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RESEARCH ARTICLE

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# Soil carbon stocks in Ethiopian forests and estimations of their future development under different forest use scenarios

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**Abstract**

Contributions from all land-uses are needed if Ethiopia is to fulfil its Paris Agreement targets. The magnitude of soil carbon stock and the role of Ethiopian forest soils in climate change mitigation has not yet been clarified. In this study, soil carbon inventory in forests was carried out as a part of the Ethiopia REDD+ Programme. The performance of soil carbon models Yasso07 and CENTURY was tested by comparing the model predictions with the empirical soil organic carbon (SOC) data provided by the field inventory. In addition to that, Global Soil Organic Carbon (GSOC) map estimates by the Food and Agriculture Organization for Ethiopia were included in the comparison. The soil inventory was carried out in 2017–2018 at a subset of permanent sampling units of the National Forest Inventory conducted in 2014–2017. A combination of soil inventory data, soil carbon models and satellite images enabled to quantify the impact of forest use intensity to future SOC sinks in Ethiopian forests in a novel way. The Yasso07 and CENTURY models provided similar SOC estimates to the measured data for all biomes, and the GSOC map overestimated in biomes with larger SOC stocks. Results showed that Moist Afromontane forest biome contains twice as much SOC per unit area compared to Combretum-Terminalia forest biome and three-times more SOC compared to Acacia-Commiphora. Results underlined that sustainable forest management has a high potential for soil carbon development in Ethiopian forests in near future, impacting the ability of the Country to achieve its Paris Agreement targets.

KEYWORDS
biomes, CENTURY, degradation, Ethiopia, Ethiopia NDC; Forest use intensification, FAO, soil carbon, soil carbon models, soil inventory, Yasso07

## 1 | INTRODUCTION

Deforestation and forest degradation cause globally substantial $CO_2$ emissions from parts of the biosphere which end up in the atmosphere, these emissions are annually 0.5–2 Pg of $CO_2$ (Quéré et al., 2016). The reduction of these emissions is one of the measures to mitigate ongoing climate change. To abate such emissions, the REDD+ (Reducing Emissions from Deforestation and Forest Degradation) Programme has been launched. The objective of the Programme's framework is to provide incentives for individual countries to break their historical trends of deforestation and forest degradation.

Ethiopia has a land area of 1.1 mill. km$^2$ and total forest cover estimate of approximately 11.4% based on the Food and Agriculture Organization (FAO) forest definition (Bekele et al., 2015). According to the FAO definition, forest land is recognised as a land with a tree canopy cover more than 10% and a minimum area of 0.5 ha, but countries may have their modifications based on local conditions. Accordingly, Ethiopia adopted its forest definition in 2015, by which forests included everything from dense forests in the high-rainfall area to dense woodlands in drylands covering in total 15.5% of the Ethiopian land area (Franks et al., 2017). Most of the natural forest cover of 35% of the Ethiopian land area (109.6 mill. ha, as estimated in 1950) during beginning of 20th century had diminished and fragmented to 11.4% by 2015. Simultaneously, other wooded lands, fulfilling the definition of forest using the aforementioned criteria, but with bushes and shrubs included, covers 37.1% of the land area, see Global Forest Resource Assessment 2015 by Keenan et al. (2015). The long-term trend in deforestation has followed Ethiopia's high population growth and consequent demand for forest products and agricultural land. The FAO (2015) estimated a forest area loss of 2.6 mill. ha between 1990 and 2015 and this corresponds to annual loss of 104,000 ha forest area. Free livestock grazing, fuelwood or charcoal production followed by farmland expansion, forest fires and unsustainable wood harvesting for construction have been the main causes of forest area loss in Ethiopia (Bekele et al., 2015).

Forest land in Ethiopia consists of natural forests, woodlands and plantations. The Ethiopian vegetation map groups land into 12 major potential vegetation types (Friis, Demissew, & Van Breugel, 2010), which have been aggregated into four biomes: Moist (MA) and Dry Evergreen Afromontane Forests (DA), Acacia-Commiphora (AC) Woodland and Bushland and Combretum-Terminalia (CT) Woodland, for more detailed description of biomes, see Asrat et al. (2018).

According to the Nationally Determined Contribution (NDC) provided by Ethiopia, there exist plans to limit projected business as usual GHG emissions for the year 2030 by 145 million tonnes of $CO_2$ eq. and to mitigate GHG emissions based on four 'pillars', of which one relies on altered forest management. Ethiopia plans to protect and re-establish forests to provide economic benefits and other ecosystem services, such as forests for carbon sequestration. Ethiopia takes part in the World Bank Forest Carbon Partnership Facility, and the national REDD+ Programme has been funded through this facility. As a part of the REDD+ Programme, the National Forest Inventory (NFI) has been established and is being conducted. Since soil is a major C pool in forests, a pilot project of soil carbon inventory was carried out as a subproject for the Ethiopia REDD+ Measurement, Reporting and Verification (MRV) project with FAO technical assistance. The empirical part of our study is based on this soil carbon inventory. During the field campaign of soil organic carbon (SOC) measurements, FAO and intergovernmental technical panel on soils (ITPS) (2018) published a global map product for soil organic carbon (GSOC), including all lands in Ethiopia.

Since soil carbon inventories are laborious and time consuming, the use of soil carbon models can support decision making when the number of repeated soil inventories is limited. Therefore, soil carbon modelling provides a complementary approach to the field inventory to estimate soil carbon stocks and soil carbon stock changes in forests. The application of soil carbon models generally requires information about the quantity and quality of litter input to the soil. Liski et al. (2006) estimated litter input to soils based on biomass components (e.g., foliage, branches, stem, stump, roots and fine roots) turnover rates by simulating the carbon pools based on forest inventory measurements. If reliable forest inventory data do not exist, one can estimate litter inputs to soils by using estimates of net primary production (NPP) for forests, assuming a proportional relationship between annual NPP and annual litter input to soil. According to Malhi, Doughty, and Galbraith (2011), a reasonable correlation between aboveground litterfall and NPP has been shown within tropical ecosystems. Also, Thum et al. (2011) used NPP as a proxy to estimate annual litter input from vegetation to soil when comparing two soil carbon models, namely CBALANCE and Yasso07.

The main objectives of this study were (a) to estimate the quantity of SOC for Ethiopian forests based on pilot soil carbon inventory, (b) to test Yasso07 and CENTURY soil carbon models with that data and (c) to evaluate the precision of the GSOC estimates by FAO and ITPS (2018). Additionally, (d) soil carbon stock responses to potential future forest degradation or improvement schemes of forest management in Ethiopia were quantified.

## 2 | MATERIALS AND METHODS

### 2.1 | Soil carbon inventory

#### 2.1.1 | Sampling design

Soil sampling was carried out from November 2017 to January 2018 on permanent sampling units (SU) established by the NFI conducted with the support from FAO these units were estblished from 2014. Soil sampling excluded the SUs from Southern and South-eastern Ethiopia, as those were identified as safety risk zones (Figure 1). US Geological Survey/NASA Shuttle Radar Topography Mission (SRTM) digital elevation data (CGIAR-CSI) were used to derive consistent elevation estimates for all NFI SUs (http://srtm.csi.cgiar.org/srtmdata). Also, estimates of stem volume, litter layer depth and plot elevations were applied as a criterion for unbiased sampling design using the *lmp1* functions from the library *Balanced Sampling* with R (Grafström & Lisic, 2016) for identification of a balanced sample of 98 SUs distributed over the four biomes. This was done to get the optimal distribution of the sample over the variation range proxies that correlate with soil carbon stocks.

It is worth noting that the forest stand character-based criteria, applied in the selection of the SUs for our soil carbon inventory, describes the average conditions of the whole SU, while soil sampling was performed at only one of the three second-order subplots of the SU.

#### 2.1.2 | Soil sampling and analysis

Soil sampling was carried out by Ethiopian Environment and Forest Research Institute (EEFRI) in collaboration with Natural Resources Institute Finland (Luke). Soil samples were collected from a total of 98 SUs. During soil sampling, some SUs were found to be inaccessible for the soil sampling crew. Hence, they were systematically replaced by new SUs of a similar vegetation type and elevation. A total of 25 out of the

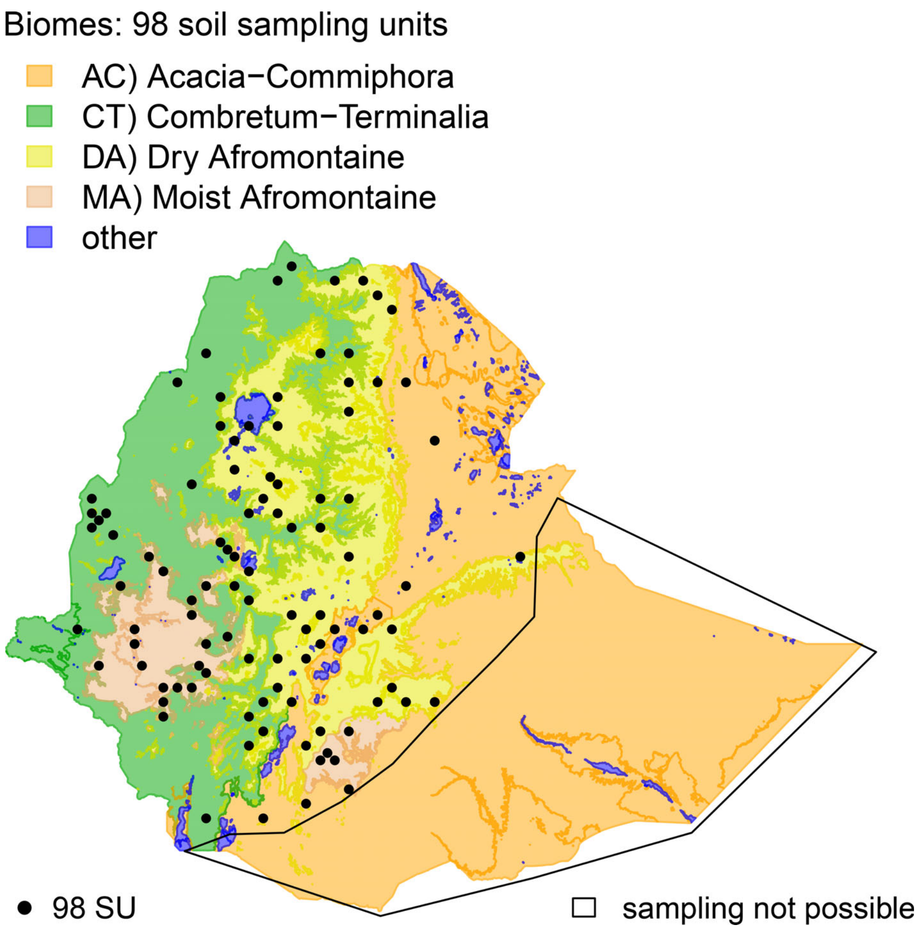


**FIGURE 1** Sampling units (SUs) for soil carbon measurements by biomes for Ethiopia. Eastern and southern parts of Ethiopia were excluded from the soil sampling due to unstable conditions. Colours indicate four major biomes, based on the aggregation of biomes by Friis et al. (2010), for grouping of original biomes, see also Asrat et al. (2018) [Colour figure can be viewed at wileyonlinelibrary.com]

98 preselected SUs were replaced in this way. Soil sampling locations were initially determined, and soil samples were taken at subplot 1, outside the southernmost rectangular subplot (Figure 2). The litter layer was cleared over the mineral soil, and a soil sampling pit was made on the west and east side of the subplot 1. Consequently, soil samples were collected from 10, 20 and 30 cm below the soil surface by using 100 mm long corer. Successive cores of each deeper layer were not taken exactly from below the previous one, thus avoiding any compression of samples from sampling the upper parts of the soil profile. The soil samples were transported to the Central Ethiopia Environment and Forest Research Centre (CE-EFRC) Laboratory in Addis Ababa for immediate analysis of dry bulk density and SOC.

Soil cores taken from mineral soil beneath the removed litter and duff layer were considered to be undisturbed and volumetric. During soil sampling, it was important to avoid taking soil cores from locations with stones that would disturb the volumetric sampling of soil by creating void spaces inside the corer. The 100 mm long corer was used, and it is a slightly conical cylinder with a sharpened lower edge of 37 mm diameter and the upper edge of 40 mm diameter. The idea of the corer design with a tap ring is to decrease soil compaction by reduced friction against the inner walls of the corer while drilling, as the inner space expands upwards.

The soil pit wall was used for measuring the depth of the litter layer and visual soil stoniness (%) according to the FAO VS-FAST procedure (McGarry, 2005). Two subsamples were combined from each respective depth layer of the two soil pits. The composites with the actual number of corer samples included were sent to the Soil Laboratory of the CE-EFRC at EEFRI for analysis of dry fine earth fraction bulk density (excluding gravel and pebbles >2 mm) and SOC content of the fine earth. The samples were analysed within one to 3 weeks from coring due to occasionally difficult transport from remote areas. The soil fine fraction part was also subjected to laser diffraction particle size analysis (HORIBA LA 960, applying Mie Scattering in wet mode and USDA software for fractionation); the results of which were used to constrain the soil model CENTURY. SOC content was analysed by using the wet combustion method (Walkley & Black, 1934), and thereafter the recovery coefficient for this method was estimated by re-analysing a sub-sample of 30 soil samples using a more accurate method based on dry oxidation (CHN, Leco). The recovery coefficient for wet oxidation was obtained from the slope of linear regression (intercept = 0) against the dry oxidation results, and it was 1.165 * Wet Oxidation result and was applied for all analyses.

### 2.1.3 | Observed soil organic carbon stocks

The stocks of organic C in soil (SOC stocks) were estimated by using the analysed soil physical properties and the proportion of organic C, $O$ as a proportion (0–1), in the samples. The organic C stock in the layer of 0–30 cm of mineral soil ($S$) was calculated as the sum of the three measured 10 cm deep soil layers:

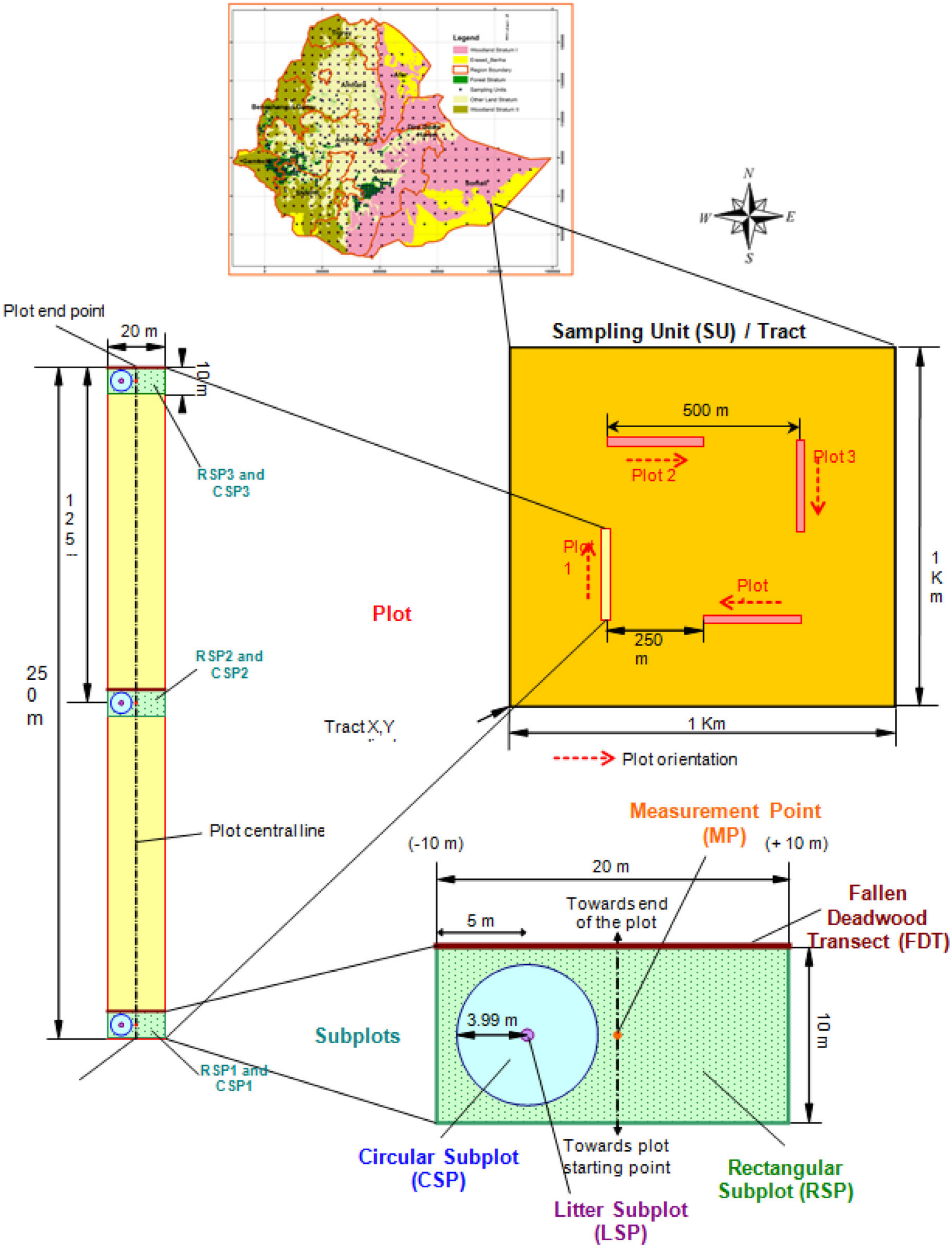


**FIGURE 2** Sampling unit, plot and subplot design for National Forest Monitoring for the REDD+ Project in Ethiopia [Colour figure can be viewed at wileyonlinelibrary.com]

$$S = \sum_{i}^{3} B_i \times O_i,$$

where $B_i$ is bulk density of fine earth in layer $i$ and $O_i$ is the proportion of organic C content in the layer $i$. The results of the estimation were provided in the units of Mg of carbon ha$^{-1}$. The SOC stock was further corrected by the stoniness fraction ($f$), varying between 0 and 1, which was visually assessed in the field, allowing us to estimate corrected SOC stock ($S_c$):

$$S_c = S \times (1 - f).$$

Data on location, biomes, MODIS NPP, litter fall estimates, soil texture and soil carbon stocks ($S_c$) are provided in Table S3.

## 2.2 | Soil carbon modelling

Soil carbon stocks were simulated for locations that correspond with SOC sampling (for 30 cm soil depth) by running Yasso07 and CENTURY soil carbon models (see more detailed description below).

SOC simulations by models were compared against soil carbon measurements and also against FAO GSOC; see Figure S1 (FAO and ITPS, 2018). To support the decisions needed to accomplish Ethiopian NDC targets, four forest management scenarios were analysed and estimated for subsequent SOC gains or losses between 2018 and 2030 based on the CENTURY model.

### 2.2.1 | Estimation of the litter input

To model soil carbon stocks by using the Yasso07 and CENTURY models, estimates for annual litter production of the vegetation were derived from the MODIS NPP maps (Figures S1 and S2) (Turner et al., 2005). Here, NASA dataset MOD17A3 was used with a resolution of 1 km and its temporal range from January 2000 to December 2010. Temporal average NPP estimates were extracted from these 11 years of data for each NFI plot from MODIS raster images, based on the location of each plot and pixel overlaying that point. Those images were downloaded through the www.africasoils.net/ service (Accessed October 10, 2018). Thereafter, it was assumed that annual litter production was proportional to annual NPP estimates, and variable litter to NPP ratios (from 50 to 70%) were applied to assess estimates for litter quantities which produce an equal distribution of soil carbon by models and by measurements (Figures S3 and S4), assuming that a fraction of NPP is used, for example, for fuelwood. With this approach, it was assumed that NPP from 2000 to 2010 can be used to approximate long term litter production of each site. The fractions of total litter to NPP ratios were specific for the soil carbon model used (see litter optimisation from Section 2.2.3 on soil carbon modelling). Total litter quantity was separated into components (leaves, branches, stems and other fine roots and coarse roots); see supplement (Tables S1 and S2 and Figure S2).

### 2.2.2 | Tree cover estimates for Ethiopia

To estimate soil carbon stocks for forests in Ethiopia, tree cover maps by Hansen et al. (2013) were used to estimate and to locate forest areas for Ethiopia. Tree cover thresholds of 10, 20 and 30% were used to estimate the number of pixels that form forest land based on the tree cover maps (Table 1). It is known that these maps provide estimates for tree cover, not for forest cover, but here the main objective was to estimate the distribution of forests across Ethiopia and by biomes. Forest area estimates with variable tree cover thresholds were compared and it was found that forest cover based on 30% tree cover estimate (10 mill. ha) was closest to FAO estimate (12.5 mill. ha) and thereafter these values by biomes based on Hansen et al. (2013) maps with 30% cover were adjusted to match with forest resource assessment data by FAO (Keenan et al., 2015).

### 2.2.3 | Soil carbon modelling with Yasso07 and CENTURY models

*Yasso07*

The Yasso07 soil carbon model (Tuomi, Rasinmäki, Repo, Vanhala, & Liski, 2011) is driven by litter quantity, litter quality and annual weather data. The model has been calibrated with Markov chain Monte Carlo (MCMC) methods using a large database of litter and wood decomposition and soil carbon stocks measurements (Liski, Ilvesniemi, Mäkelä, & Starr, 1998; Liski, Palosuo, Peltoniemi, & Sievänen, 2005; Tuomi et al., 2011).

The Yasso07 model is a simple dynamic model with fluxes and state variables and it has been parametrised against a large database of decomposition- and soil carbon measurements. The model has five compartments: acid, water-soluble, ethanol-soluble, non-soluble and humus. Organic matter originating from the litter fall flows between these compartments and to the atmosphere driven by weather conditions. The fractionation of the organic matter in the model has been based on the solubility of the material, which is a proxy for the litter quality in the model.

Here, the Yasso07 model was driven with maximum a posteriori global parameters, as reported by Tuomi et al. (2011). Here, the s parameter (diameter of decomposing wood) was set to 2 cm as most of the large-diameter wood is used for fuelwood. The Yasso07 model was applied with an annual time-step. The model in default settings simulates SOC down to 1 m. To simulate SOC down to 30 cm, the

**TABLE 1** Forest cover estimates based on Hansen et al. (2013) tree cover maps and based on Food and Agriculture Organization Forest Resource Assessment 2015 for Ethiopia

| Tree cover (%) | Acacia-Commiphora | Combretum-Terminalia | Dry Afromontane | Moist Afromontane | Other | Total area (ha) |
|---|---|---|---|---|---|---|
| 10% | 2,440,091 | 13,668,517 | 4,487,181 | 5,399,987 | 164,082 | **25,995,776** |
| 20% | 749,519 | 8,753,741 | 1,901,062 | 4,882,555 | 95,617 | **16,286,878** |
| 30% | 308,368 | 4,550,938 | 936,730 | 4,031,416 | 53,729 | **9,827,451** |
| FRA 2015 | | | | | | **12,499,356** |

*Note:* Bold values are shown Assessment 2015 for Ethiopia. Estimates for forest area by various tree covers and by FAO 201.

model has been empirically optimised with the different levels of litter input and the agreement between means of simulated and observed SOCs. This optimisation was based on comparing SOC stock distributions of model estimates and those based on measurements. For the Yasso07 model, the optimum level of total litter input was found to correspond to 60% of NPP (Figure S3).

To run the Yasso07 model, litter must be fractionated according to chemical quality (Acid, Water, Ethanol and Non-soluble fraction) (see Supplement). The AWEN fractionation of leaves (non-woody) and branches (fine-woody) was determined from the litter of the dominant species (*Podocarpus falcatus* and *Juniperus procera*) of Chilimo forest (N 9.07, E 38.15), according to the chemical fractionation method of (Guendehou et al., 2014; Vávrová et al., 2008), see Table S2. Thereafter, the Yasso07 model was driven for 1,000 years to estimate the equilibrium SOC (when litter input equals soil respiration).

*CENTURY*

In addition to the Yasso07 model, also the CENTURY soil model (Parton, Ojima, & Schimel, 1994; Parton, Schimel, Cole, & Ojima, 1987) was applied for carbon stock estimation following the approach presented by Ťupek et al. (2016), where soil submodel v.4 was applied. This CENTURY soil submodel consists of active, slow and passive pools. For source code, see Ťupek et al. (2016). The default version of the model simulates soil carbon stock changes down to 20 cm, while here, SOC was simulated down to 30 cm by the empirically optimising quantity of litter input so that the simulated SOC distribution would fit that of SOC observations (Figure S4). For the CENTURY model, the optimum level of total litter input was found to correspond to 70% of NPP (Figure S4). The CENTURY model estimates decomposition of the organic matter as a function of temperature, soil moisture, litter quality (nitrogen and lignin contents) and soil texture. The importance of these drivers varies according to the soil model pools. To run the CENTURY model, the litter was fractionated by C and lignin to N ratios, with default parameters from the site, 'CWT Coweeta', for deciduous trees. The parameter file was available online from the model source code site: [http://www.nrel.colostate.edu/projects/century/century-description.php]

Here, a general parameterisation of the CENTURY model was applied from the parameter file 'tree.100', which was available from the model source code. Specific site parameters to run the model included SUs geographic coordinates, soil texture (measured sand, silt, clay content and bulk density) and environmental parameters (long-term monthly mean temperatures and precipitation sums). Similar to the Yasso07 model, the CENTURY model was driven in a spin-up simulation for 1,000 years.

### 2.2.4 | Weather data

The models require monthly (CENTURY) or annual (Yasso07) precipitation and air temperature. The long-term (1986–2017) data on monthly mean, minimum and maximum air temperature and precipitation sum were provided by the Ethiopian Meteorological Agency (http://www.ethiomet.gov.et) from 73 weather stations located across Ethiopia. Precipitation was used directly based on the nearest proximity between sample plots and the location of the weather station. The air temperature required correction by elevation due to vertical temperature profile and large variation in elevation between the weather stations and sample plots. Based on elevation data from the weather stations, linear month specific temperature regression models were estimated with the mean error 1.8°C and applied to the measured elevation of each SU. Thereafter, mean monthly and mean annual weather variables were estimated for each SU to be applied with CENTURY and Yasso07 models, respectively. Biome specific distributions of annual temperature and precipitation values can be seen in Figure S5.

## 2.3 | FAO global soil carbon map for Ethiopia

The Ethiopian soil carbon map was also included in the analysis (raster product by FAO was downloaded December 20, 2017). This soil carbon map has been provided by the FAO; see FAO and ITPS (2018). The soil carbon map for Ethiopia was based on upscaling different soil carbon measurements, and the work was done by the Ministry of Agriculture and Natural Resources of Ethiopia. Auger measurements down to 20 cm depth without bulk density data were obtained from the EthioSIS project (Hengl et al., 2017). Bulk density estimates were extracted for the locations of EthioSIS data based on the Harmonised World Soil Database (Batjes, 2009). In addition to that, 214 pedons (1,037 horizons) with variable depth intervals containing bulk density measurements were obtained from the CASCAPE project (Hengl et al., 2017). Thereafter, soil carbon stocks were extrapolated to cover 0–30 cm depth. To up-scale results for Ethiopia, various covariates were loaded from the AfSIS and ISRIC websites. Finally, covariates were used with the *randomForest* algorithm (Liaw & Wiener, 2002) of the R program to predict a soil carbon stocks map for Ethiopia with validation statistics of (ME = 0.0041, RMSE = 1.88 and $R^2$ = 0.54).

## 2.4 | Statistical analysis between measurements and models

To judge the agreement between SOC measurements and model estimates, results were based on distributions of data (observations and models). Model results were also evaluated by one-to-one plots, having measured and modelled data against each other. On these one-to-one plots, regression and root mean square error (RMSE) analysis were also added. It was also tested if measurements and model estimates differed between each other by biomes. First, distributions of data and model estimates were visually examined by biomes and it was found that those all were nearly symmetrically distributed. Both Kruskal-Wallis and Student *t*-tests were conducted, where Kruskal-Wallis tested whether there were significant differences between different methods, while the *t*-test one was used to conduct a pairwise comparison between measurements and model estimates.

### 2.5 | Scenarios for the degree of forest use

To support the forest management decisions and attainment of Ethiopian NDC 2030 targets to reduce $CO_2$ emissions, four potential forest use scenarios and subsequent SOC developments were evaluated. These scenarios quantify the impact of altered forest management to NPP and further to SOC stocks for 12 years (2018–2030). The potential forest use scenarios were estimated by modifying the degree of human utilisation of forest NPP levels. It was assumed that the present NPP level was the same as the mean derived from the MODIS NPP maps from 2000–2010 by Turner et al. (2005). Near future scenarios included reduced net use of forests (meaning that NPP and litter input would increase by 10%) and three scenarios with varying degrees of degradation (later referred as 'slight-, moderate- and intense- degradation', meaning NPP would decrease by 10, 30 and 50%, respectively). Reduced forest net-use can be achieved through several sustainable management activities, such as lowering harvesting intensity, increasing forest density or reforestation of forest gaps after harvesting. The forest degradation scenarios correspond to various degrees of forest use intensification. The CENTURY model was applied for forest use scenario SOC simulations, since it includes soil texture impacts to SOC change and aggregation. This feature of the model is important here because soil texture properties vary substantially between biomes. The total litter input of CENTURY equalled a fraction of 70% of NPP that was either increased or reduced as described above (70% of NPP multiplied by 1.1, 0.9, 0.7 and 0.5, respectively).

## 3 | RESULTS

### 3.1 | Predictions of soil models and FAO's GSOC-map with SOC stocks provided by the field inventory

Predictions of SOC stocks produced by the Yasso07 and CENTURY soil models explained between 33 and 35% of the observed variance for Ethiopian forests (Figure 3). The relatively low accuracy of the models resulted from known model behaviour, where models agree on the mean level but perform poorly with values in the low and high range of SOC. The model-based SOC estimates (namely, Yasso07, CENTURY and FAO GSOC) thus showed almost identical coefficients of determination ($R^2$ values) but differed in their precision (RMSE) (Figure 3). The Yasso07 model had lower RMSE than the CENTURY model indicating higher precision for Yasso07.

The country-level SOC distributions of observations agreed best with the CENTURY estimates when judging based on the shape and width of distributions (Figure 4). The Yasso07 SOCs had a narrower distribution than those of the CENTURY model and measurements, while SOCs distribution by FAO GSOC covered systematically larger values when compared to measurements. However, the mean levels of the Yasso07 and CENTURY models corresponded to the observations (Figure 4). Unlike the mean of FAO SOCs, which showed overestimation (Figure 4).

Both models (Yasso07 and CENTURY) overestimated small SOC stocks and underestimated large SOC stocks in comparison to the empirical SOC stocks determined on the basis of the soil sampling in the field. Predictions given by Yasso07 were closest to the measured SOC stocks, having a RMSE of 28.41 Mg C ha$^{-1}$, while the CENTURY model had an RMSE of 30.19 Mg C ha$^{-1}$and FAO GSOC had an RMSE of 45.68 Mg C ha$^{-1}$ (Figure 3). Concurrently, the predictions of SOC stocks given by FAO's GSOC Map were systematically greater than those based on field inventory (Figures 3 and 4, Table 2). Based on the intercept of the linear regression between the FAO GSOC map and observations, the GSOC values overestimated SOC stock by 36 Mg C ha$^{-1}$ with low SOC values (Figure 3), but for high SOC stocks, FAO's GSOC map agreed better than the Yasso07 and CENTURY. According to variance analysis by biomes, it was found that model estimates by Yasso07 and CENTURY did not differ from SOC measurements (Figure 5), while GSOC estimates differed for all other biomes but not for the AC biome.

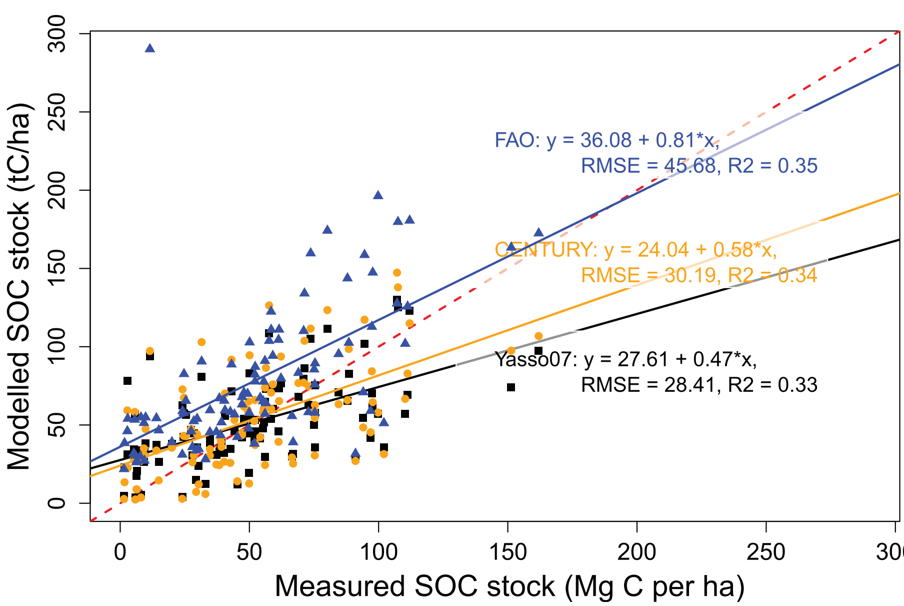


**FIGURE 3** Goodness of fit between measured and modelled data. The root mean squared error (RMSE) here has been estimated between measured data and model estimates. Linear regressions describe systematic differences between measured data and the model, where (*x*) denotes measured soil carbon, while (*y*) denotes modelled soil carbon [Colour figure can be viewed at wileyonlinelibrary.com]

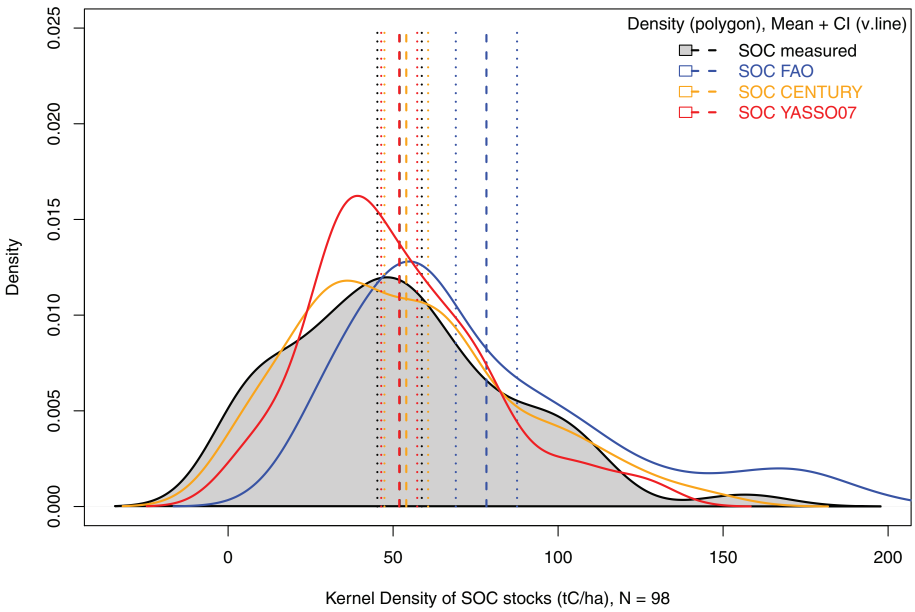


**FIGURE 4** Kernel density distributions for estimated soil carbon stocks with different methods (soil organic carbon measurements, Food and Agriculture Organization soil carbon map, CENTURY model and Yasso07 model). Dotted lines represent 95% CI. Note that density distributions can visually expand to the negative values contrary to histograms [Colour figure can be viewed at wileyonlinelibrary.com]

**TABLE 2** Soil carbon stock (0–30 cm) for Ethiopian forest by biomes based on SOC inventory, soil models and FAO GSOC map. Including means and standard errors of the mean

| Biome | | NPP MODIS | LitterCENT | LitterY07 | Tmean | Precip. | Tampl. | SOC OBS | SOC CENT | SOC Y07 | SOC FAO |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Unit | Var | Mg C ha$^{-1}$ | Mg C ha$^{-1}$ | Mg C ha$^{-1}$ | °C | mm | °C | Mg C ha$^{-1}$ | Mg C ha$^{-1}$ | Mg C ha$^{-1}$ | Mg C ha$^{-1}$ |
| AC | Mean | 4.32 | 3.05 | 2.62 | 22.81 | 851 | 6.89 | 34.25 | 25.04 | 33.11 | 48.38 |
| CT | Mean | 6.79 | 4.8 | 4.11 | 22.52 | 1,304 | 6.87 | 41.56 | 42.95 | 42.83 | 63.1 |
| DA | Mean | 6.8 | 4.8 | 4.12 | 17.39 | 1,180 | 6.44 | 53.08 | 57.99 | 54.07 | 82.1 |
| MA | Mean | 11.9 | 8.4 | 7.2 | 19.11 | 1,607 | 6.58 | 83.89 | 89.01 | 79.33 | 122.36 |
| AC | SE | 0.52 | 0.37 | 0.32 | 0.73 | 75.92 | 0.06 | 5.13 | 3.27 | 3.22 | 4.7 |
| CT | SE | 0.62 | 0.44 | 0.38 | 0.43 | 69.45 | 0.04 | 4.64 | 4.38 | 3.64 | 3.92 |
| DA | SE | 0.58 | 0.41 | 0.35 | 0.44 | 54.75 | 0.04 | 5.65 | 5.49 | 4.72 | 9.99 |
| MA | SE | 0.76 | 0.54 | 0.46 | 0.45 | 78.77 | 0.04 | 8.41 | 6.62 | 5.93 | 9.45 |

Abbreviations: AC, Acacia-Commiphora; CENT, CENTURY; CT, Combretum-Terminalia; DA, Dry Afromontane; FAO, Food and Agriculture Organization; MA, Moist Afromontane; NPP, net primary production; OBS, observation; SOC, soil organic carbon; Y07, Yasso07.

## 3.2 | The impact of forest use scenarios

The simulated SOC change with the CENTURY model for the period between 2018 and 2030 ranked the Moist Afromontane (MA) biome as the most vulnerable to SOC loss under intensified forest use. The intensification of forest use by 10% resulted in SOC loss of 2.1 Mg C ha$^{-1}$ in the MA biome by 2030, whereas in AC soils lost 0.8 Mg C per ha$^{-1}$ for the same scenario (Figure 6, Table 3). The largest SOC loss vulnerability resulted from the largest initial SOC and largest NPP found in MA compared to other biomes (Figure S2). When the total area of the biomes was taken into an account, the largest Ethiopian SOC changes relative to NPP scenarios mainly affected the Afromontane forest biomes (MA and DA, respectively) (Figure 6).

The CENTURY model simulations of SOC sinks and losses in Ethiopia largely depended on whether forest use is reduced or intensified. For the reduced forest use, where litter input to soil increased by 10%, the soil would sequester 19.5 Tg more carbon (71.5 Tg of $CO_2$) by 2030 compared to the present (2018) level of forest use intensity. In contrast, the 10% forest use intensification, linked with a decrease in litter input, would increase soil carbon emissions from Ethiopian forests by 19.4 Tg C (71.1 Tg of $CO_2$) between 2018 and 2030 (Table 3).

## 4 | DISCUSSION

The relatively simple process based SOC models (Yasso07 and CENTURY) were able to map overall trends in SOC across strong elevational and ecological gradients in Ethiopian forests. However, as expected from a similar model comparison with observations (Guenet et al., 2013;

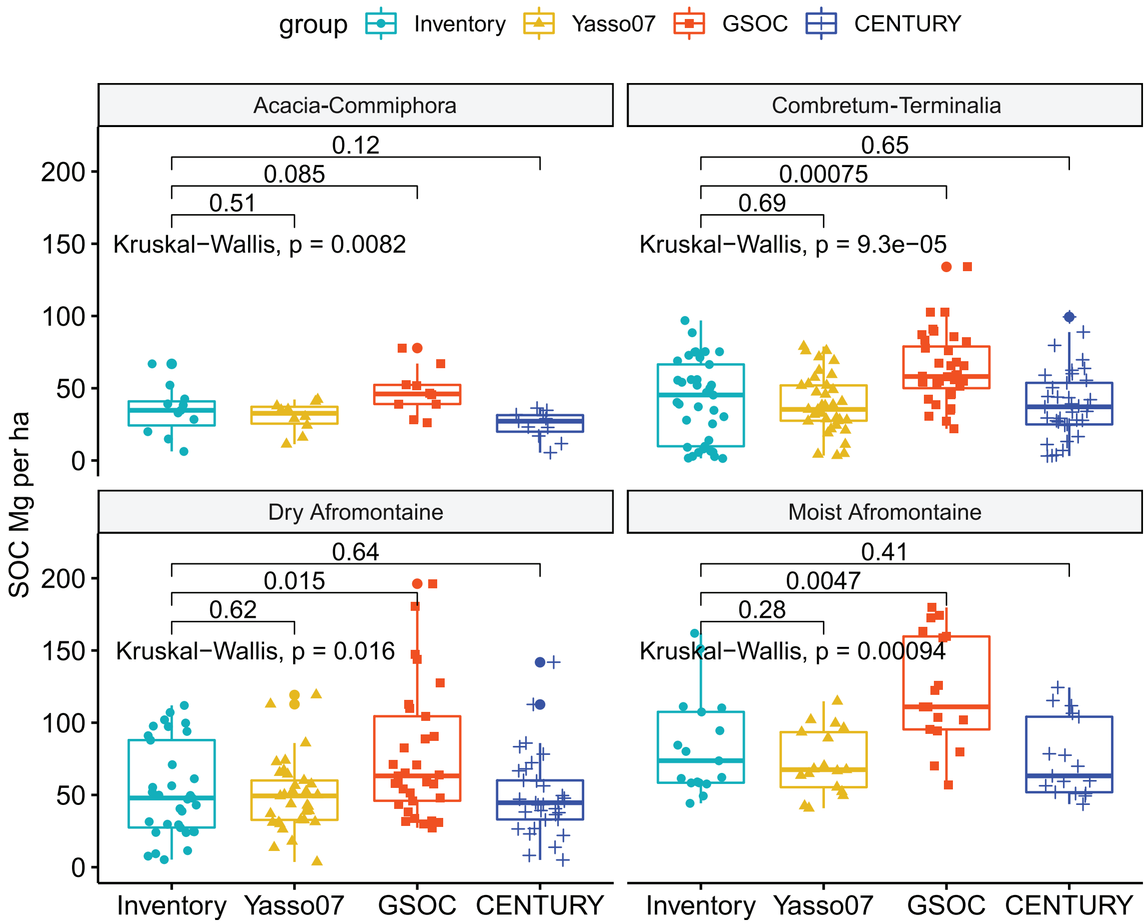


**FIGURE 5** Comparison of measured (0–30 cm) soil organic carbon stocks [Mg C ha$^{-1}$] with model runs (Yasso07 and CENTURY) and global soil organic carbon map values for the same sites, separated by biomes. The whiskers denote 95% CI. The values of Kruskal-Wallis show if there is significant difference between different methods, while the *t*-test shows a pairwise comparison between different groups [Colour figure can be viewed at wileyonlinelibrary.com]

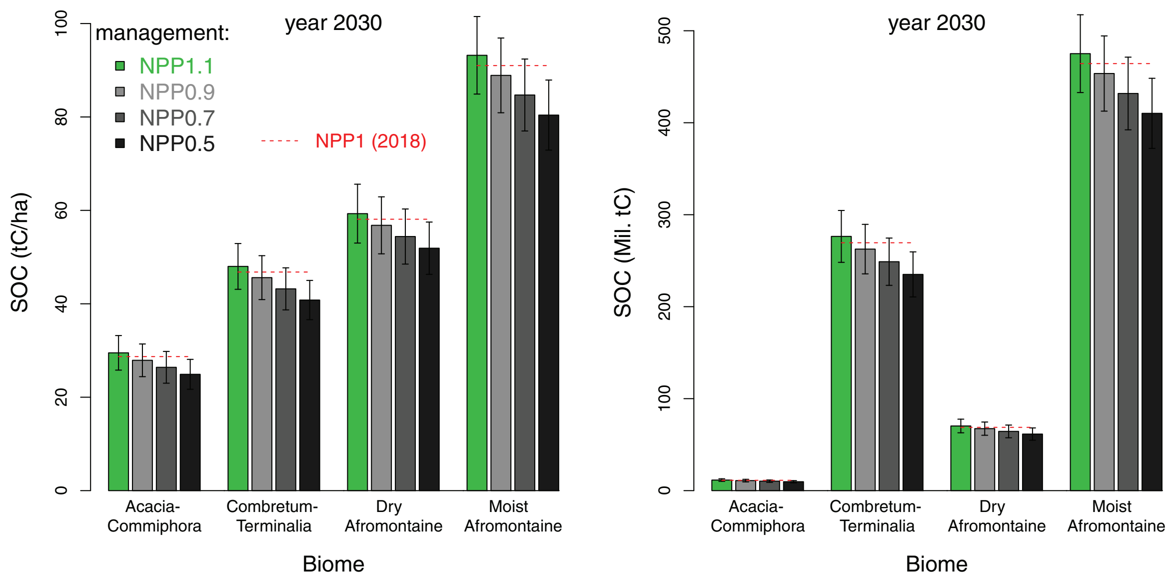


**FIGURE 6** CENTURY model estimates of soil organic carbon change between 2018 and 2030 for four forest use scenarios expressed by variable NPP. The NPP in 2018 was adopted from the MODIS map (Turner et al., 2005), and it was increased (110%) and decreased (90, 70 and 50%) and referred to as reduced, slight, moderate and intense net use of forests. Whiskers indicate standard error of the mean for each biome. NPP, net primary production [Colour figure can be viewed at wileyonlinelibrary.com]

**TABLE 3** Soil carbon stock (0–30 cm) for Ethiopian forest for 2018 and for 2030 by biomes and by different forest use based on the CENTURY model

| Biome | NPP change (%) | SOC 2018 Mg C per ha | SOC 2030 Mg C per ha | SOC 2030 SE Mg C per ha | Total SOC 2018 Tg C | Total SOC 2030 Tg C | Total SOC 2030 SE Mg C | SOC change up to 2030 Mg C per ha | Total SOC change by 2030 Tg C |
|---|---|---|---|---|---|---|---|---|---|
| AC | 110 | 28.7 | 29.5 | 3.7 | 11.2 | 11.5 | 1.4 | 0.8 | 0.3 |
| AC | 90 | 28.7 | 27.9 | 3.5 | 11.2 | 10.9 | 1.4 | −0.8 | −0.3 |
| AC | 70 | 28.7 | 26.4 | 3.4 | 11.2 | 10.3 | 1.3 | −2.3 | −0.9 |
| AC | 50 | 28.7 | 24.9 | 3.2 | 11.2 | 9.7 | 1.2 | −3.8 | −1.5 |
| CT | 110 | 46.8 | 48 | 4.9 | 269.5 | 276.4 | 28.2 | 1.2 | 6.9 |
| CT | 90 | 46.8 | 45.6 | 4.7 | 269.5 | 262.6 | 26.9 | −1.2 | −6.9 |
| CT | 70 | 46.8 | 43.2 | 4.5 | 269.5 | 248.9 | 25.7 | −3.6 | −20.6 |
| CT | 50 | 46.8 | 40.8 | 4.2 | 269.5 | 235.1 | 24.5 | −6 | −34.4 |
| DA | 110 | 58.1 | 59.3 | 6.3 | 68.8 | 70.3 | 7.4 | 1.2 | 1.5 |
| DA | 90 | 58.1 | 56.8 | 6.1 | 68.8 | 67.4 | 7.2 | −1.3 | −1.4 |
| DA | 70 | 58.1 | 54.4 | 5.9 | 68.8 | 64.4 | 6.9 | −3.7 | −4.4 |
| DA | 50 | 58.1 | 51.9 | 5.6 | 68.8 | 61.5 | 6.7 | −6.2 | −7.3 |
| MA | 110 | 91 | 93.2 | 8.3 | 464.3 | 475.1 | 42.3 | 2.2 | 10.8 |
| MA | 90 | 91 | 88.9 | 8 | 464.3 | 453.5 | 40.9 | −2.1 | −10.8 |
| MA | 70 | 91 | 84.7 | 7.7 | 464.3 | 431.8 | 39.5 | −6.3 | −32.5 |
| MA | 50 | 91 | 80.4 | 7.5 | 464.3 | 410.2 | 38.1 | −10.6 | −54.1 |

Abbreviations: AC, Acacia-Commiphora; CT, Combretum-Terminalia; DA, Dry Afromontane; MA, Moist Afromontane; NPP, net primary production; SOC, soil organic carbon.

*Note:* The intensity of the forest use has been approximated by varying net primary productivity (NPP) from the current level, by following multipliers 110, 90, 70 and 50%.

Todd-Brown et al., 2013), the models performed poorly for the observed values further from the mean and could explain only 1/3 of the variance in data. The Yasso07 SOC estimates were more precise than those of CENTURY. Both, Yasso07 SOC estimates and observations were slightly skewed to lower values. If only analysing data from the MA biome with larger SOC stock, then the comparison would likely favour the CENTURY over the Yasso07 model. It should also be noted that the $CO_2$ emissions related to SOC changes from the largest C stocks are of greater importance.

The reasons behind the mismatch between modelled and measured SOC data can be attributed not only to differences in the representation of decomposition between the models (Parton et al., 1987; Tuomi et al., 2011) but also to local factors missing from these models, for example, intensive forest use or unknown land-use history of those sites. In general, both models failed to estimate the largest SOC stocks, which might be simply due to a combination of high productivity and high precipitation conditions, which are rare in the model calibration data. Anyhow, the results based on Yasso07 and CENTURY models for Ethiopia were promising, but still, assumptions made here on litter fall and steady state conditions should be critically reviewed against empirical data as has been done for example, by Ťupek et al. (2016). In this study, Yasso07 and CENTURY had different optimal litter fall shares from NPP, indicating that their performance differed for Ethiopia, underlining the need for better parametrisations for African conditions for both models. It is also important to understand that in this study, the estimation of the uncertainty of SOC change was not possible, noting that according to Lehtonen and Heikkinen (2016), the relative confidence intervals were ca. 30% for SOC change estimate for forests in Finland. Nevertheless, models are needed for SOC change estimation, as repeated SOC measurements are expensive and time consuming and hardly ever available for less developed countries.

The global soil carbon map by FAO (FAO and ITPS, 2018) is a valuable product that can be improved and updated constantly. The relative accuracy of this map product was, on average, good but showed a systematic and significant overestimation of SOC when compared to the measurements from forest lands (Figure 4). This discrepancy between the FAO GSOC map and measurements was probably due, in part, to the fact that the map was based on data driven upscaling methods (Random Forest) and SOC data originated from agricultural soils. Hopefully, in the future, new data, for example, those published here, will be utilised to update the SOC map for Ethiopia and especially for forest areas.

According to the Ethiopian NDC, the country will reduce emissions from the projected business as usual scenario of 400 Tg of $CO_2$ annually down to 145 Tg of $CO_2$ in 2030. While the annual emissions due to deforestation and degradation are 55 Tg of $CO_2$, Ethiopia aims for emission reductions of 130 Tg of $CO_2$ from its forestry sector (Federal Democratic Republic of Ethiopia, 2017). The simulation by the CENTURY model showed that intensification of current forest use (degradation of NPP by 10%) resulted in additional annual emissions of 6 Tg $CO_2$ up to 2030 from forest soils. Reduction of the use of forest resources (increase in NPP) by 10% increased carbon sinks with a similar magnitude during the following 12 years. The simulation results indicate that changes in forest use affecting the share of NPP entering soils and further affecting forest SOC are of great importance to the national carbon budget, meaning that by reducing net-use of the forest, for example, by increasing forest biomass over time, mainly in CT and MA biomes, Ethiopia would greatly reduce forest soil $CO_2$ emissions (Figure 4, Table 3). Results agree well with the findings on SOC dynamics in Ethiopian agricultural lands, where alternative management practices, such as agroforestry, terracing and restrained grazing, have proven to be effective means to increase litter input to soil systems and thus increase SOC (Gelaw, Singh, & Lal, 2014; Rimhanen, Ketoja, Yli-Halla, & Kahiluoto, 2016).

The results of the study also show that biomes are very different concerning SOC. Effective protection efforts targeted at areas with the largest C stocks would, thus, most efficiently prevent carbon losses due to degradation and deforestation. The MA forest biome contains twice as much SOC per unit area compared to CT forest biome and three times more SOC compared to AC. Simultaneously, Dry Afromontaine (DA) forest biome showed second largest SOC per ha (Figure 6) but its spatial extent in Ethiopia was relatively low. However, its large SOC per ha means large potential for both emissions if area would be further reduced but even larger potential for soil carbon sequestration if the land which has lost its productivity would be restored by afforestation. Compared to the total land area of Ethiopia (over 110 mill. ha), MA forests cover a relatively small area between 4 and 5.5 mill. ha (an estimate depending on the definition of the forest). However, the SOC of MA forests in 0–30 cm depth equals 336 Tg C, when assuming average measured SOC (84 Mg C per ha) and a land area of 4 mill. ha (Tables 1 and 2). If this amount of SOC in a top layer of the MA biome would be, in the worst scenario, mobilised due to degradation, its $CO_2$ equivalent (1,232 Tg $CO_2$) would equal almost 10 years of current total emissions of Ethiopia (2010 emissions from NDC). In addition to MA SOC loss, together with the tree biomass of these forests that constitutes 434 Tg C (Moges, Eshetu, & Nune, 2010), the total MA biome emissions would thus equal 20 years of current Ethiopian annual $CO_2$ emissions. The SOC estimates in this study were quantified only for the top layer of soil, although for the whole soil profile SOC quantity could be larger; as deeper soil layers may have many times more SOC compared to 0–30 cm layer (Jobbágy & Jackson, 2001).

The forest related implementation of Ethiopia's ambitious NDC goal in its climate commitment (offsetting 130 Tg $CO_2$ emissions per year by 2030), as reported by FDRE (2017), requires reversing the anticipated forest emissions by increasing the sinks. According to our study, this can be achieved by taking measures to adequately protect and manage the existing forest C storage (e.g., by reforestation of newly emerging forest gaps with indigenous species and by introducing an additional average ∼6 Tg $CO_2$ annual sink by increasing forest density country-wide, which comes with a related increase in NPP, by more than 10%) (Table 3). This value is not exact, as our estimate is the cumulative sum of SOC gain over 12 years, excluding C in trees. However, to reach the climate commitment, fostering forest soils would be an efficient means. This could be obtained either by investing in the increase of biomass increment or by reducing the amount of unsustainable harvesting of forest biomass that controls the fraction of NPP entering soils.

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## SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of this article.

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