estimation using the RF model

Table 3 shows the results of RF modelling approach in three calibration phases: single watershed, leave-one-watershed-out and all watersheds combined dataset. The results show that combining dataset from all the four watersheds outperform a single watershed calibration for modelling within a sampled watershed. The leave-one-watershed-out strategy tell us how well the RF model can be expected to work if applied in unsampled watersheds. The use of a single watershed data to build a predictive model results in high performance in the training period (R^2 = 0.78–0.93 and RMSE = 8.1–14.4 Mg C ha-1) but the performance dramatically decreased in the testing dataset (R^2 = 0.21–0.34 and RMSE = 11.8–14.4 Mg C ha-1) (Table 3). The poor model performance during the testing dataset indicates that the models built for a single watershed, with relatively few data points, is susceptible for overfitting problem i.e. a case where the model is perfectly fitting the data during the training period but unable to explain the data during the testing period. This could be due to the smaller data size to capture the variabilities in the dataset and produce a robust model. Similarly, in the case of leave-one-watershed-out, the model performance for testing dataset is poor most likely due to the fact that the variabilities in the testing dataset are not captured by the other three watersheds used to train the model. In other words, it is most probably because RF model does not scale very well for a new data that lies outside the range of training dataset. This tells us that the model shall not be applied in areas where no local samples are included in the model calibration dataset. When combining all the dataset, the predictive capacity of the model has improved, and in fact the model performance was almost equal for training and testing. Comparison between the two years, during the training, the model performance was higher when predicting the 2018 data. In 2010, for the training dataset, the model performance was R^2 = 0.55 and RMSE = 13.8 Mg C ha-1, and for the testing dataset, the model performance was R^2 = 0.50 and RMSE = 13.2 Mg C ha-1. Similarly, in 2018, the model performance for the training dataset is about R^2 = 0.56 and RMSE = 14.5 Mg C ha-1, whereas for testing case, the model performance is R^2 = 0.55 and RMSE = 14.1 Mg C ha-1. The results obtained during the testing can be taken as equivalent to the predictive capacity of the model in any areas within the four watersheds where there is no soil measurement available. Those results obtained in both years are relatively high in comparison to SOCst models presented in literature in the region and beyond (Owusu et al., 2020; Forkuor et al., 2017; Keskin et al., 2019; Mahmoudzadeh et al., 2020; Tajik et al., 2020). A recent study by Owusu et al. (2020) developed a similar spatially explicit predictive model of SOCst in Ghana and achieved R^2 = 0.34.

One of the key challenges of SOCst modelling is to identify which factors are responsible for SOC dynamics. Here, we presented the importance of covariates considered in the model inputs to clarify which data are useful for SOCst prediction in both years. The order of the importance of variables varies from year to year (Fig. 3). In 2010, clay, soil pH, NDVI, TPI and topographic slope were the five top important variables for predicting SOCst. In the case of 2018, NDVI, soil pH, bulk density, TPI and Sand are the top five covariates used to predict the SOC in the four watersheds. There is high overlap between the two years in terms of rank of importance (Fig. 3). It is noted that the climate element during the rainy season (Kiremt) is not as important as the dry season in both cases. Generally, non-rainy season precipitation and temperature are more important variables than the annual and Kiremt (June, July, Auguest) season. Contrary to Gomez et al. (2008), our result shows that the SOC is highly related to vegetation cover, i.e. NDVI index, and it influences SOC prediction (Fig. 3). Many studies confirmed that soil parameters predominantly influence SOC stocks at different spatial scale (Hobley et al., 2015; Schulp and Verburg, 2009; Wiesmeier et al., 2014a; Xiong et al., 2014). Specifically, strong correlation between SOC stocks and clay content is found in many studies (Arrouays et al., 2006; Zinn et al., 2007). At the watershed scale, Wiesmeiera et al. (2019) also reviewed that topographic and vegetation information are considered to be important driver of SOC stock.

3.3. Mapping SOCst and sequestration potential

The spatial patterns of SOCst predicted by the RF model for four watersheds in the years 2010 and 2018 are shown in Fig. 4. In addition

Table 3
Model performance indicators (R^2 and RMSE) for random forest based estimation of SOCst in four SLMP watersheds of Ethiopia using three modelling strategies.

Model building strategy	Dataset	2010		2018		2018 with SLMP scenarios	
		Training (R^2/RMSE [Mg C ha-1])	Testing (R^2/RMSE [Mg C ha-1])	Training (R^2/RMSE [Mg C ha-1])	Testing (R^2/RMSE [Mg C ha-1])	Training (R^2/RMSE [Mg C ha-1])	Testing (R^2/RMSE [Mg C ha-1])
Watershed specific	Yesir	0.83 (14.4)	0.34 (14.7)	0.87 (15.2)	0.21 (16.01)		
	Gafera	0.78 (11.2)	0.16 (10.5)	0.78 (10.3)	0.07 (16.1)		
	Azuga shuba	0.88 (13.6)	0.22 (12.2)	0.88 (13.1)	0.50 (12.3)		
	Adi Tsegore	0.93 (8.1)	0.21 (11.8)	0.92 (8.6)	0.03 (14.1)		
All watersheds combined	All watersheds combined	0.55 (13.8)	0.50 (13.22)	0.56 (14.5)	0.55 (14.1)	0.68 (10.2)	0.52 (11)
Leave-one-watershed-out	Case 1	0.57 (13.1)	0.04 (16.2)	0.55 (14.8)	0.03 (16.2)		
	Case 2	0.32 (14.0)	0.03 (18.5)	0.43 (14.8)	0.01 (14.6)		
	Case 3	0.53 (13.5)	0.003 (17.2)	0.54 (13.7)	0.02 (24.9)		
	Case 4	0.55 (12.1)	0.04 (22.5)	0.63 (12.4)	0.01 (25.6)		

Case 1 (training watersheds Yesir, Gafera, and Adi Tsegore; and testing watershed Azuga suba);
Case 2 (training watersheds Yesir, Gafera, and Azuga suba, and testing watershed Adi Tsegore);
Case 3 (training watersheds Yesir, Adi Tsegore, and Azuga suba, and testing watershed Gafera);
Case 4 (training watersheds Gafera, Adi Tsegore, and Azuga suba, and testing watershed Yesir).

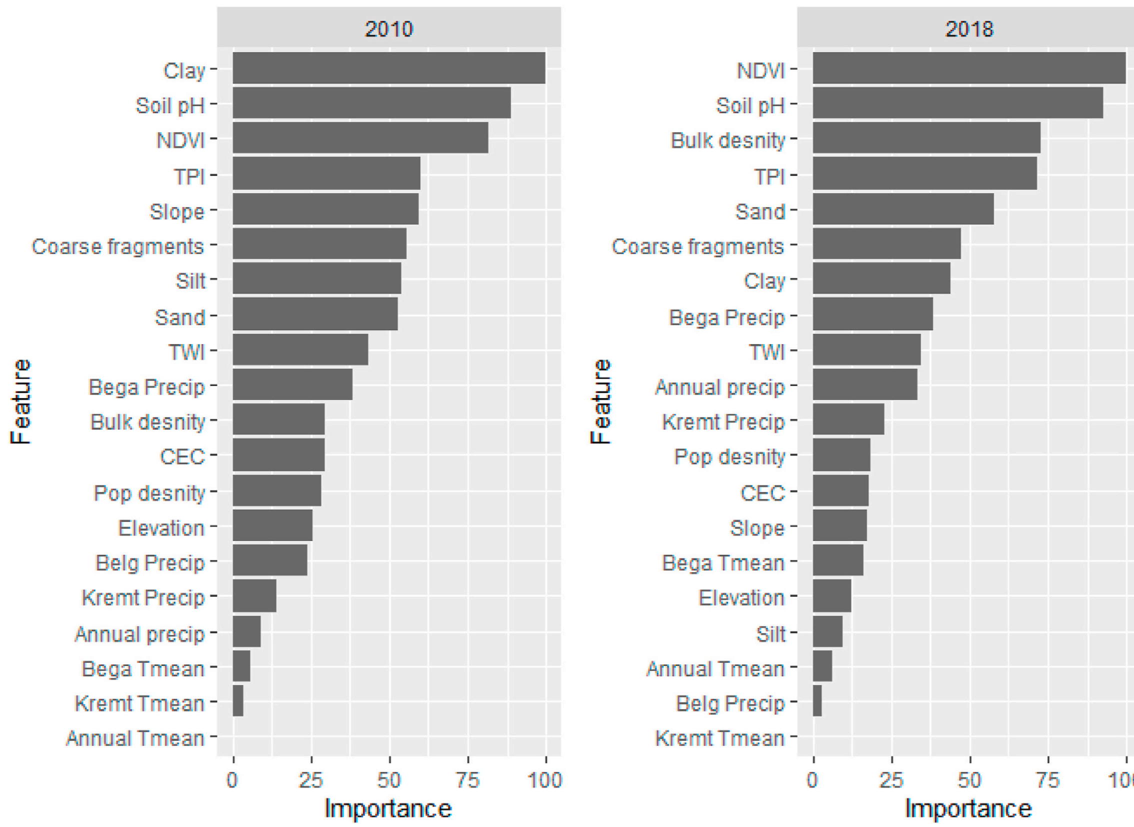

Fig. 3. Important variables for predicting SOCst in before (2010) and after (2018) SLM interventions in Ethiopia as identified based on RF model. Predictors are explained in Table 2.

to the two period SOCst maps, the difference between the two is also mapped as SOC sequestration in the 8 years. The spatial pattern of SOCst in all watersheds show low values for the year 2010 and higher values for 2018. This corresponds with the implementation and SLM options that started after 2010. The prediction maps show mostly gradual SOCst changes across the study areas and spatial variabilities within sites are pertinent. For example, for Adi Tsegora watershed, large values are predicted in the eastern and northeastern parts (Fig. 4A). The highest SOCst sequestration has occurred in the central eastern part of the Yesir watershed (Fig. 4B) whereas the lowest is observed in the northern tip part of the watershed most likely due to steep slope that can facilitate SOC removal in the form of erosion (Martinez-Mena et al., 2018). In the Gafera watershed relatively high SOCst sequestration is observed between 2010 and 2018 across all parts of the watershed compared to the other sites. SOCst sequestration increased from south to north, with the highest stocks in the northern part of the watershed, most probable because of increasing rainfall and altitude gradients with high biomass production. In the Azuga shuba watershed, SOCst sequestration is observed in all parts of the watershed, the amount varying in the northern and southern parts. The low SOCst sequestration areas in the upper part of the watershed are dominated by high elevation and crop lands whereas the high SOCst sequestration areas are in the lowlands characterized by concave curvature.

3.4. Achievable SOC sequestration at landscape scale

Achievable SOC sequestration potential shows ‘a positive gap’ in most SLMP watersheds indicating that there is still potential for improvements in terms of retaining more SOC (Fig. 5). The specific location of improvement (where within each landscape there is potential to sequester more carbon) is mapped spatially in the achievable SOC sequestration maps. On average at watershed level, the highest amount of SOCst achievable sequestration potential is predicted in the Yesir watershed (34.7 Mg C ha−1), followed by Azuga shuba watershed (33.2 Mg C ha−1). The lowest achievable SOCst potential is observed at Adi Tsegora watershed (13.7 Mg C ha−1), followed by Gafera watershed (15.8 Mg C ha−1) (Fig. 6). Predicted rate of SOCst sequestration potential at Adi Tsegora watershed is the lowest because the area is characterized by low precipitation, poor vegetation cover and steep slope landscape. This means implementing additional SLM practices would not bring significant improvement in SOCst sequestration. Similarly, in Gafera watershed, the prospect to sequester more SOCst due to conservation measures and conservation agricultural practices are limited most likely because the watershed is dominated by forest cover resulting in high current SOCst that is close to the target SOCst level. The other two watersheds (Yesir and Azuga shuba), which are characterized by agricultural land and medium level of current SOCst have higher achievable SOC sequestration. Spatially distributed assessment of achievable SOC sequestration potentials is important to develop targeted land management and climate change mitigation measures and guide investments on the land and soil fertility management practices. For instance, locations with low SOCst, but with high achievable sequestration potential may be targeted for SLMP and conservation agriculture practices compared to those sites which show saturated SOCst sequestration potential. The maps in Figs. 4–5 and the density functions in Fig. 6 show that there is variation in achievable SOC within the watersheds. The positive impact of sustainable management practice program in Ethiopia on SOC storage already substantiated by many studies (Abera et al., 2020; Abegaz et al., 2016, 2020; Woolf et al., 2018; Hishe et al., 2017; Aynekulu et al., 2017). Our study extended these works and showed how SOC stocks have changes due to these interventions spatially.

The effects of SLM practices on SOCst are presented in Fig. 7. No-tillage (NT) slightly improved SOC by 0.8 Mg C ha−1 compared to

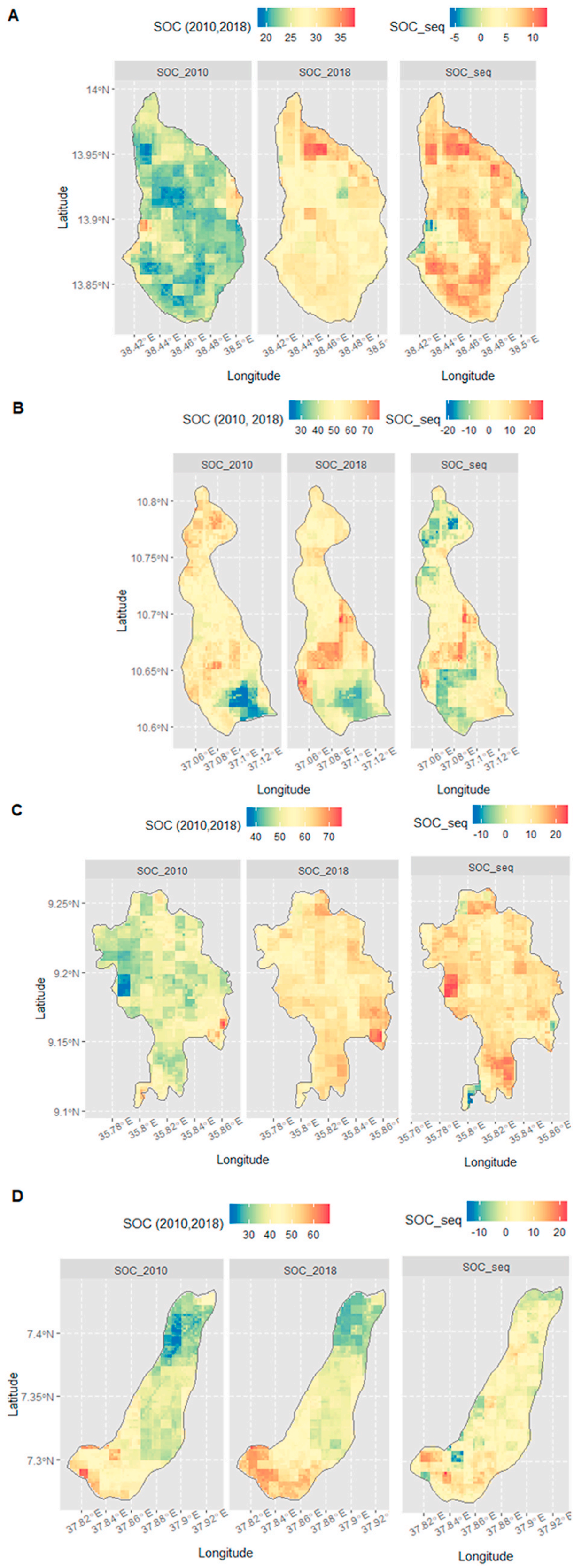

Fig. 4. Spatial distribution of SOC stocks (Mg ha-1) using RF model in 2010, 2018; and difference (SOC sequestration in 8 years) in the four SLMP watersheds of Ethiopia: A) Adi Tsegora, B) Yesir, C) Gafera, D) Azuga shuba watershed.

conventional tillage (CT) (Fig. 7). It is obvious that NT showed a high increase in comparison to CT and reduced tillage (RT), as it is the highest form of conservation agriculture. A study by Namirembe et al. (2020) also confirms that the SOC increases by various conservation tillage practices. On the contrary, RT shows lower SOCst in comparison to the CT practices. There are other factors determining if conservation tillage practices affect the SOC such as the duration of practices, the nature of the soil, the availability of vegetation cover (Luo et al., 2010). In terms of biophysical measures, the lowest effect on SOC stock is observed for bund interventions (Fig. 7). Trench structure, however, has a higher effect on SOCst, and equal effect to biological intervention. The combined effect of biological and physical measures as it is implemented in some locations in Ethiopia has shown highest SOCst. Hailu et al. (2012) has also showed significant effect of physical structures particularly fanyajuu on SOC change in western part of Ethiopia. Similar findings are observed in Abera et al. (2020) that the combined effect of physical and biological (mostly grasses along the physical structure) has a good effect on soil fertility status in Ethiopia. Overall, the effect of the two SLM practices are minimal, with maximum effect of 3 Mg C ha-1.

4. Conclusions and recommendations

SLM practices have various benefits in arresting land degradation and enhancing soil fertility, generating enabling conditions for food security of small farmers. This study is conducted to study 1) the impact of SLM practice, implemented in the last 8 years, on SOC stock, 2) identify SOC sequestration hotspots, and achievable SOC sequestration potential spatially. The following results are obtained:

- Generally, soils in the Gafera watershed contain the highest amount of SOC stock and soil in Adi Tsegora have the lowest SOC stock.
- Comparing SOCst in 2010 and 2018, significant differences between the two years are observed in two watersheds (i.e. Gafera watershed in southwest Ethiopia and Adi Tsegora watershed in Northern Ethiopia).
- We used the RF model to predict the spatial distribution characteristics of SOC at two periods (2010 and 2018), based on which we determined the key environmental factors affecting their spatial-temporal changes.
- The use of a single watershed to build a predictive model using RF resulted in overfitting, where the model performance is very good during the training dataset and very low during testing.
- Combining all the four watersheds data improves the RF model predictive capacity, and this strategy is used to predict the SOC maps spatially. The model performance is better than those reported in literature in the region.
- The relatively poor performance of the leave-one-watershed-out model evaluation showed that it is essential to include data from the area in question when parameterizing RF models for SOC prediction.
- The results of variable importance show that clay, NDVI, soil pH and TPI are some of important covariates that explain the spatial variability of SOC.
- SOCst sequestration levels between the 2010 and 2018 are estimated spatially in four watersheds in the highland of Ethiopia, with a good accuracy.
- Achievable SOCst sequestration potentials are spatially mapped to facilitate land management targeting to achieve the target SOCst at landscape level.
- The highest amount of achievable SOCst sequestration potential is obtained in Yesir watershed (34.7 Mg C ha−1), followed by Azuga shuba watershed (33.2 Mg C ha−1), followed by Gafera watershed (15.8 Mg C ha−1), and Adi Tsegora watershed (13.7 Mg C ha−1) for this eight year period.

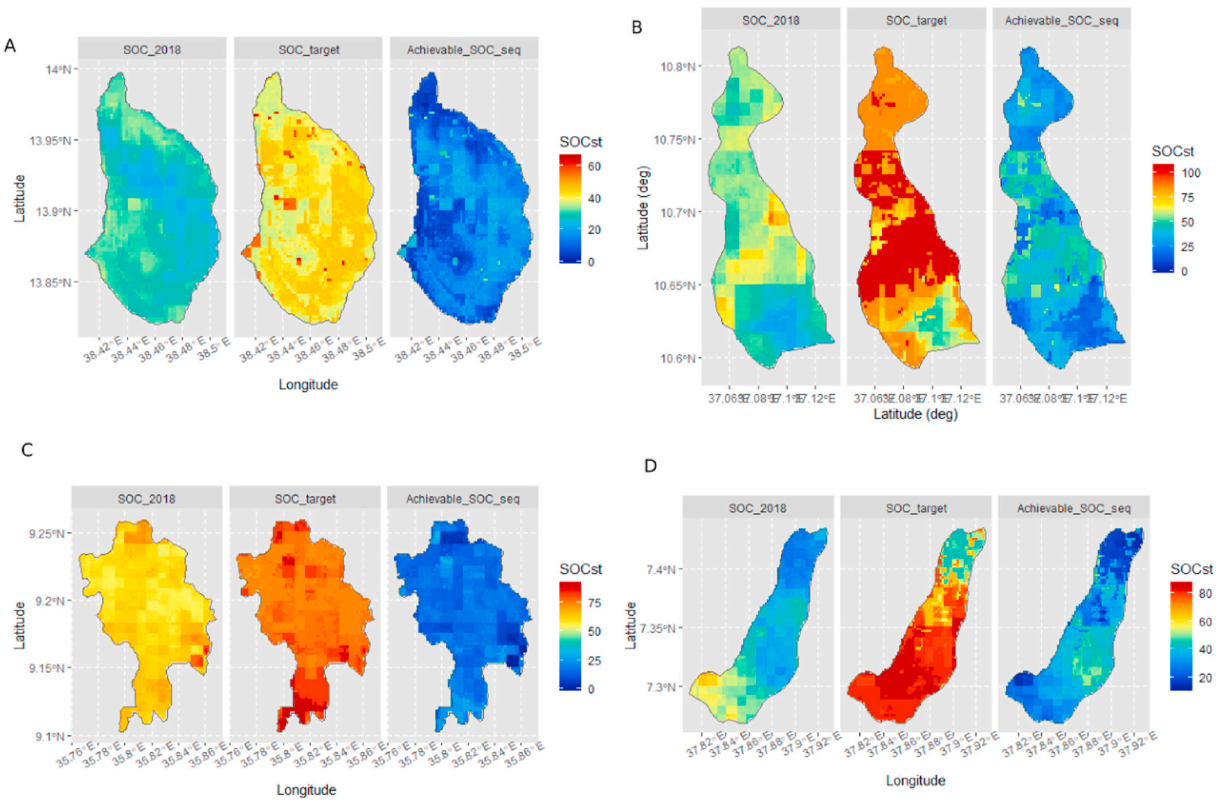

Fig. 5. Spatial distribution of SOC stocks (Mg ha-1) in 2018 (after SLMP practice interventions), target SOC sequestration level, and achievable SOC sequestration potential in A) Adi Tsegora, B) Yesir, C) Gafera, D) Azuga shuba watershed.

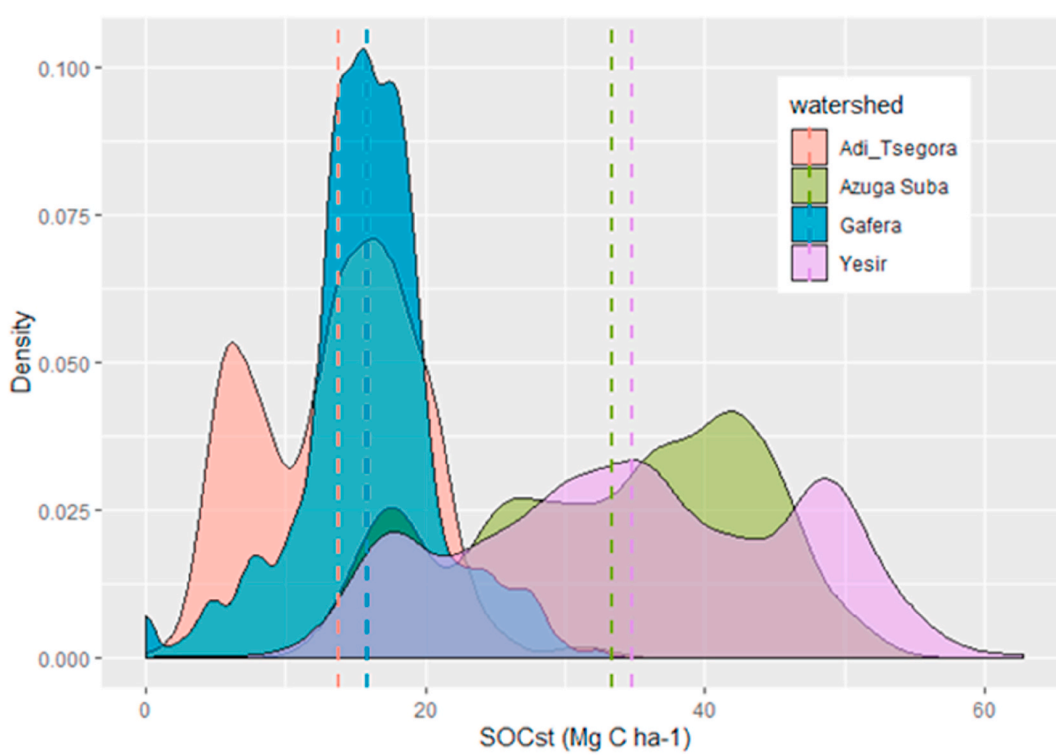

Fig. 6. The density distribution of achievable SOC sequestration potential of four SLMP watersheds in Ethiopia.

- The overall effect of physical and conservation agriculture on SOCst, on average, is minimal, which is about 3.5 Mg C ha−1. No tillage (NT) increased SOC in all watersheds.
- The highest SOC stock is obtained for a combination of physical and biological interventions ("bunds + vegetations" or "terraces + vegetations") followed by the biological intervention.

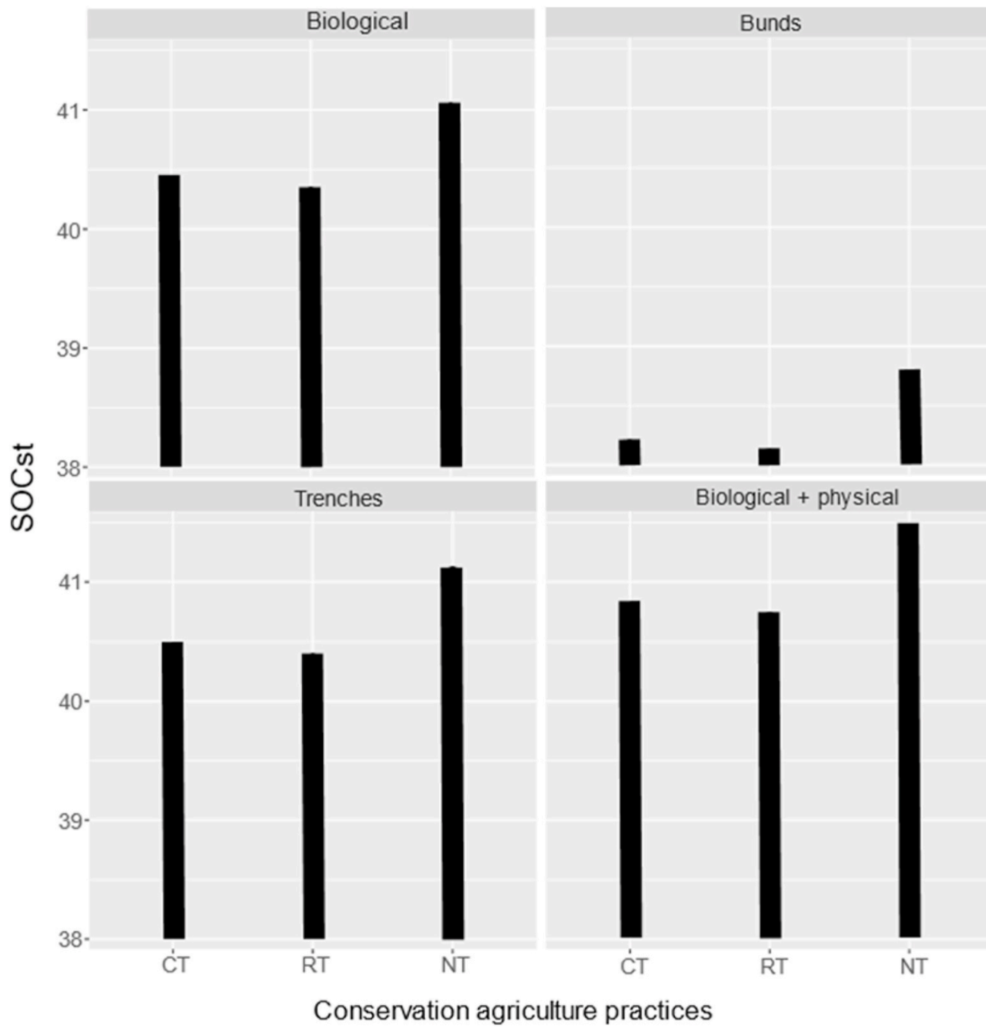

Fig. 7. The marginal effect of selected SLM practices on SOC stock in four SLMP watersheds of Ethiopia. CT - Conventional tillage, RT- Reduced tillage, NT- No tillage.

Credit author statement

Wuletawu Abera, Conceptualization, Methodology, Software, Writing – original draft, Writing – review & editing. Lulseged Tamene. Conceptualization, Data curation, Supervision, Writing – review & editing. Assefa Abegaz, Investigation, Conceptualization, Writing – review & editing. Habtamu Hailu, Writing – review & editing. Kirstin Piikki, Conceptualization, Writing – review & editing. Mats Söderström, Conceptualization, Writing – review & editing. Evan Girvetz, Writing – review & editing, Funding acquisition. Rolf Sommer, Conceptualization, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work is conducted as part of the Federal Ministry for Economic Cooperation and Development, Germany (BMZ) funded project on “Scaling up soil carbon enhancement interventions for food security and climate across complex landscapes in Kenya and Ethiopia (contract: 81206681)”. The USAID Feed the Future program funded Africa RISING project in the highlands of Ethiopia has provided staff time to the first two authors. The project was carried out within the CGIAR Research Program on Water, Land, and Ecosystems (WLE). The first two authors are also partly supported by the CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS) through its creating climate resilience landscapes project.

References

Abegaz, A., Tamene, L., Abera, W., Yaekob, T., Hailu, H., Nyawira, S.S., Sommer, R., 2020. Soil organic carbon dynamics along chrono-sequence land-use systems in the highlands of Ethiopia. Agric. Ecosyst. Environ. 300, 106997.

Abegaz, A., Winowiecki, L.A., Vågen, T.G., Langan, S., Smith, J.U., 2016. Spatial and temporal dynamics of soil organic carbon in landscapes of the upper Blue Nile Basin of the Ethiopian Highlands. Agric. Ecosyst. Environ. 218, 190–208.

Abera, W., Tamene, L., Tibebe, D., Adimassu, Z., Kassa, H., Hailu, H., et al., 2020. Characterizing and evaluating the impacts of national land restoration initiatives on ecosystem services in Ethiopia. Land Degrad. Dev. 31 (1), 37–52.

Abdalla, M., Hastings, A., Chadwick, D.R., Jones, D.L., Evans, C.D., Jones, M.B., et al., 2018. Critical review of the impacts of grazing intensity on soil organic carbon storage and other soil quality indicators in extensively managed grasslands. Agric. Ecosyst. Environ. 253, 62–81.

Adimassu, Z., Langan, S., Barron, J., 2018. Highlights of Soil and Water Conservation Investments in Four Regions of Ethiopia, vol. 182. International Water Management Institute (IWMI). http://www.iwmi.cgiar.org/Publications/Working_Papers/working/wor182.pdf.

Álvarez-Cabria, M., González-Ferreras, A.M., Peñas, F.J., Barquín, J., 2017. Modelling macroinvertebrate and fish biotic indices: from reaches to entire river networks. Sci. Total Environ. 577, 308–318.

Ajami, M., Heidari, A., Khormali, F., Gorji, M., Ayoubi, S., 2016. Environmental factors controlling soil organic carbon storage in loess soils of a subhumid region, northern Iran. Geoderma 281, 1–10.

Akpa, S.I., Odeh, I.O., Bishop, T.F., Hartemink, A.E., Amapu, I.Y., 2016. Total soil organic carbon and carbon sequestration potential in Nigeria. Geoderma 271, 202–215.

Araya, T., Cornelis, W.M., Nyssen, J., Govaerts, B., Bauer, H., Gebreegziabher, T., et al., 2011. Effects of conservation agriculture on runoff, soil loss and crop yield under rainfed conditions in Tigray, Northern Ethiopia. Soil Use Manag. 27 (3), 404–414.

Arrouays, D., Saby, N., Walter, C., Lemercier, B., Schvartz, C., 2006. Relationships between particle-size distribution and organic carbon in French arable topsoils. Soil Use Manag. 22 (1), 48–51.

Aynekulu, E., Mekuria, W., Tsegaye, D., Feyissa, K., Angassa, A., de Leeuw, J., Shepherd, K., 2017. Long-term livestock exclosure did not affect soil carbon in southern Ethiopian rangelands. Geoderma 307, 1–7.

Aynekulu, E., Vagen, T.G., Shepherd, K.D., Winowiecki, L.A., 2011. A Protocol for Measurement and Monitoring Soil Carbon Stocks in Agricultural Landscapes.

Balehegn, M., Haile, M., Fu, C., Liang, W., 2019. Ecosystem-based adaptation in Tigray, Northern Ethiopia: a systematic review of interventions, impacts, and challenges. In: Leal Filho, W. (Ed.), Handbook of Climate Change Resilience. Springer Nature Switzerland. https://doi.org/10.1007/978-3-319-71025-9-117-1.

Beare, M.H., Hendrix, P.F., Coleman, D.C., 1994. Water-stable aggregates and organic matter fractions in conventional-and no-tillage soils. Soil Sci. Soc. Am. J. 58 (3), 777–786.

Blanco-Canqui, H., Ruis, S.J., 2018. No-tillage and soil physical environment. Geoderma 326, 164–200.

Chabbi, A., Lehmann, J., Ciais, P., Loescher, H.W., Cotrufo, M.F., Don, A., et al., 2017. Aligning agriculture and climate policy. Nat. Clim. Change 7 (5), 307–309.

Cotrufo, M.F., Ranalli, M.G., Haddix, M.L., Six, J., Lugato, E., 2019. Soil carbon storage informed by particulate and mineral-associated organic matter. Nat. Geosci. 12 (12), 989–994.

Dinku, T., Thomson, M.C., Cousin, R., del Corral, J., Ceccato, P., Hansen, J., Connor, S.J., 2018. Enhancing national climate services (ENACTS) for development in Africa. Clim. Dev. 10 (7), 664–672.

Elith, J., Leathwick, J.R., Hastie, T., 2008. A working guide to boosted regression trees. J. Anim. Ecol. 77 (4), 802–813.

Fantappiè, M., L'Abate, G., Costantini, E.A.C., 2010. Factors influencing soil organic carbon stock variations in Italy during the last three decades. In: Land Degradation and Desertification: Assessment, Mitigation and Remediation. Springer, Dordrecht, pp. 435–465.

Forkuor, G., Hounkpatin, O.K., Welp, G., Thiel, M., 2017. High resolution mapping of soil properties using remote sensing variables in south-western Burkina Faso: a comparison of machine learning and multiple linear regression models. PloS One 12 (1).

Fusaro, C., Sarria-Guzmán, Y., Chávez-Romero, Y.A., Luna-Guido, M., Muñoz-Arenas, L. C., Dendooven, L., Estrada-Torres, A., Navarro-Noya, Y.E., 2019. Land use is the main driver of soil organic carbon spatial distribution in a high mountain ecosystem. PeerJ 7, e7897. https://doi.org/10.7717/peerj.7897.

Gomez, C., Rossel, R.A.V., McBratney, A.B., 2008. Soil organic carbon prediction by hyperspectral remote sensing and field vis-NIR spectroscopy: an Australian case study. Geoderma 146 (3–4), 403–411.

Grinand, C., Le Maire, G., Vieilledent, G., Razakamanarivo, H., Razafimbelo, T., Bernoux, M., 2017. Estimating temporal changes in soil carbon stocks at ecoregional scale in Madagascar using remote-sensing. Int. J. Appl. Earth Obs. Geoinf. 54, 1–14.

Hailu, W., Moges, A., Yimer, F., 2012. The effects of 'fanyajuu'soil conservation structure on selected soil physical & chemical properties: the case of Goromti watershed, western Ethiopia. Resour. Environ. 2 (4), 132–140.

Hishe, S., Lyimo, J., Bewket, W., 2017. Soil and water conservation effects on soil properties in the Middle Silluh Valley, northern Ethiopia. Int. Soil and Water Conserv. Res. 5 (3), 231–240.

Hobley, E., Wilson, B., Wilkie, A., Gray, J., Koen, T., 2015. Drivers of soil organic carbon storage and vertical distribution in Eastern Australia. Plant Soil 390 (1–2), 111–127.

Hunt, E.R., Fahnestock, J.T., Kelly, R.D., Welker, J.M., Reiners, W.A., Smith, W.K., 2002. Carbon sequestration from remotely-sensed NDVI and net ecosystem exchange. In: From Laboratory Spectroscopy to Remotely Sensed Spectra of Terrestrial Ecosystems. Springer, Dordrecht, pp. 161–174.

Jarvis, A., Reuter, H.I., Nelson, A., Guevara, E., 2008. Hole-filled SRTM for the globe version 4. Available from the CGIAR-CSI SRTM 90m database, 15, 25–54. http://srtm.csi.cgiar.org.

Jobbágy, E.G., Jackson, R.B., 2000. The vertical distribution of soil organic carbon and its relation to climate and vegetation. Ecol. Appl. 10 (2), 423–436.

Johnson, A.M., Hoyt, G.D., 1999. Changes to the soil environment under conservation tillage. HortTechnology 9 (3), 380–393.

Kemmitt, S.J., Wright, D., Goulding, K.W., Jones, D.L., 2006. pH regulation of carbon and nitrogen dynamics in two agricultural soils. Soil Biol. Biochem. 38 (5), 898–911.

Keskin, H., Grunwald, S., Harris, W.G., 2019. Digital mapping of soil carbon fractions with machine learning. Geoderma 339, 40–58.

Khaledian, Y., Miller, B.A., 2020. Selecting appropriate machine learning methods for digital soil mapping. Appl. Math. Model. 81, 401–418.

Kuhn, M., 2008. Building predictive models in R using the caret package. J. Stat. Software 28 (5), 1–26.

Lamichhane, S., Kumar, L., Wilson, B., 2019. Digital soil mapping algorithms and covariates for soil organic carbon mapping and their implications: a review. Geoderma 352, 395–413.

Liang, Z., Chen, S., Yang, Y., Zhou, Y., Shi, Z., 2019. High-resolution three-dimensional mapping of soil organic carbon in China: effects of SoilGrids products on national modeling. Sci. Total Environ. 685, 480–489.

Linard, C., Gilbert, M., Snow, R.W., Noor, A.M., Tatem, A.J., 2012. Population distribution, settlement patterns and accessibility across Africa in 2010. PloS One 7 (2).

Liu, E., Teclemariam, S.G., Yan, C., Yu, J., Gu, R., Liu, S., et al., 2014. Long-term effects of no-tillage management practice on soil organic carbon and its fractions in the northern China. Geoderma 213, 379–384.

Luo, Z., Wang, E., Sun, O.J., 2010. Can no-tillage stimulate carbon sequestration in agricultural soils? A meta-analysis of paired experiments. Agric. Ecosyst. Environ. 139 (1–2), 224–231.

Mahmoudzadeh, H., Matinfar, H.R., Taghizadeh-Mehrjardi, R., Kerry, R., 2020. Spatial Prediction of Soil Organic Carbon Using Machine Learning Techniques in Western Iran. Geoderma Regional, e00260.

Martin, D., Lal, T., Sachdev, C.B., Sharma, J.P., 2010. Soil organic carbon storage changes with climate change, landform and land use conditions in Garhwal hills of the Indian Himalayan mountains. Agric. Ecosyst. Environ. 138 (1–2), 64–73.

Martinez-Mena, M., Lopez, J., Almagro, M., Boix-Fayos, C., Albaladejo, J., 2008. Effect of water erosion and cultivation on the soil carbon stock in a semiarid area of South-East Spain. Soil Tillage Res. 99 (1), 119–129.

Miller, A.J., Amundson, R., Burke, I.C., Yonker, C., 2004. The effect of climate and cultivation on soil organic C and N. Biogeochemistry 67 (1), 57–72.

Minasny, B., McBratney, A.B., Malone, B.P., Wheeler, I., 2013. Chapter one–digital mapping of soil carbon. BS (Breed. Sci.): Agro Sur 118, 1–47 doi: 10.1016.B978-0-12-405942-9.00001-3.

Murty, D., Kirschbaum, M.U., Mcmurtrie, R.E., Mcgilvray, H., 2002. Does conversion of forest to agricultural land change soil carbon and nitrogen? A review of the literature. Global Change Biol. 8 (2), 105–123.

Nedessa, B., Yirga, A., Seyoum, L., Gebrehawariat, G., 2015. A Guideline on Documentation of Sustainable Land Management Best Practices in Ethiopia; Ministry of Agriculture. Natural Resource Sector: Addis Ababa, Ethiopia.

Namirembe, S., Piikki, K., Sommer, R., Söderström, M., Tessema, B., Nyawira, S.S., 2020. Soil organic carbon in agricultural systems of six countries in East Africa–a literature review of status and carbon sequestration potential. S. Afr. J. Plant Soil 1–15.

Novara, A., Favara, V., Novara, A., Francesca, N., Santangelo, T., Columba, P., et al., 2020. Soil carbon budget account for the sustainability improvement of a mediterranean vineyard area. Agronomy 10 (3), 336.

Nyawira, S.S., Nabel, J.E., Don, A., Brovkin, V., Pongratz, J., 2016. Soil carbon response to land-use change: evaluation of a global vegetation model using observational meta-analyses. Biogeosciences (19), 5661–5675.

Owusu, S., Yigini, Y., Olmedo, G.F., Omuto, C.T., 2020. Spatial prediction of soil organic carbon stocks in Ghana using legacy data. Geoderma 360, 114008.

Patton, N.R., Lohse, K.A., Seyfried, M.S., Godsey, S.E., Parsons, S.B., 2019. Topographic controls of soil organic carbon on soil-mantled landscapes. Sci. Rep. 9 (1), 1–15.

Paustian, K., Lehmann, J., Ogle, S., Reay, D., Robertson, G.P., Smith, P., 2016. Climate-smart soils. Nature 532, 49–57.

Piikki, K., Söderström, M., Sommer, R., Da Silva, M., Munialo, S., Abera, W., 2019. A boundary plane approach to map hotspots for achievable soil carbon sequestration and soil fertility improvement. Sustainability 11 (15), 4038.

Powlson, D.S., Gregory, P.J., Whalley, W.R., Quinton, J.N., Hopkins, D.W., Whitmore, A. P., Goulding, K.W., 2011. Soil management in relation to sustainable agriculture and ecosystem services. Food Pol. 36, S72–S87.

Ramesh, T., Bolan, N.S., Kirkham, M.B., Wijesekara, H., Freeman II, O.W., Korres, N.E., Ullah, H., 2019. Soil organic carbon dynamics: impact of land use changes and management practices: a review. In: Dvances in Agronomy, vol. 159, pp. 1–107.

Ratnayake, R.R., Kugendren, T., Gnanavelrajah, N., 2014. Changes in soil carbon stocks under different agricultural management practices in North Sri Lanka. J. Natl. Sci. Found. Sri Lanka 42 (1).

Schlesinger, W.H., Bernhardt, E.S., 2013. Biogeochemistry: an Analysis of Global Change, third ed. Academic Press, Elsevier, New York.

Schulp, C.J.E., Verburg, P.H., 2009. Effect of land use history and site factors on spatial variation of soil organic carbon across a physiographic region. Agric. Ecosyst. Environ. 133 (1–2), 86–97.

She, D., Xuemei, G., Jingru, S., Timm, L.C., Hu, W., 2014. Soil organic carbon estimation with topographic properties in artificial grassland using a state-space modeling approach. Can. J. Soil Sci. 94 (4), 503–514.

Smith, P., House, J.I., Bustamante, M., Sobocká, J., Harper, R., Pan, G., et al., 2016. Global change pressures on soils from land use and management. Global Change Biol. 22 (3), 1008–1028.

Svetnik, V., Liaw, A., Tong, C., Culberson, J.C., Sheridan, R.P., Feuston, B.P., 2003. Random forest: a classification and regression tool for compound classification and QSAR modeling. J. Chem. Inf. Comput. Sci. 43 (6), 1947–1958.

Tajik, S., Ayoubi, S., Zeraatpisheh, M., 2020. Digital mapping of soil organic carbon using ensemble learning model in Mollisols of Hyrcanian forests, northern Iran. Geoderma Reg., e00256

Tamene, L., Vlek, P.L.G., 2007. Assessing the potential of changing land use for reducing soil erosion and sediment yield of catchments: a case study in the highlands of northern Ethiopia. Soil Use Manag. 23 (1), 82–91.

Vågen, T.G., Winowiecki, L.A., 2013. Mapping of soil organic carbon stocks for spatially explicit assessments of climate change mitigation potential. Environ. Res. Lett. 8 (1), 15011.

Wang, J., Ding, J., Abulimiti, A., Cai, L., 2018. Quantitative estimation of soil salinity by means of different modeling methods and visible-near infrared (VIS–NIR) spectroscopy, Ebinur Lake Wetland, Northwest China. PeerJ 6, e4703.

Were, K., Bui, D.T., Dick, Ø.B., Singh, B.R., 2015. A comparative assessment of support vector regression, artificial neural networks, and random forests for predicting and mapping soil organic carbon stocks across an Afromontane landscape. Ecol. Indicat. 52, 394–403.

West, T.O., Post, W.M., 2002. Soil organic carbon sequestration rates by tillage and crop rotation. Soil Sci. Soc. Am. J. 66 (6), 1930–1946.

Wiesmeier, M., Barthold, F., Spörlein, P., Geuß, U., Hangen, E., Reischl, A., et al., 2014. Estimation of total organic carbon storage and its driving factors in soils of Bavaria (southeast Germany). Geoderma Reg. 1, 67–78.

Wiesmeier, M., Urbanski, L., Hobley, E., Lang, B., von Lützow, M., Marin-Spiotta, E., et al., 2019. Soil organic carbon storage as a key function of soils-a review of drivers and indicators at various scales. Geoderma 333, 149–162.

Woolf, D., Solomon, D., Lehmann, J., 2018. Land restoration in food security programmes: synergies with climate change mitigation. Clim. Pol. 18 (10), 1260–1270.

Woldearegay, K., Tamene, L., Mekonnen, K., Kizito, F., Bossio, D., 2018. Fostering food security and climate resilience through integrated landscape restoration practices and rainwater harvesting/management in arid and semi-arid areas of Ethiopia. Rainwater-Smart Agriculture in Arid and Semi-arid Areas. Springer, Cham, pp. 37–57.

Wright, M.N., Ziegler, A., 2015. Ranger: A Fast Implementation of Random Forests for High Dimensional Data in C++ and R arXiv preprint arXiv:1508.04409.

Xiong, X., Grunwald, S., Myers, D.B., Ross, C.W., Harris, W.G., Comerford, N.B., 2014. Interaction effects of climate and land use/land cover change on soil organic carbon sequestration. Sci. Total Environ. 493, 974–982.

Xu, E., Zhang, H., Xu, Y., 2019. Effect of large-scale cultivated land expansion on the balance of soil carbon and nitrogen in the tarim basin. Agronomy 9 (2), 86.

Yan, Y., Tian, J., Fan, M., Zhang, F., Li, X., Christie, P., et al., 2012. Soil organic carbon and total nitrogen in intensively managed arable soils. Agric. Ecosyst. Environ. 150, 102–110.

Zhu, M., Feng, Q., Qin, Y., Cao, J., Zhang, M., Liu, W., et al., 2019. The role of topography in shaping the spatial patterns of soil organic carbon. Catena 176, 296–305.

Zinn, Y.L., Lal, R., Bigham, J.M., Resck, D.V., 2007. Edaphic controls on soil organic carbon retention in the Brazilian Cerrado: texture and mineralogy. Soil Sci. Soc. Am. J. 71 (4), 1204–1214.

Zomer, R.J., Bossio, D.A., Sommer, R., Verchot, L.V., 2017. Global sequestration potential of increased organic carbon in cropland soils. Sci. Rep. 7 (1), 1–8.