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Soil carbon under current and improved land management in Kenya, Ethiopia and India

Dynamics and sequestration potentials

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Soil carbon under current and improved land management in Kenya, Ethiopia and India

Dynamics and sequestration potentials

Rolf Sommer¹
Mayesse da Silva¹
Sylvia Nyawira¹
Wuletawu Abera¹
Lulseged Tamene¹
Tesfaye Yaekob^{1,3}
Job Kihara¹
Kristin Piikki^{1,2}
Mats Söderström^{1,2}
Andrew Margenot⁴

¹ International Center for Tropical Agriculture (CIAT)

² Swedish University of Agricultural Sciences (SLU), Skara, Sweden

³ Ethiopian Institute of Water Resources (EIWR), Addis Ababa University, Ethiopia

⁴ Department of Crop Sciences, University of Illinois Urbana-Champaign, USA

Centro Internacional de Agricultura Tropical
International Center for Tropical Agriculture
Regional Office for Africa
PO Box 823-00621
Nairobi, Kenya
Website: www.ciat.cgiar.org

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About the authors

Rolf Sommer, Soils and Water Management Principal Scientist, Agroecosystems and Sustainable Landscapes (ASL) research area, CIAT - Nairobi, Kenya

Mayesse da Silva, Soils and Water Management focal point for Latin America and the Caribbean, ASL research area, CIAT - Headquarters, Cali, Colombia

Sylvia Nyawira, Ecosystem Services and Environmental Impacts focal point for Africa, ASL research area, CIAT - Nairobi, Kenya

Wuletawu Abera, Soils and Water Management Researcher, ASL research area, CIAT - Addis Ababa, Ethiopia

Lulseged Tamene, Landscape Restoration focal point for Africa, ASL research area, CIAT - Addis Ababa, Ethiopia

Tesfaye Yaekob, Associate Researcher, Ethiopian Institute of Water Resources (EIWR) and CIAT

Job Kihara, Senior Scientist, ASL research area, CIAT - Nairobi, Kenya

Kristin Piikki, Associate Professor and Researcher, Swedish University of Agricultural Sciences (SLU) and CIAT

Mats Söderström, Associate Professor and Researcher, SLU and CIAT

Andrew Margenot, Department of Crop Sciences, University of Illinois Urbana-Champaign, USA

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Acronyms and abbreviations

BCR	benefit-cost ratios
C	carbon
CO ₂ eq	carbon dioxide equivalent
CSA	climate-smart agriculture
CSS	climate-smart soil
CA	conservation agriculture
CT	conventional tillage
GIZ	Deutsche Gesellschaft für Internationale Zusammenarbeit [German Agency for International Cooperation]
DRIFTS	diffuse reflectance infrared Fourier transform spectroscopy
DEM	digital elevation model
DSM	digital soil mapping
FYM	farm yard manure
RES1	first sensitivity simulation
BMZ	German Federal Ministry for Economic Cooperation and Development
GHG	greenhouse gases
ha	hectare
ISFM	Integrated Soil Fertility Management
IPCC	Intergovernmental Panel on Climate Change
ILRI	International Livestock Research Institute
Mt	megatons
m.a.s.l.	meters above sea level
CH ₄	methane
MIR	mid-infrared
NIR	near-infrared
N	nitrogen
N ₂ O	nitrous oxide
NGOs	non-governmental organizations
PLS	partial least squares
PTF	pedotransfer function
POXC	permanganate-oxidizable C
R	residue retention
RES2	second sensitivity simulation
SRTM	Shuttle Radar Topography Mission
SOC	soil organic carbon

SOM	soil organic matter
STD	standard
SSA	Sub-Saharan Africa
TAs	terrain attributes
t	tons
TSC	total soil carbon
TSPF	Tropical Soil Biology and Fertility Institute
WOTR	Watershed Organisation Trust
yr	year
OT	zero tillage
BG	β -glucosidase

Contents

Acknowledgement.....	iii
Acronyms and abbreviations	iv
Research highlights	2
Where from here	3
Introduction and rationale.....	4
Definition of technical terms and concepts	6
Soil sampling and analysis	7
Kenya	7
Ethiopia	10
India	13
Results and discussion	15
General overview of soil carbon data from western Kenya	15
The impact of land use history on soil carbon stocks	17
Nandi forest, Kenya.....	17
Highlands of Ethiopia.....	18
The impact of land management on soil carbon stocks.....	21
Conservation agriculture - Bungoma, Kenya	21
Land enclosures - Ethiopia	22
Watershed management - India.....	23
Soil carbon and agronomic performance - evidence from CIAT's long-term trials	25
Soil carbon dynamics.....	25
Agronomic performance.....	26
Does soil organic carbon affect yields?	27
Model-based assessment of critical levels of inputs required to rehabilitate soils.....	28
Mapping and quantifying the potential impact of soil protection and rehabilitation on soil carbon.....	32
Soil organic carbon mineral saturation and deficit.....	33
Potential of CA to increase SOC in croplands	36
Rapid indicators of soil health	38
Permanganate-oxidizable C (POXC)	38
β -glucosidase activity.....	39
Scopes of using infrared spectroscopy	40
Conclusion	43
Appendices	44
References	45

Figures

Figure 1	GHG emissions per hectare distinguished by major sources and farm types in Zou and Collines counties of Benin	5
Figure 2	Sampling locations in western Kenya	7
Figure 3	Soil sampling locations and major land use types in the Murugusi watershed.....	9
Figure 4	Soil sampling location in/around Nandi forest	9
Figure 5	Location of sampling points in Ethiopia.....	10
Figure 6	Histogram distribution of major land form elements in the study location, Ethiopia.....	11
Figure 7	Different forest structures selected for sampling locations in the Wofwasha forest, central highlands of Ethiopia	12
Figure 8	Soil sampling locations and land use in Kumbharwadi (restored) and Warvandi (control; not restored) watersheds in India	14
Figure 9	Box-whisker plots of carbon contents in 0–20 cm depth of the three sampled sites.....	15
Figure 10	Regression tree model of topsoil (0–20 cm) soil carbon (g/100 g) of all sampled sites of western Kenya.....	16
Figure 11	Distribution of soil carbon by land use of the three major western Kenya sites.....	16
Figure 12	Comparison of topsoil organic carbon (SOC) stocks (Mg/ha) over the years since pristine forest conversion in western Kenya	17
Figure 13	Comparison of topsoil organic carbon (SOC) stocks (Mg/ha) of different land use types in western Kenya	17
Figure 14	Carbon content (average of top and subsoil) of different land use types in highland Ethiopia.....	18
Figure 15	Comparison of topsoil organic carbon stocks along the observed latitudinal gradient ($R^2 = 0.43$)	18
Figure 16	Comparison of SOC at 0–20 cm (bottom) and 20–40 cm (top) of pristine forests with neighboured croplands in Denkoro, Desae, Munesa and Wofwasha	19
Figure 17	Comparison of topsoil carbon between cropland under business as usual (BAU), managed cropland, and cropland under fallow	20
Figure 18	Box-whisker plots of cropland topsoil soil carbon in response to years of conversion.....	20
Figure 19	Comparison of soil organic carbon (SOC) stocks (Mg/ha) of conservation agriculture (CA) and business-as-usual (BAU) systems of farmers in western Kenya	21
Figure 20	Comparison of topsoil organic carbon (SOC) stocks (Mg/ha) of conservation agriculture (CA) and business-as-usual (BAU) systems of farmers in western Kenya	22
Figure 21	Soil carbon stocks of top and subsoil in response to land enclosure (animal exclusion) in grazing systems in Andikelkel and Merere in Tigray and Gimbi in western Oromia.....	23
Figure 22	Soil organic carbon content comparison between a restored (Kumbharwadi) and unprotected watershed (Warvandi). Topsoil differences are significant at $P < 0.01$	24
Figure 23	Topsoil organic carbon stocks at Kumbharwadi (restored) and Warvandi (control) watershed in India.....	24
Figure 24	Changes of topsoil organic carbon of identical CT1 and INM3 treatments.....	25
Figure 25	Maize and soybean yields observed under different tillage and residue management over 26 seasons in western Kenya	26

Figure 26	Relationships between maize grain yield and soil organic carbon (SOC) in 2009 and 2012, and treatment specific yield and SOC data for 2009 and 2012.....	27
Figure 27	Temporal responses of soil C in the upper 40 cm in treatments with manure application and residue retention	29
Figure 28	Simulated annual soil carbon losses for the standard treatment (STD) and for the sensitivity simulations (2004-2014). Avoided soil carbon losses that can be achieved through additional manure application.....	30
Figure 29	Simulated annual soil carbon losses for the standard treatment (STD) (2004 to 2014) Avoided soil carbon losses achieved through increased residue retention	31
Figure 30a	Spatial distribution of soil organic carbon stocks at the Murugusi watershed, western Kenya.....	32
Figure 30b	Spatial distribution of soil texture at the Murugusi watershed, western Kenya.....	33
Figure 31	Soil organic carbon mineral saturation model for western Kenya	34
Figure 32	Soil organic carbon saturation map (Mg/ha) at the Murugusi watershed, western Kenya.....	35
Figure 33	Soil organic carbon deficit/excess map (Mg/ha) of the Murugusi watershed, western Kenya	35
Figure 34	Soil organic carbon stocks (Mg/ha) in the Murugusi watershed assuming that conservation agriculture (CA) is implemented on all cropland.....	36
Figure 35	Soil organic carbon offset potential when conservation agriculture (CA) is implemented in croplands at the Murugusi watershed, western Kenya	37
Figure 36	Impact of length of cultivation around Nandi forest on permanganate oxidizable (POX) C contents of topsoil and subsoil samples.....	38
Figure 37	Impact of length of cultivation around Nandi forest on soil C contents, and correlation between POXC and soil total soil C.....	38
Figure 38	Ratios of POXC and soil C to clay content distinguishing soil samples from pristine forest and agricultural land.....	39
Figure 39	Impact of length of cultivation on β -glucosidase	39
Figure 40	Impact of length of cultivation on the ratio of β -glucosidase to soil C	40
Figure 41	DRIFTS spectra of Nandi soil samples distinguished by years of land use (0–25, 25–50 and 50–75 years)	40
Figure 42	PLS loading plot scoring the first 2 factors of MIR (4000–400 cm^{-1} wave number) spectra of Nandi soil samples.....	41
Figure 43	Prediction of clay content using mid-infrared spectroscopy	42
Figure 44	Prediction of permanganate oxidizable C (POXC) using mid-infrared spectroscopy.....	42
Figure A1	Increase in the yields per season resulting from the avoided losses in soil carbon for the farm yard manure application sensitivity simulations.....	44
Figure A2	Yield differences per season resulting from the avoided losses in soil carbon for the residue retention sensitivity simulations.....	44

Tables

Table 1	Study sites in Ethiopia, their land use, elevation, agroecological zones and soil types	13
Table 2	Soil carbon sequestration potential of the Murugusi watershed	37



Photo: Neil Palmer/CIAT

Research highlights



We summarize results from an assessment of the impact of land use and (improved) soil management practices in Kenya, Ethiopia and India on soil carbon (C) dynamics and potential sequestration of C in soils. We present insights on suitable indicators of soil health, biophysical model-based simulation studies, soil carbon-yield relationships and the impact of soil protection and rehabilitation at watershed level.



Soils in western Kenya have lost between 30 and 50% of their topsoil C over a period of 15–75 years of native forest conversion to land use. Likewise, conversion of forest land into agricultural land entailed a significant reduction in soil C stocks in all sites sampled in Ethiopia (43–62% of its original stocks at 0–40 cm).



Our research reveals a huge potential of fine and medium-textured soils in western Kenya to store C if adequate soil management is implemented, such as conservation agriculture (CA). The results are less obvious for areas (enclosures) in Ethiopia, with some sites gaining soil carbon but others not.



Bio-physical model-based results underpin these observations in the humid tropical highlights of western Kenya. Increased crop residues retention and farmyard manure application have the potential to reduce soil carbon losses, as had been observed in CIAT's long-term trial experiments. To maintain soil C levels, however, as much as 8 tons of farmyard manure per hectare would have to be applied, and at least 2 t of maize stover residues retained each season. This is an unrealistic amount that most smallholder farmers in western Kenya would be unable to source. Hence, to maintain carbon levels at or above about 20 g/kg (=2%), other means of conserving soils must be included into such "package", for example, green manure cover cropping and minimum tillage. It must also be noted that such research results cannot be transferred to other agro-ecologies. Previous similar research for Ethiopia,

for instance, has shown that 3 t/ha manure and 50% retention of wheat straw is sufficient to stabilize soil carbon in farmers' fields in Amhara.



Based on the predominating soil texture (mineralogy), the Murugusi watershed (western Kenya) has an approximate average C saturation potential of 80 t C/ha in the top 20 cm of soil, which is more than double the soil C that we currently find in this watershed. This means that C sequestration in soils of these agro-ecosystems is currently not constrained by an upper physio-chemical saturation limit. If CA was practiced on all agricultural land in Murugusi, an approximate 131,000 tons of C could be sequestered in soils in this watershed.



The Watershed Organisation Trust (WOTR) and partners invested some decades of work on rehabilitation of the Kumbharwadi watershed in semi-arid Maharashtra, India. This included physical soil conservation structures and a range of practices to improve soil health. Soil C contents in such treated watershed increased by on average 0.41 t C/ha in 19 years. While this is much less than what we observed in western Kenya, it is the total land area that matters: if scaled to the entire semi-arid land of India (95.7 Mha), an approximate 39 Mt C or 144 Mt CO₂eq could be sequestered in soils by improved land management and conservation, which is equivalent to 12% of all of India's GHG emissions from land use in 2010.



Our long-term trials teach us that we cannot predict with confidence that the adoption of certain improved land management practices in the tropical highlands of East Africa leads to true sequestration of soil C. The initial soil organic carbon (SOC) status, which is a consequence of past land use, determines whether soils can gain C or whether adoption of improved soil management practices 'only' slows down losses. However, both, sequestration *and* avoided losses, qualify for payments for environmental services, in this case voluntary carbon credits.



Soil carbon-yield relationships analysed in CIAT's CA long-term trial varied by seasons and were weak altogether, most likely because of the overlaying effect of rainfall. Nevertheless, practices like zero tillage and residue retention that support C sequestration merit adoption by farmers given the observed superior economic and yield stability performance.



Infrared spectroscopy proved a valuable, fast and comparably cheap way of predicting a whole range of potentially suitable soil chemical variables and soil health indicators. The

soil health indicators, however, that we tested – the labile fraction of soil carbon (POX-C) and β -glucosidase activity – showed limited “indication” of soil health and/or degradation.



Here, the β -glucosidase-soil C ratio was the parameter most sensitive to time of cultivation across the chronosequence, and hence seems the one most promising in terms of deriving more universally applicable thresholds that could indicate critical degradation levels for certain agro-ecosystems, and in turn potentials of soil to sequester C.

Where from here?

Based on evidence provided in this report, we suggest to the GIZ *Soil Protection and Rehabilitation for Food Security Program* to:

- continue promoting conservation agriculture (CA) in western Kenya and organic management practices in India, as a means to improve soil health and sequester or stabilize soil carbon;
- include CA practices into the current work on integrated soil fertility management (ISFM+) in Ethiopia, i.e. in particular reduced tillage and continuous surface coverage by residue retention or, alternatively, inclusion of cover crops, as both practices can enhance the beneficial impact of ISFM on soil carbon;
- consider inclusion of improved forages and associated enhancement of livestock management into the research portfolio, as livestock is the major contributor to farm-level greenhouse gas emissions in the three countries and improvements have notable beneficial impacts;
- develop and include payment for environmental services schemes, in this particular case carbon sequestration, into their portfolio of advice to stakeholders or policy makers at regional or national level;
- develop a monitoring system to better capture the quantitative and qualitative impacts of improved soil management on various ecosystem services, such as carbon sequestration and greenhouse gas emission reduction, as well as improved farm household resilience and prosperity.



Photo: Neil Palmer/CIAT

Introduction and rationale

Agriculture is a major contributor to climate change, emitting the three major greenhouse gases (GHGs) – carbon dioxide (CO₂), methane and nitrous oxide – into the atmosphere. According to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC), the *Agriculture, Forestry and Other Land Use* sector “is responsible for just under a quarter (~10–12 Gt CO₂eq/yr) of [all] anthropogenic GHG emissions mainly from deforestation and agricultural emissions from livestock, soil and nutrient management”. Land use change – often associated with deforestation – contributes about 11.2% to this share, while agricultural production is responsible for 11.8% (IPCC, 2014).

To reduce emissions from agriculture, while providing and maintaining global food security, there is a growing interest to develop and promote low-emission green-growth pathways for future agricultural production systems. Sub-Saharan Africa (SSA) faces two concerns in that respect: a) agriculture is the major emitter of GHGs on this sub-continent, and b) agriculture is largely underperforming. To feed a growing population, productivity and total production need to increase significantly. To achieve this while reducing emissions from agriculture at the same time is a major challenge. Climate-smart agriculture (CSA) sets out to address this challenge by transforming agricultural systems affected by the vagaries of climate change. CSA aims at improving food security and system’s resilience while addressing climate change mitigation.

The BMZ-funded and GIZ-implemented program on ‘Soil Protection and Rehabilitation for Food Security’, as part of Germany’s Special Initiative “One World–No Hunger,” invests in sustainable approaches to promoting soil protection and rehabilitation of degraded soil in Kenya, Ethiopia, Benin, Burkina Faso and India. The underlying notion is that food security can only be achieved and maintained with/on healthy, fertile and productive soils. However, soil rehabilitation is often evaluated for productivity and food security benefits, while the climate change mitigation part often receives less attention. Likewise, CSA initiatives have not given due attention to soil protection and rehabilitation. To address the issue, the GIZ Soil Program commissioned CIAT to produce detailed information on the climate smartness of ongoing soil protection and rehabilitation measures in the five countries. Results of the “climate-smart soil” (CSS) project for each individual country have been published in five CIAT working papers, and have been communicated to GIZ and their implementation partners. Figure 1 exemplarily shows the results of the GHG inventory of five distinguished farm types in Zou and Collines counties of Benin, where GIZ implements soil protection and rehabilitation technologies (see Birnholz et al. 2017 for further details). While total CO₂eq emissions vary greatly by farm type, per-hectare emissions are comparably low altogether.

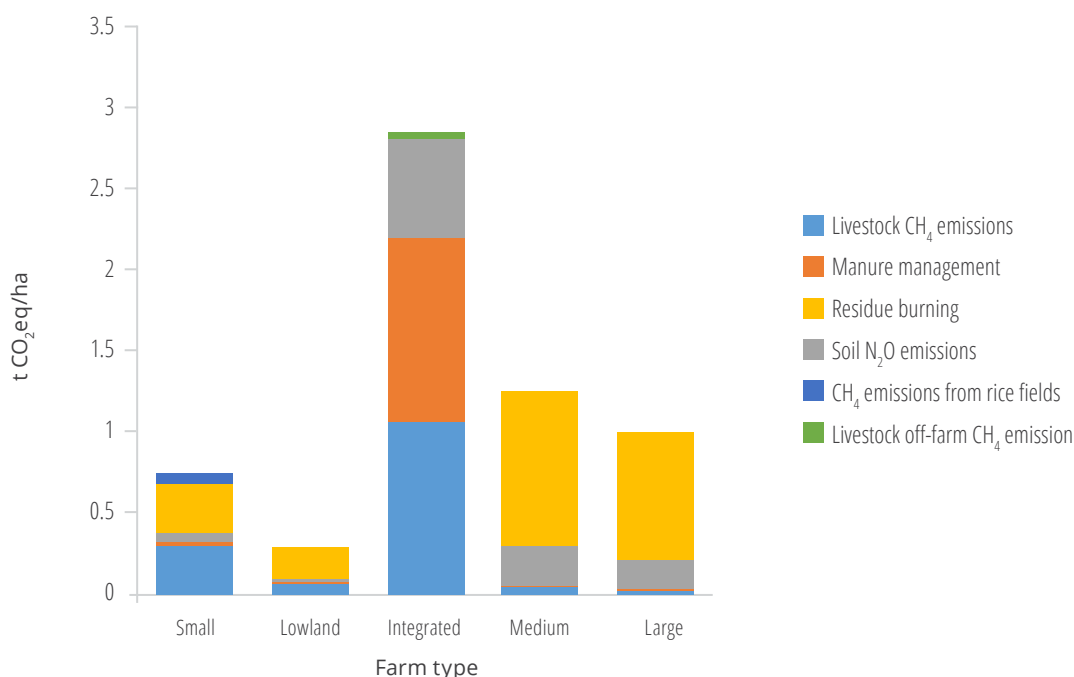


Figure 1 GHG emissions per hectare distinguished by major sources and farm types in Zou and Collines counties of Benin (Birnholz et al., 2017). CO₂ equivalents (eq.) are used to sum up different greenhouse gases in a common unit, whereas methane (CH₄) and nitrous oxide (N₂O) are converted using standard conversion rates based on their respective global warming potential.

One aspect that received less attention in the CSS project, given the short period and various tasks at hand, was the role that soils could play by increasingly storing carbon (C) when well managed; a process referred to as soil C sequestration. In the example provided in Figure 1, total GHG emissions did not surpass 2.9 t CO₂eq/ha at maximum; an amount low enough to potentially be fully balanced by C sequestration in soils, even more so in this particular case if residue burning was replaced by incorporation of residues into the soil.

To elaborate further on this potential, GIZ engaged CIAT scientists in an extension phase to the CSS project, to investigate the climate change mitigating role that soil C sequestration could play in western Kenya and Ethiopia.

While soil protection and rehabilitation interventions in Kenya and Ethiopia are rather recent, soil restoration and watershed management in the State of Maharashtra in India had been implemented by various NGOs supported by GIZ already some decades ago, and fully restored

watersheds are available. This allowed us to assess the impact of soil and landscape improvement on soil C by means of digital soil mapping comparing such watershed with a neighbouring “untreated” watershed, assuming that the impact of some decades of improved soil protection and management increased soil C significantly. This work was also implemented as part of the extension phase to the CSS project.

This technical report summarizes results of this extension phase. We present results from soil sampling along a land use chronosequence and from fields under conservation agriculture (CA) and land exclosures highlighting the impact of land use history and recent soil management on soil C. We present insights on research about suitable indicators of soil health and how they could be used to describe potentials for C sequestration. And finally we quantify the impact of soil protection and rehabilitation if implemented at watershed level as the preferable scale of intervention.

Definition of technical terms and concepts



Conservation agriculture

Conservation agriculture (CA) is a crop management system which was developed and improved in the Americas and Australia during the last four decades. Its term has been coined to clearly distinguish itself from other (tilled) agriculture systems. CA is based on three main principles: a) minimum soil disturbance, which implies minimum- or even zero-tillage; b) crop residue retention with living or dead plants or plant material; c) diversified crop rotations or associations.



Integrated soil fertility management

Integrated Soil Fertility Management (ISFM) is a concept that had been developed in the late 1990s - early 2000s, among others, by the Tropical Soil Biology and Fertility (TSPF) Institute of the International Center of Tropical Agriculture (CIAT), Nairobi, as the major ISFM-advocating international agricultural research centre. The concept emerged out of the so-called Second Paradigm formulated by the soil scientist Pedro Sánchez who, beyond sole application of mineral fertilizer, acknowledged the importance of organic inputs and input use efficiently. ISFM built on this approach, however, also embracing social, cultural and economic processes regulating soil fertility management strategies. Mineral fertilizer application has been identified as an entry point to ISFM furthermore requiring improved, fertilizer-responsive germplasm. Thus, ISFM is defined as: 'The application of soil fertility management practices, and the knowledge to adapt these to local conditions, which maximize fertilizer and organic resource use efficiency and crop productivity.'



Digital elevation model

Digital elevation model (DEM) is a digital representation of earth surface topography referenced to a vertical datum either in 1) a two-dimensional array of numbers that represent the spatial distribution of elevations on a regular grid; 2) a set of x, y, and z coordinates for an irregular network of points; 3) contour strings stored in the form of x, y coordinate pairs along each contour line of specified elevation. Grid DEM are the most common used data in generating other terrain features for soil digital mapping, hydrology and spatial analysis.



Digital soil mapping

"The creation and population of spatial soil information systems by numerical models inferring the spatial and temporal variations of soil types and soil properties from soil observation and knowledge and from related environmental variables" (Lagacherie and McBratney, 2007).



Enclosure

Enclosure refers to complete area closure from grazing and cultivation for a specified duration of time to allow regeneration of vegetation. Enclosure – protection of degraded communal area from human and animal interferences to promote natural rehabilitation – has been a common type of intervention in the highlands of Ethiopia.



Photo: Georgina Smith/CIAT

Soil sampling and analysis

Kenya

In western Kenya, our study relied on soil sampling done in strategic regions and land use systems in the three counties, Kakamega, Bungoma and Siaya. We analysed soil samples from our two long-term trials, and we took new soil samples along a chronosequence in/around Nandi forest, in a selected watershed (Murugusi) and on conservation agriculture (CA) fields in Bungoma (Figure 2).



Figure 2 Sampling locations in western Kenya.

CIAT long-term trials

Since 2003, CIAT maintains two long-term, researcher managed, on-farm trials in Kenya. The first trial, CT1, compares soil fertility and agronomic performance of CA to conventional agriculture. The second trial, INM3, focuses on Integrated Soil Fertility Management (ISFM). Both trials are located in western Kenya, 50 km northwest of the city of Kisumu.

Both long-term trials host 44 treatments in total. CT1 compares two tillage systems – zero tillage (OT) and conventional tillage (CT), and two residue retention (R) levels – one on which 2 t/ha maize stovers are retained (R+) and the second one where all residues are removed after harvest (R-). Crop rotations comprise continuous maize (M-M), soybean-maize rotation (M-S or S-M¹) and continuous maize-soybean intercropping (MS). INM3 compares the impact of farm yard manure (FYM) application – plus (4 t dry matter per ha per season) or minus, and – as CT1 – residue retention. Crop rotations in this trial are continuous maize (M-M), *Tephrosia*-maize (T-M or M-T), and maize-soybean intercropping (MS). *Tephrosia candida* is a green manure cover crop (poisonous) legume. In addition, each trial compares different levels of nitrogen (N) and phosphate fertilizer application rates.

Standard measurements in both trials comprise the quantification of seasonal yield and biomass of the various treatments at harvest. More detailed measurements have been carried out on selected soil health indicators over the years. The paper *Agronomic management controls microbial populations in soils of western Kenya* summarizes latest findings on soil health (Kihara et al., 2018). From 2004 onwards, soil samples at 0–15 cm were taken twice a year, in-between seasons. INM3 topsoil samples of September 2005, 2007, 2009, 2011, 2013 and 2015, and sample of CT1 from September 2006, 2009, 2012, 2013 and 2015 were analysed for total C and N.

Conservation agriculture (CA) farms in western Kenya

In addition to the researcher-managed on-farm long-term trials, soil samples at 0–20 cm and 20–40 cm depth were collected mid-2017 on fields of 10 farmers located in Bungoma County in western Kenya that had adopted CA some 10 years ago in 2007 – within a CA project implemented by the African Conservation Tillage Network (Peter Kuria, personal communication). As a comparison, conventionally managed neighboured fields ($n=10$) were sampled as well. CA farms' geographic

locations were recorded, and farmers were interviewed about the land use history (total length of land use) and detailed management (crops grown, organic and inorganic fertilizer application, tillage and lime applied if any) of the CA field of the past six seasons. The position in the landscape (summit or backslope) and slope-% of the land was also recorded. The bulk density of the soil was quantified taking undisturbed soil samples of known volume. Soil samples were then analysed for pH, texture (hydrometer method), and total C and N content (elemental analyser) at ILRI/CIAT lab in Nairobi.

Murugusi watershed

To showcase potential C-sequestration gains and quantities for an entire watershed – as the preferred scale of implementing soil and land restoration practices, we selected Murugusi, a typical watershed, in which also GIZ soil protection and rehabilitation activities are implemented (Figure 3). We applied a stratified targeted sampling design as implemented in the R (R Core Team, 2018) package SurfaceTortoise (Piikki and Söderström, 2018), to best capture the spatial variation of soil properties in the watershed. We used Shuttle Radar Topography Mission (SRTM) (USGS, 2017) digital elevation model (DEM) as target covariate. These were projected onto the UTM 36 N coordinate system, which resulted in an approximate spatial resolution of 30 m × 30 m. The sampling design procedure is based on the principle that a surface is iteratively sampled and reconstructed by inverse distance weighting interpolation. Where the difference between the original surface and the reconstructed surface is the largest, a new sample is placed. This method was applied until 160 samples had been placed. We furthermore constrained the sampling by using a stratification grid, meaning when a sample had been located in a stratum, no more samples were allocated to that cell. In addition to this, 30 random samples and 10 hand-picked samples were added in a small area of cropland which, according to Landsat data, around 1980 had still been covered by native forest. At each sample location, two soil samples were taken; one from 0–20 cm and one from 20–40 cm depth. Similar to the CA farms in Bungoma, the position in the landscape (summit or backslope) and slope-% of the land were also recorded. The bulk density of the soil was quantified taking undisturbed soil samples of known volume. Soil samples were then analysed for pH, texture (hydrometer method), and total C and N content (elemental analyser) at ILRI/CIAT lab in Nairobi. A land use map was also produced at resolution of 30 m based on Sentinel-2 image from 2017 combined with ground truth observations

1 The sequence of letters indicates which crop is grown when – either in the long rainy season (first letter) or short rainy season (second letter).

Legend

- Soil sampling locations
- Murugusi watershed

Land use

- Water
- Tree cover; including dense bush
- Tree cover; in 2017 cropland
- Tree cover; in 2017 barren
- Cropland; including pasture
- Barren land

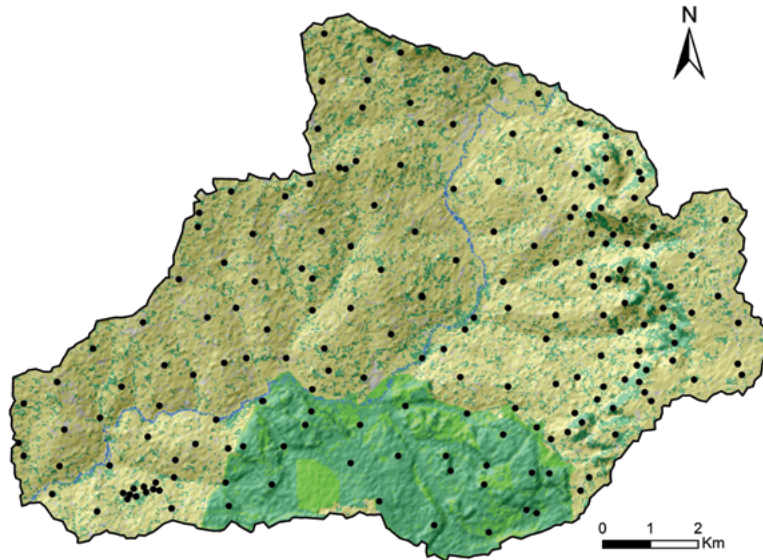


Figure 3 Soil sampling locations (black dots) and major land use types in the Murugusi watershed.

obtained in October 2017. Continuous SOC stocks and soil texture maps were created using a digital soil mapping (DSM) approach based on soil geomorphology and fuzzy logic at resolution of 30m (Da Silva et al., 2016; Zhu, 1997).

Nandi chronosequence

In Nandi, locations were manually determined based on a time series of 14 Landsat images from 1972 to 2017 that delineated forest cover change over the years (Figure 4).

A transect was chosen to construct a false time series of time since deforestation. At 24 locations along this transect, three samples were collected to represent different landscape positions, i.e. summit, backslope, and footslope. Again, samples were taken at 0–20 and 20–40 cm depths. In addition, we were able to acquire the exact geographic location of soil sampling sites of a previous similar study carried out by Kinyangi (2008), from which we selected 14 locations. We added six new locations according to variations in the satellite images, in an effort to include a few more newly deforested sites, and four sites still within the pristine forest.

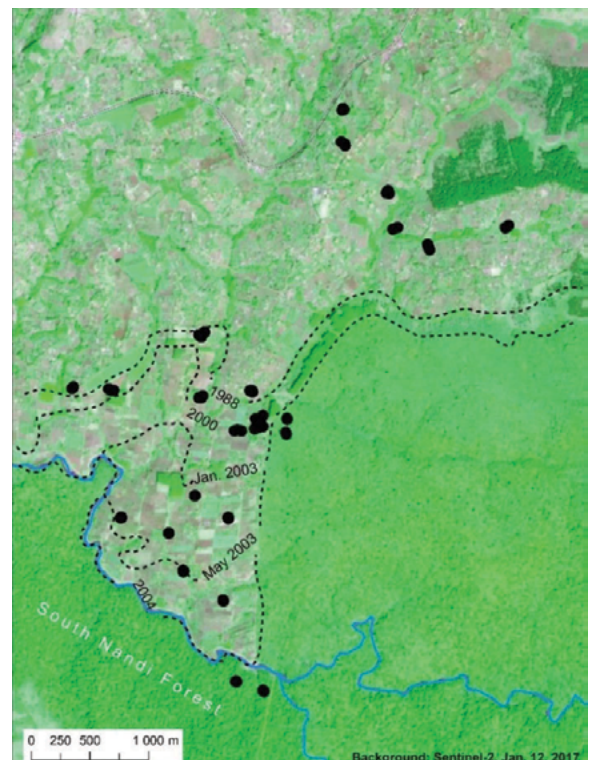


Figure 4 Soil sampling location (black dots) in/around Nandi forest. The current forest is the homogenous light-green area. Dotted lines show forest boundaries at certain points in time.



Photo: Georgina Smith/CIAT

Ethiopia

In Ethiopia, we collected samples from four pristine forest reserves (Borena Saynt, Desae, Munesa, and Wofwasha), three enclosures (Andikelkel, Gimbi, and Merere), and some other managed landscapes distributed in different agroecological locations (Figure 5). Enclosure refers to complete area closure from grazing and cultivation for a specified duration of

time to allow regeneration of vegetation (Behnke, 1986). As a comparison, conventionally managed neighboured fields were sampled as well. Data were collected as well from conventional open grazing (control) and controlled grazing systems. In addition to the conventional grassland, samples were also collected from natural Afro-alpine highland *Festuca* grasslands.

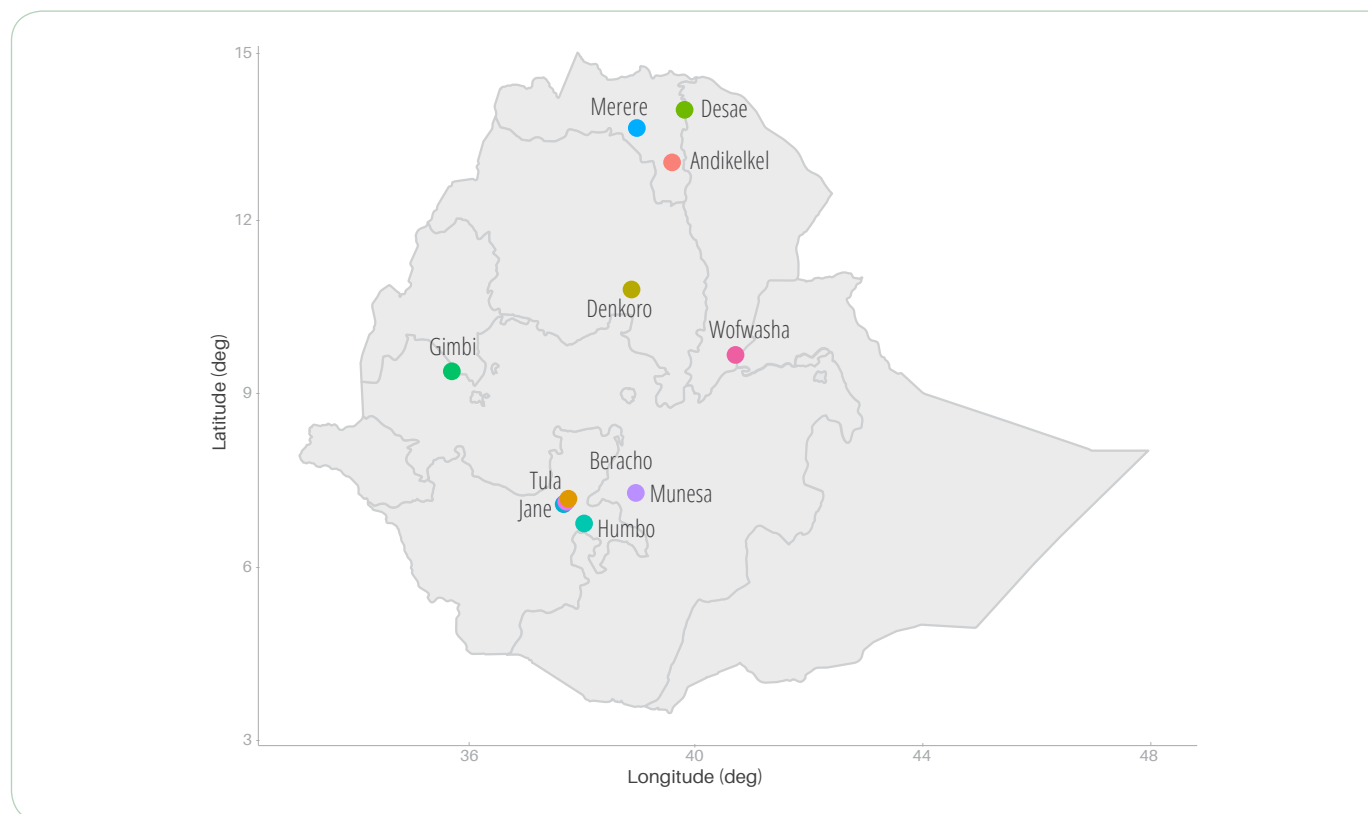


Figure 5 Location of sampling points in Ethiopia.

To capture the spatial variability, we considered different landforms, dominant species and land use when locating sampling sites. To classify and identify dominant landforms from DEM, we used a pattern recognition approach (Jasiewicz and Stepinski, 2013). The corresponding tool, *r.geomorphon*, which is imbedded in the GrassGIS platform extension, was used to generate 'landscape catena'. The tool requires one raster data set (DEM) and two scalar parameters (lookup distance and flatness threshold) as inputs. We used Aster DEM with 30 m resolution. An important parameter for obtaining landform classification is the lookup distance (search radius). We used different cells value (3, 20, 30, 40, 60, 80 and 100) to find out if they affect the landform distribution. Observation of results showed that 80 is an optimal value as we didn't observe a significant difference after that value. Accordingly, the dominant land form types were derived for the study areas. Results show that the dominant land form types (catenary positions) in all study locations include slope, spur, hollow, valley and ridge (Figure 6). Most of the sampling locations fell within these major land forms.

Pristine sites were selected based on vegetation structure considering the dominant tree species (Table 1). The final sample site selection was based on group discussions with local elders and local experts. For instance, in the Wofwasha forest, *Erica*, *Festuca*, *Juniper*, *Olea*, *Podocarpus* and *Hagenia* were the dominant species and samples were selected from these sites (Figure 7). In each pristine forest, six sites were selected inside the forest and another 12 surrounding sites selected outside the forest based on three approximate land use ages – Emperor regime (<1974), Derg regime (1974 to 1987) and current Ethiopian state – and number of fallow years in every district. Three replications in each site were chosen based on landscape position (summit, backslope and footslope). Soils were sampled at 0–20 and 20–40 cm depth. For composite auger sampling, three points across the slope with a 5-m interval were used. A core sampler was used for soil bulk density sampling.

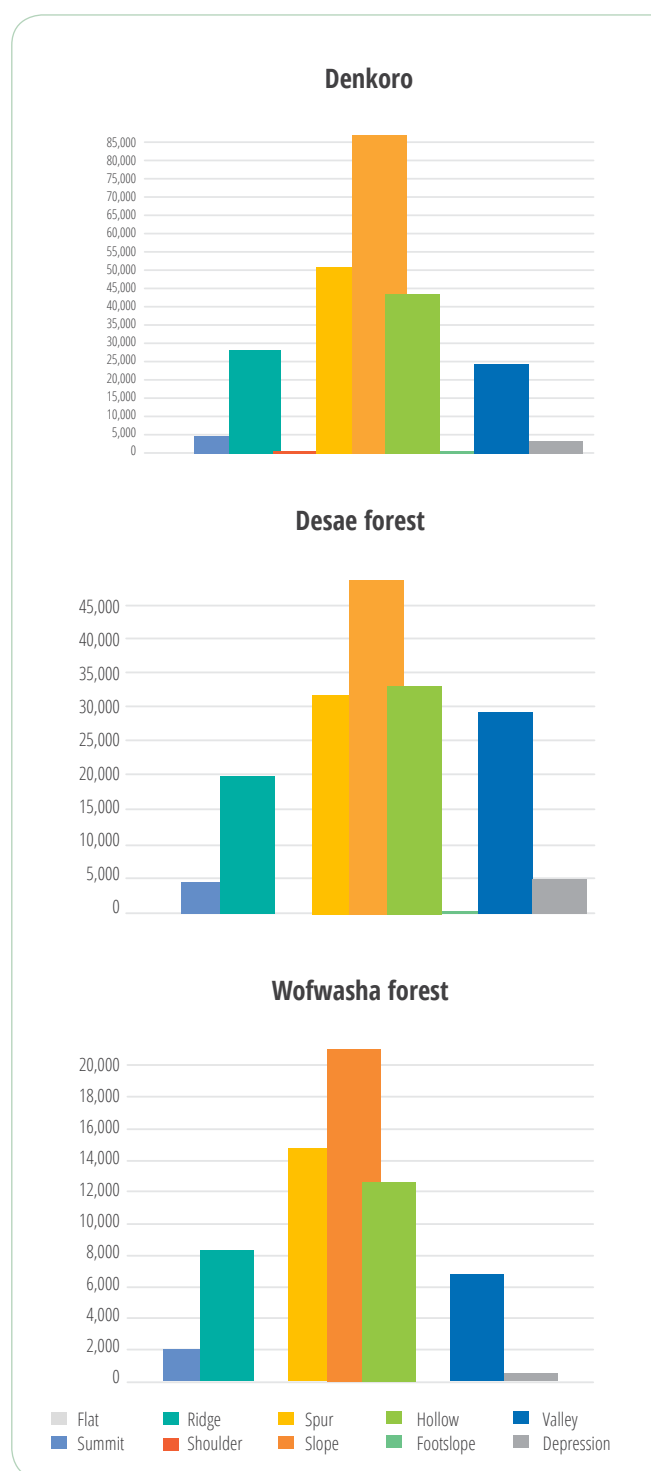


Figure 6 Histogram distribution of major land form elements in the study location, Ethiopia.



Figure 7 Different forest structures selected for sampling locations in the Wofwasha forest, central highlands of Ethiopia (photos by Tesfaye Yaekob/EIWR–CIAT).

Table 1 Study sites in Ethiopia, their land use, elevation, agroecological zones and soil types

LOCATION	LAND USE	ELEVATION RANGE (m)	AGROECOLOGICAL ZONE	TYPE
Wofwasha	Forest, cropland, Festuca grass	1961–3532	Moist highlands	Eutric Cambisols
Denkoro	Forest, cropland, enclosure, grass, Festuca grass	2493–3337	Sub-moist highlands	Eutric Cambisols
Munesa	Forest, plantation, cropland	1890–2607	Sub-moist highlands	Eutric Nitosols
Gimbi	Heavy grazing, control grazing, enclosure	1816–1867	Sub-humid mid highlands	Humic Cambisols
Andikelkel	Heavy grazing, enclosure	2231–2274	Sub-moist mid highlands	Eutric Nitosols
Berabicho	Cropland	2364–2427	Sub-humid mid highlands	Eutric Nitosols
Humbo	Cropland, enclosure	1512–1570	Sub-humid low highlands	Haplic Xerosols
Jane	Cropland	2443–2470	Sub-humid mid highlands	Eutric Nitosols
Merere	Heavy grazing, enclosure	1893–1908	Sub-moist mid highlands	Cambic Arenosols
Tula	Cropland	2652–2681	Sub-humid upper highlands	Eutric Nitosols

India

To assess the improvement of soil and landscape when restoring degraded lands in India, two watersheds, Kumbharwadi (restored) and Warvandi (control) in the State of Maharashtra were chosen for SOC stocks mapping and comparison (Figure 8). The Kumbharwadi watershed (1042 ha) has been restored since 1998 by the Watershed Organization Trust (WOTR) and partners. Restoration efforts included physical soil conservation structures (terracing, buffer strips, stone and grass bunds), afforestation, as well as a range of practices to improve soil health, such as vermi-compost and bio-fertilizer application. On the other hand, the Warvandi watershed (1264 ha) did not undergo any such kind of restoration. Elevation ranges from 594 to 781 m, and the climate in both watersheds is semi-arid with average annual precipitation of 470 mm and temperature of 25 °C.

A digital soil sampling strategy based on existing co-variables that contribute to soil variability across the landscape in both watersheds was conducted and 400 soil samples distributed in 200 sites were taken at

two different soil depths: 0–20 cm and 20–40 cm. We used the SRTM digital elevation model with 30 m resolution to generate the co-variables related to topography, such as the terrain attributes (TAs), slope, topographic wetness index, landforms based on the Geomorphons method (Jasiewicz and Stepinski, 2013), curvature (profile and plan), and relative slope position. The ISRIC digital soil class map with 250 m resolution and the land use map provided by our partners from WOTR were also included as co-variables to define the sampling sites. Since climate did not show variation in this region, it was not included as co-variable. Soil samples were analysed in the Soil Laboratory of Mahatma Phule Krishi Vidyapeeth University (Maharashtra, India) for SOC content, texture, and bulk density. In addition, percentage of gravel was recorded and – being quite significant – included in the C stock calculation. A DSM approach based on soil geomorphology and fuzzy logic was applied to create continuous SOC stocks maps at resolution of 30 m (Da Silva et al., 2016; Zhu, 1997).

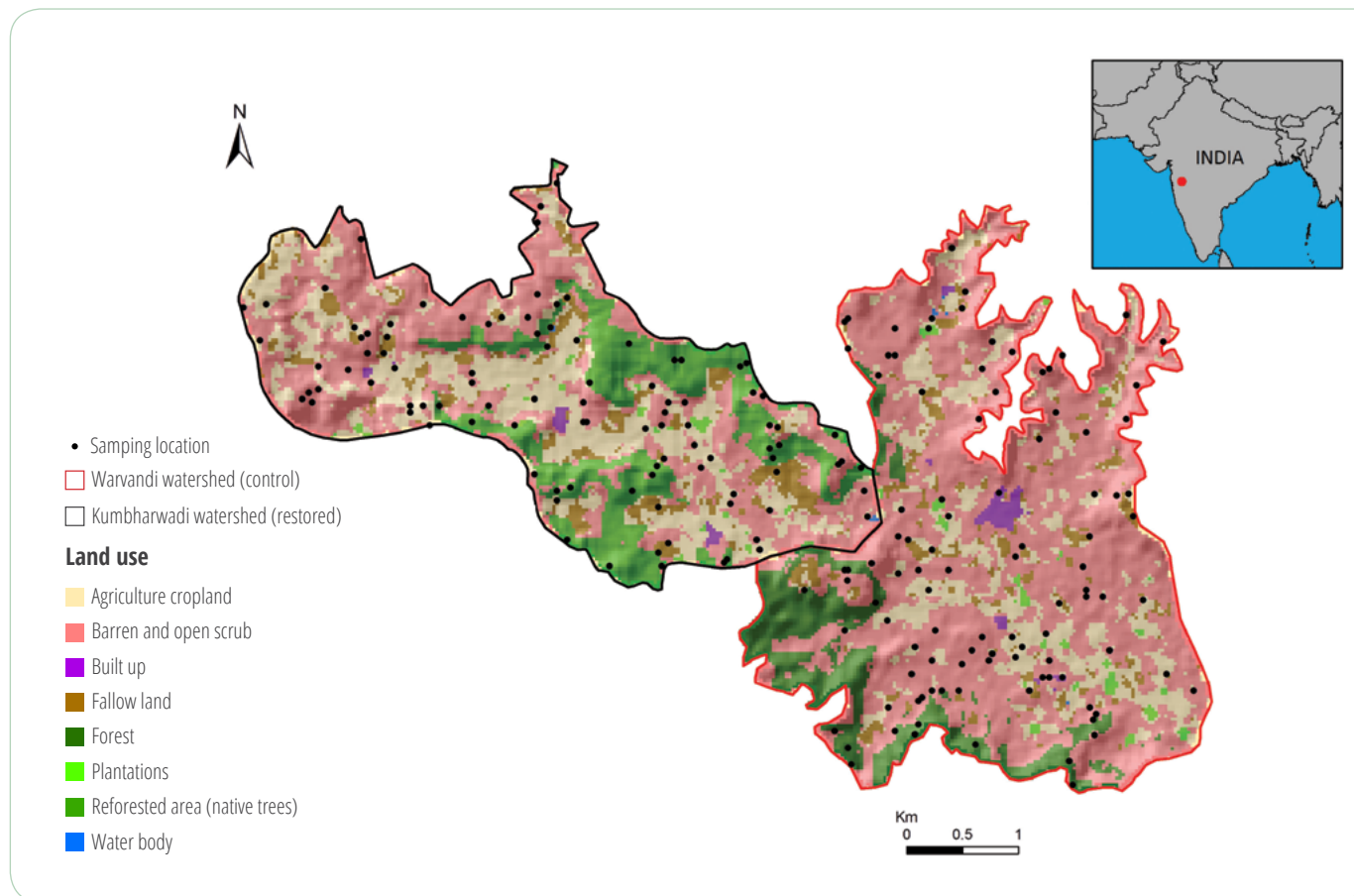


Figure 8 Soil sampling locations and land use in Kumbharwadi (restored) and Warvandi (control; not restored) watersheds in India.



Photo: Georgina Smith/CIAT

Results and discussion

General overview of soil carbon data from western Kenya

The three different sites sampled in western Kenya, namely Bungoma (conservation agriculture), Murugusi and Nandi, differed in their average C contents at 0–20 cm depth (Figure 9).

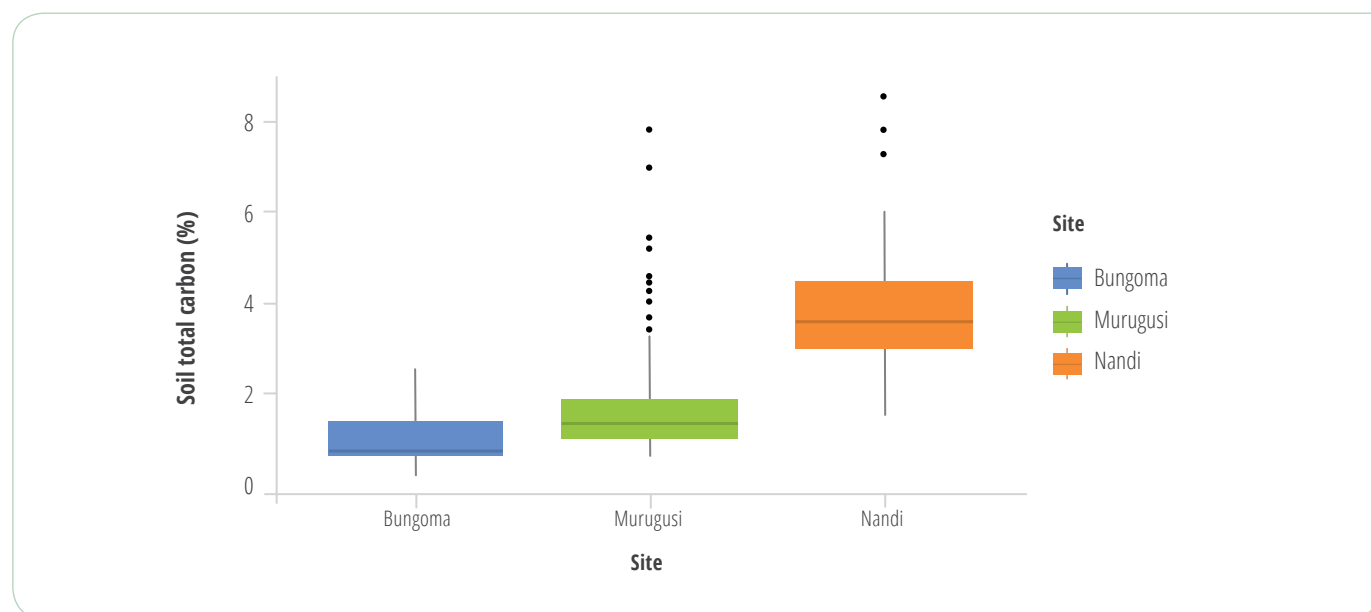


Figure 9 Box-whisker plots of carbon contents in 0–20 cm depth of the three sampled sites. Boxes enclose the 25–75% percentile, whiskers denote the 5% and 95% percentile, dots are outliers (above the 95% percentile), and the lines within the boxes show the median of all data.

Elevation, clay content and number of years since conversion from natural vegetation were key factors influencing soil C content (Figure 10).

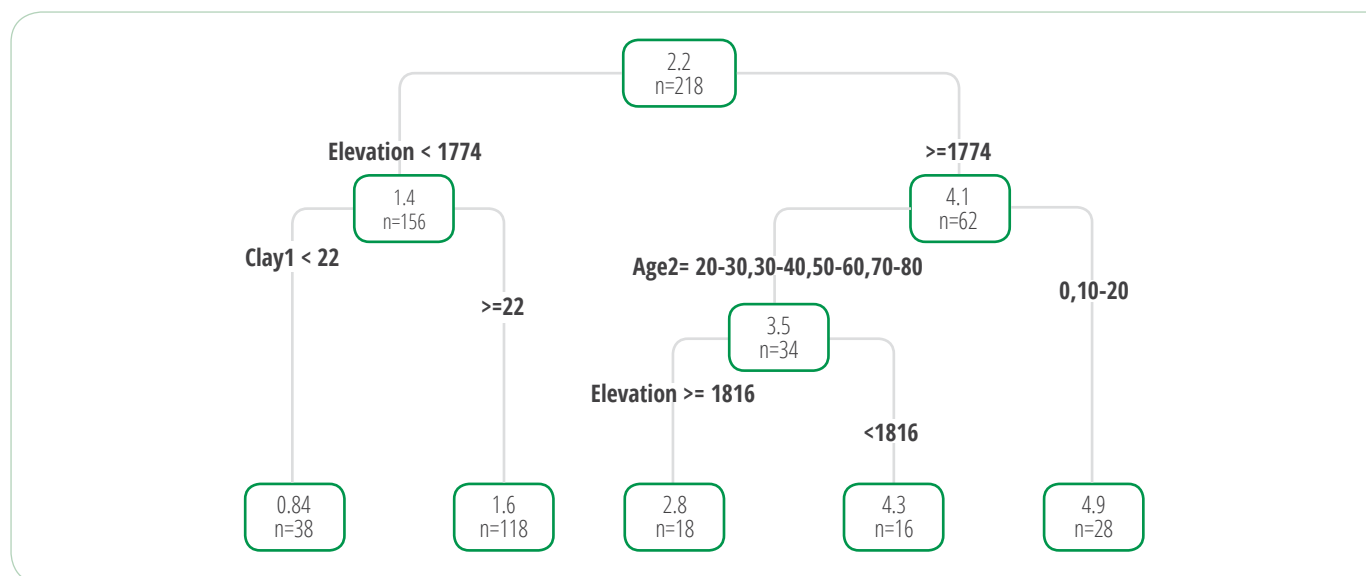


Figure 10 Regression tree model of topsoil (0–20 cm) soil carbon (g/100 g) of all sampled sites of western Kenya; Clay1 = clay content (%); Age2 = number of years since conversion from natural vegetation; elevation in meters above sea level (m.a.s.l.).

Overall, topsoil C was higher for sites at higher elevation (>1774 m.a.s.l., i.e. mainly Nandi) than for the low elevation sites (mostly Bungoma and Murugusi). For the high elevation sites, years since conversion from native forest influenced soil C, with sites younger than 20 years having higher C contents. Interestingly, the sites with a long history of cultivation, the highest elevation (>1816 m.a.s.l.), were associated with lower C than those at intermediate elevation (between 1774 and 1816 m.a.s.l.). Clay was the key variable influencing C at elevations <1774 m.a.s.l., with almost double C when clay content was at least 22%. Using the regression model in Figure 10 for predictions (33% of

all available data) resulted in 0.58% C as mean absolute error of prediction.

Land management within individual sites was an important determinant of soil C (Figure 11). In Bungoma, for example, cropland under conservation agriculture increased C relative to business as usual (see subsequent chapters for further details), i.e. mainly cereal/legume cropping under conventional tillage. In Nandi, cropland and tea plantations had lower C than the pristine forest which had the highest C contents. In Murugusi, croplands had lost C as compared to the forests – including also afforested sites planted with Eucalyptus, Pine, Cypress and shrubs – and grassland.

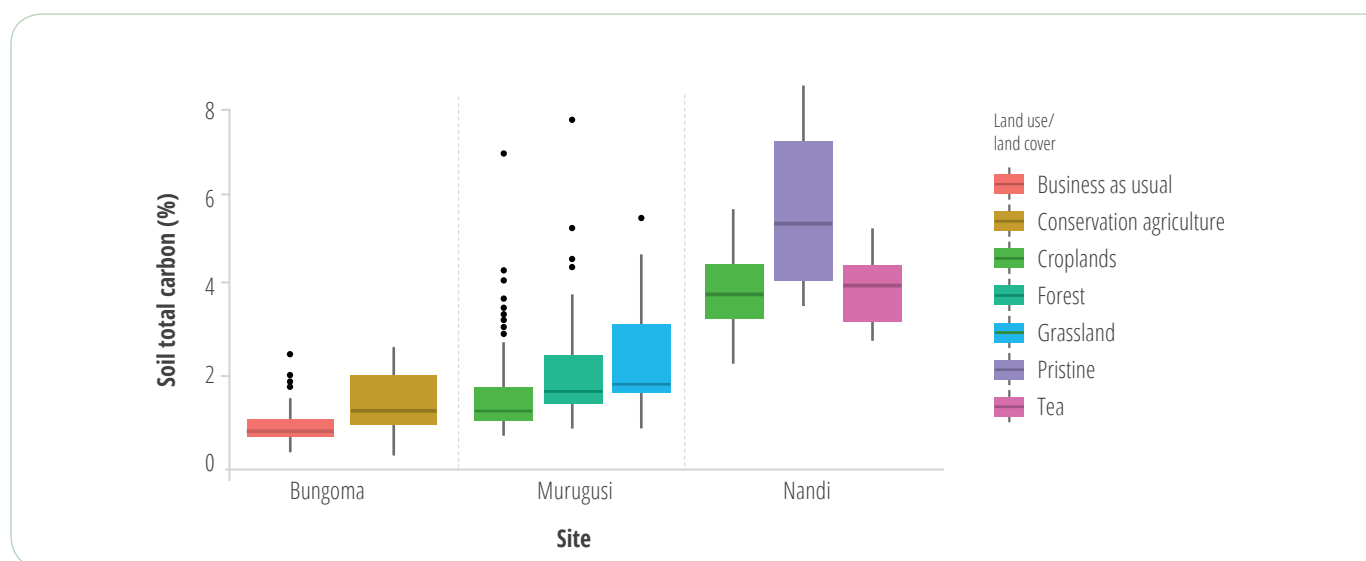


Figure 11 Distribution of soil carbon by land use of the three major western Kenya sites.

The impact of land use history on soil carbon stocks

Nandi forest, Kenya

In general, over a period of 15–75 years, converted forest soils lost between ~30 and 50% of their topsoil C (Figure 12). Different types of land use affected soil C stocks, whereas the afforested sites had significantly lower SOC stocks than the remainder land use types, crop, tea or grassland (Figure 13).

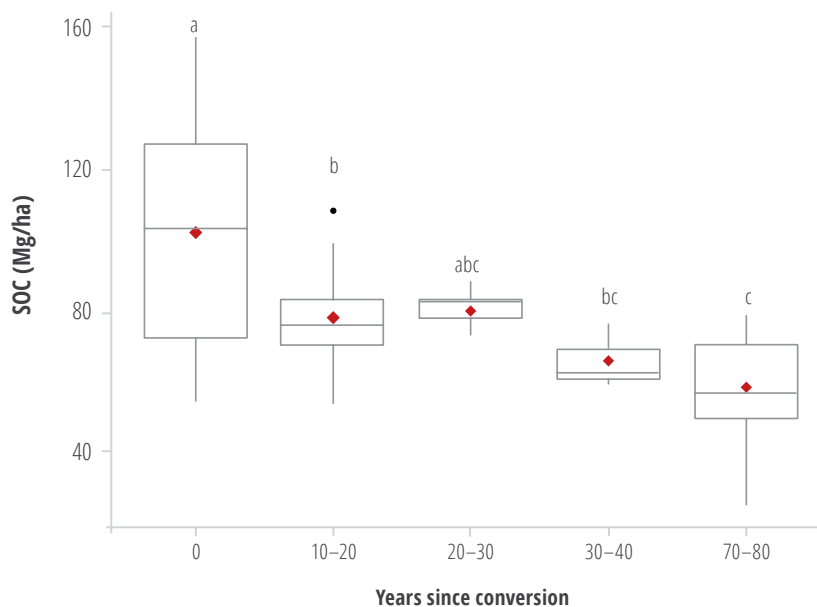


Figure 12 Comparison of topsoil organic carbon (SOC) stocks (Mg/ha) over the years since pristine forest conversion in western Kenya. Different letters denote statistically significant differences at $P < 0.05$.

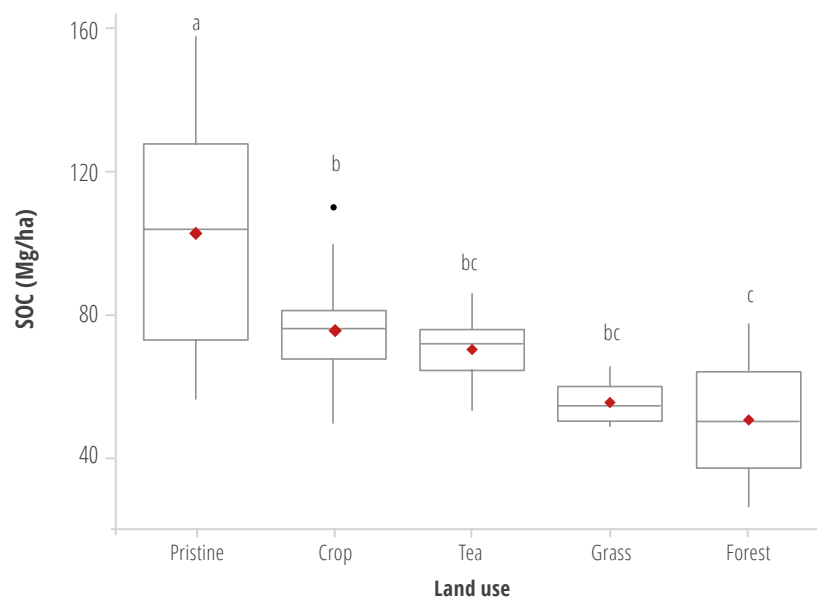


Figure 13 Comparison of topsoil organic carbon (SOC) stocks (Mg/ha) of different land use types in western Kenya. Different letters denote statistically significant differences at $P < 0.05$.

Highlands of Ethiopia

Combining data from all sites, highest average C contents were found for the natural, afro-alpine *Festuca* grassland (10.8%), followed by pristine forests (7.9%) and grazing lands (6.2%) (Figure 14).

The distribution of SOC along the continuum of land use practices, reflecting historical land use trajectories, is similar to the conceptual framework presented by Deakin et al. (2016). The high SOC under *Festuca* is most likely due to the high fine root biomass combined with reduced organic matter breakdown in response to low soil temperatures in this high-altitude environment.

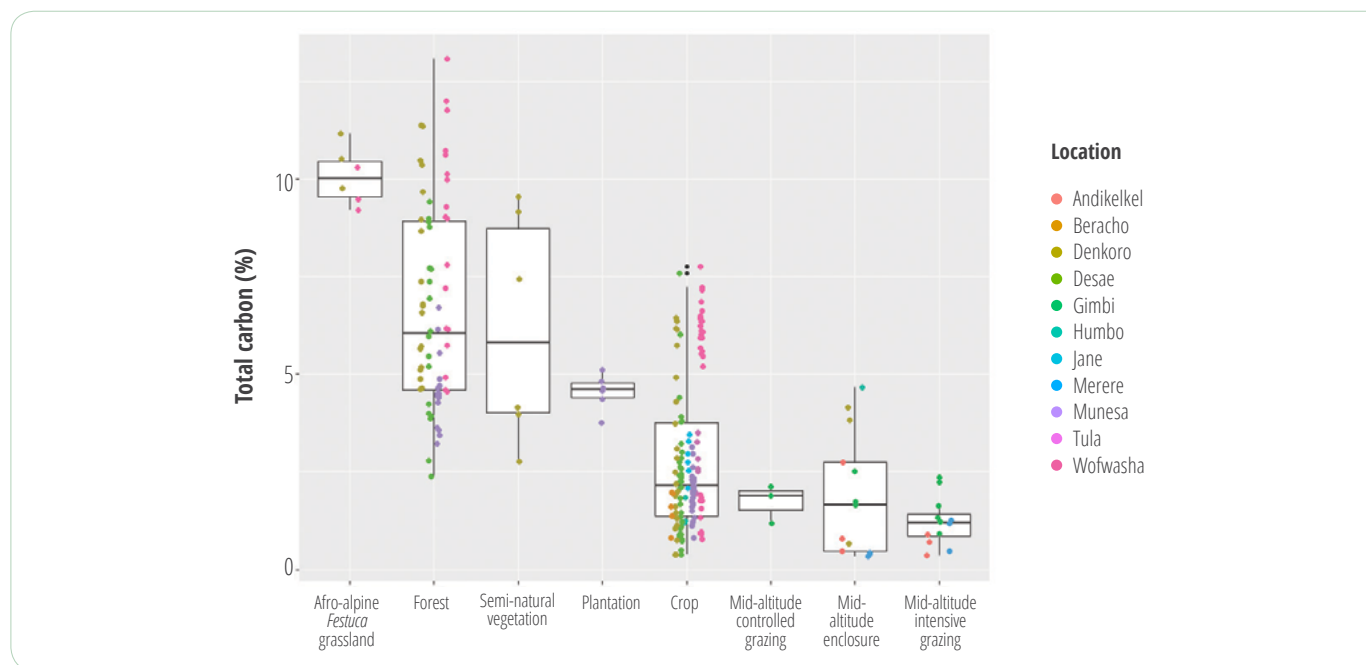


Figure 14 Carbon content (average of top and subsoil) of different land use types in highland Ethiopia.

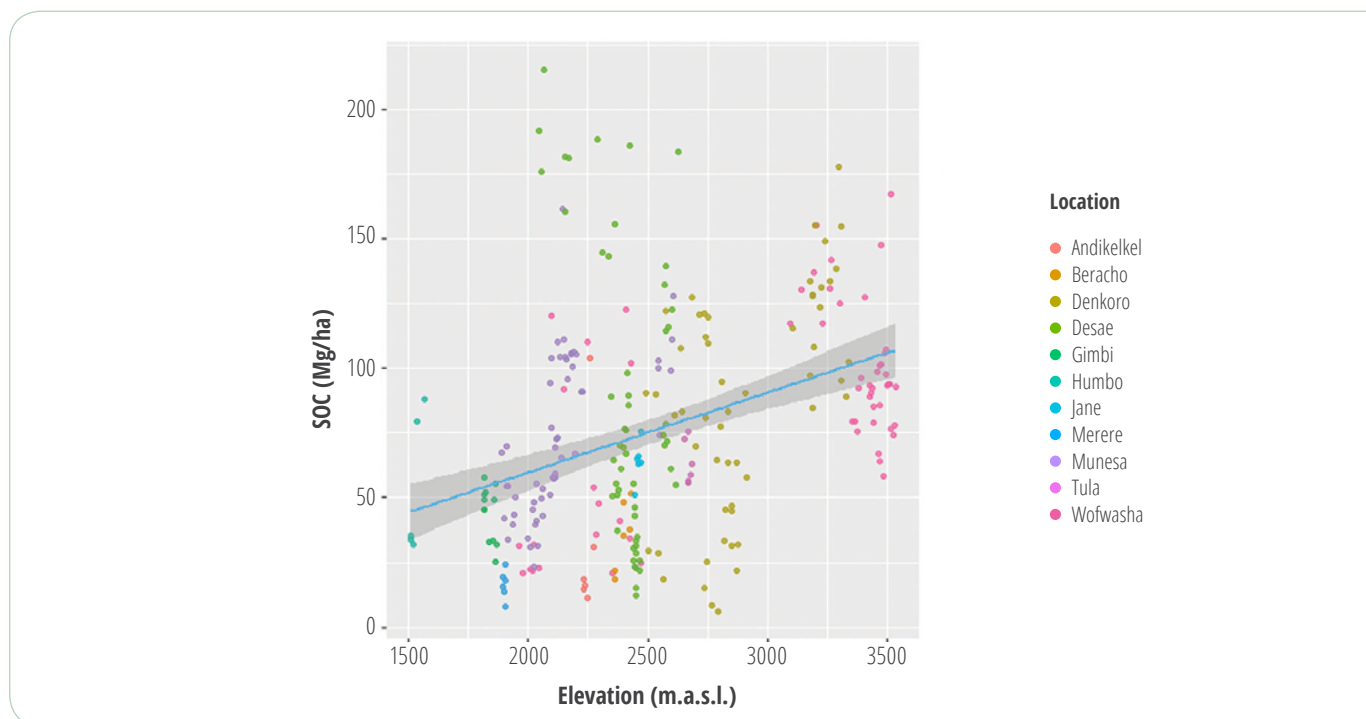


Figure 15 Comparison of topsoil organic carbon stocks along the observed latitudinal gradient ($R^2 = 0.43$).

Analogously, given the notable differences in altitude observed across sites, altitude was a major driver of soil C (Figure 15). Overlaying on top of this trend was the observed impact of land use presented in Figure 14.

As was observed for the Kenya-Nandi site, conversion of forest land into agricultural land entailed a significant reduction in soil C stocks in all sites sampled in Ethiopia (Figure 16).

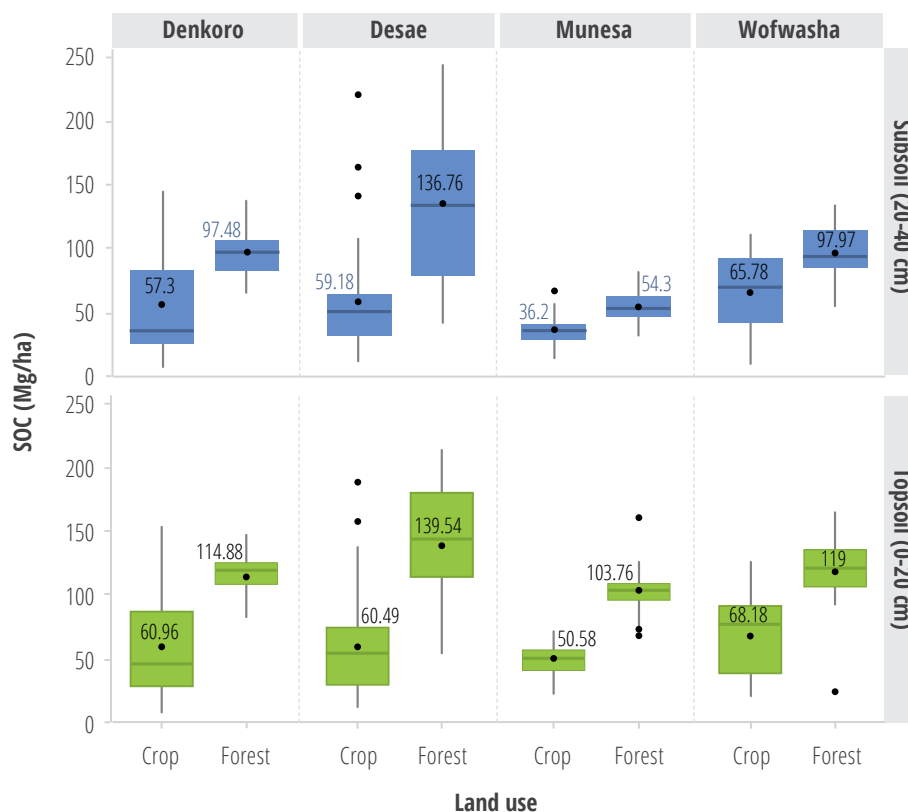


Figure 16 Comparison of SOC at 0–20 cm (bottom) and 20–40 cm (top) of pristine forests with neighboured croplands in Denkoro, Desae, Munesa and Wofwasha. The mean difference between cropland and forest land is significant for all locations.

Top soil (0–20 cm) C losses ranged between 51 t C/ha (Wofwasha) and 79 t C/ha (Desae). At 20–40 cm depth, this was between 18 t C/ha (Munesa) and 78 t C/ha (Desae). Total losses of C to a depth of 40 cm amounted to as much as 157 t C/ha in Desae. Hence in relation to pristine conditions, soils to a depth of 40 cm had lost 43–62 % of its original C.

Compared to practicing cropping business as usual (BAU in Figure 17), integrated water and soil management farming practices (Crop-Managed) on average almost doubled soil C. Soil C stocks of cropland under fallow varied significantly; the range encompassing BAU and managed cropland, and in that regard reflecting the expected increasing impact of length of fallow.

As outlined earlier (see Figure 16), soil C of all sites decreased after forest conversion to cropland. However, once converted, the downward trend of C with length of land use was not as obvious as observed for the Kenya-Nandi site. Munesa site, for instance, seemed to lose significant amounts of C within the first 10 years of land use, but soil C then seemed to level off at around 50 t C/ha at 0–20 cm depth (Figure 18). Clearly, other biophysical factors and the few replications at that level of detail entailed significant heterogeneity observed in all four sites.

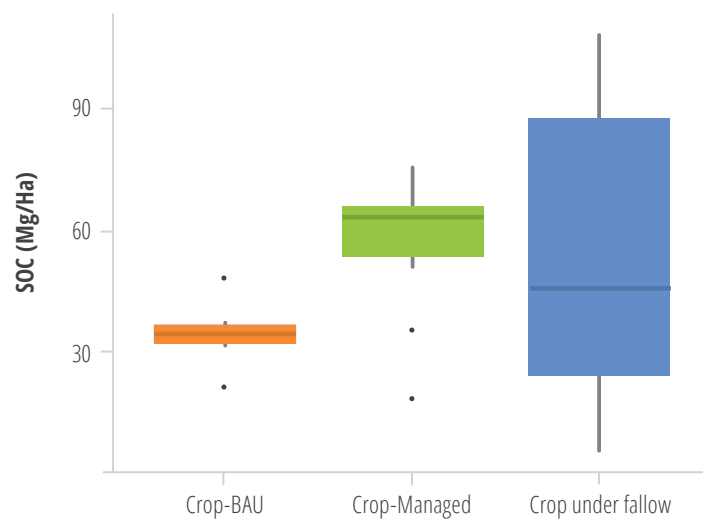


Figure 17 Comparison of topsoil carbon between cropland under business as usual (BAU), managed cropland, and cropland under fallow.

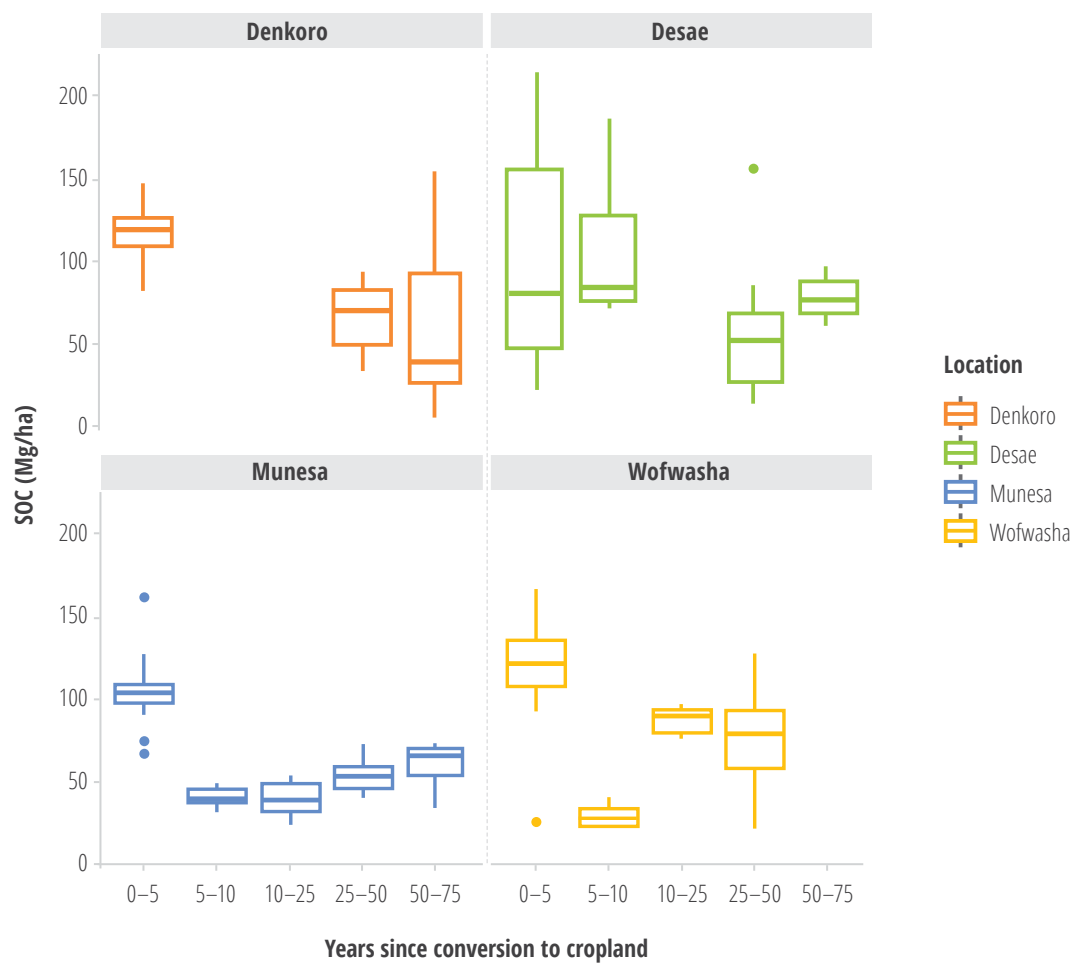


Figure 18 Box-whisker plots of cropland topsoil soil carbon in response to years of conversion.

The impact of land management on soil carbon stocks

Conservation agriculture – Bungoma, Kenya

Compared to business as usual (BAU), adoption of CA increased significantly the C stocks in the top 20 cm. C stocks were not different at 20–40 cm, and only at a 10%-significance level for both layers combined (Figure 19).

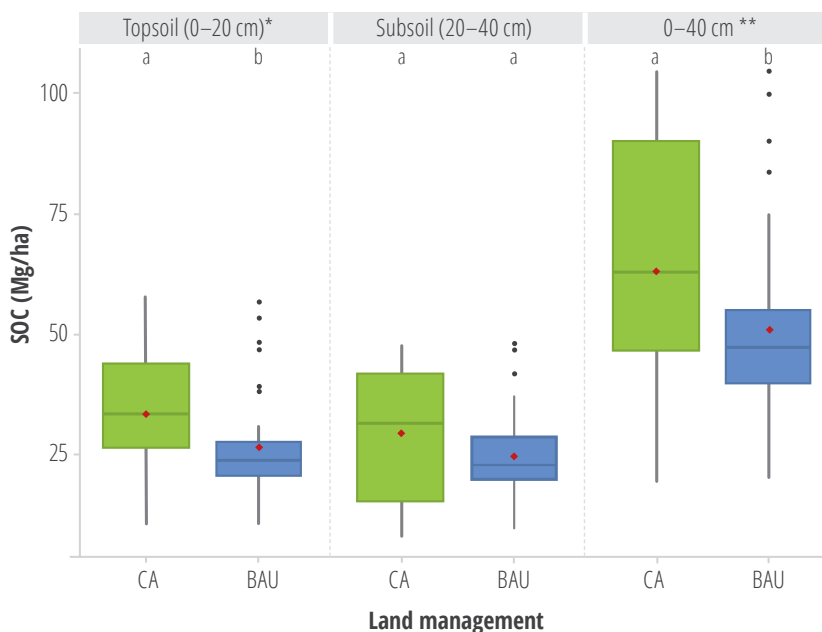


Figure 19 Comparison of soil organic carbon (SOC) stocks (Mg/ha) of conservation agriculture (CA) and business-as-usual (BAU) systems of farmers in western Kenya. Boxes enclose the 25–75 % percentile, whiskers denote the 5% and 95% percentile, the lines within the boxes show the median and asterisks the average of all data. Different letters denote statistically significant differences, with * at $P < 0.05$ and ** at $P < 0.10$.

The difference at 0–20 cm accounted to 7.2 t C/ha on average. Given a total CA land use of 10 years, this is equal to an average annual rate of 720 kg C/ha. Expressed in CO₂eq, this is 2.6 t/ha/yr. As there is no information available of the C contents of these soils at the onset of implementing CA, we cannot say whether observed differences are because of true C sequestration under CA, or 'only' because of CA avoiding C losses. However, if this was sequestration, adoption of CA alone would allow mixed crop-livestock smallholder farms in western Kenya to become GHG neutral.

Soil texture was a key factor determining topsoil C variability between and within land management (Figure 20). Between land management, CA showed a significantly larger potential of reducing losses or sequestering SOC when implemented in medium-textured soils. On the other hand, coarse soils seem to be less prone to SOC sequestration. Within management systems, both CA and BAU showed higher SOC in fine-textured soils (difference of approximately 15 t C/ha between fine- and medium-textured soils), reinforcing the important role of clay content on SOC storage.

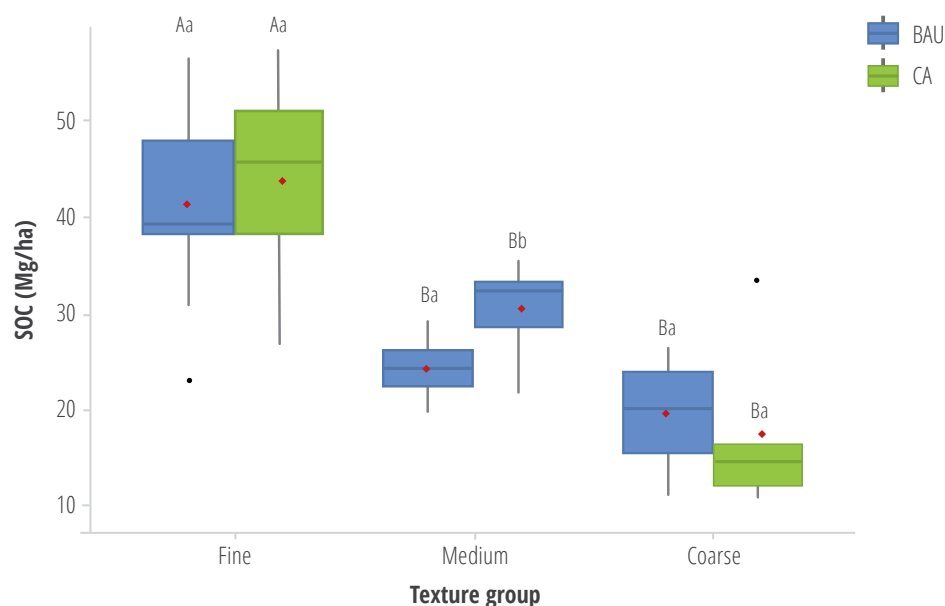


Figure 20 Comparison of topsoil organic carbon (SOC) stocks (Mg/ha) of conservation agriculture (CA) and business-as-usual (BAU) systems of farmers in western Kenya. Different small letters within the same texture group denote statistically significant differences, while different capital letters denote statistically significant differences between texture groups at $P < 0.01$.

Land enclosures – Ethiopia

We compared the impact on soil C stocks of enclosures, i.e. fenced ('enclosed') areas where grazing had been abolished, with surrounding intensively grazed areas in three different regions, namely Andikelkel (sub-moist mid highlands) and Merere (sub-moist mid highlands) in Tigray and Gimbi (sub-humid mid highlands) in western Oromia. There was no clear trend visible, with Gimbi displaying no response to the enclosure, Andikelkel some improvement in the topsoil (though highly variable), and Merere even an increase of topsoil C in response of intensive grazing. Given the large heterogeneity encountered, none of these differences

turned out statistically significant (Figure 21). A more intensive sampling would be required to shed further light into the issue. On the other hand, this inconclusive result is in line with a similar comparative study carried out in the southern Ethiopian dry savannah rangelands (Aynekulu et al., 2017). As site differences between C contents were significant, construction of a *false* time-series, or chronosequence, of the impact of length of enclosure on C stocks, was not possible, and hence the temporal dynamics of C stocks in response to this type of management practice remains to be explored further.

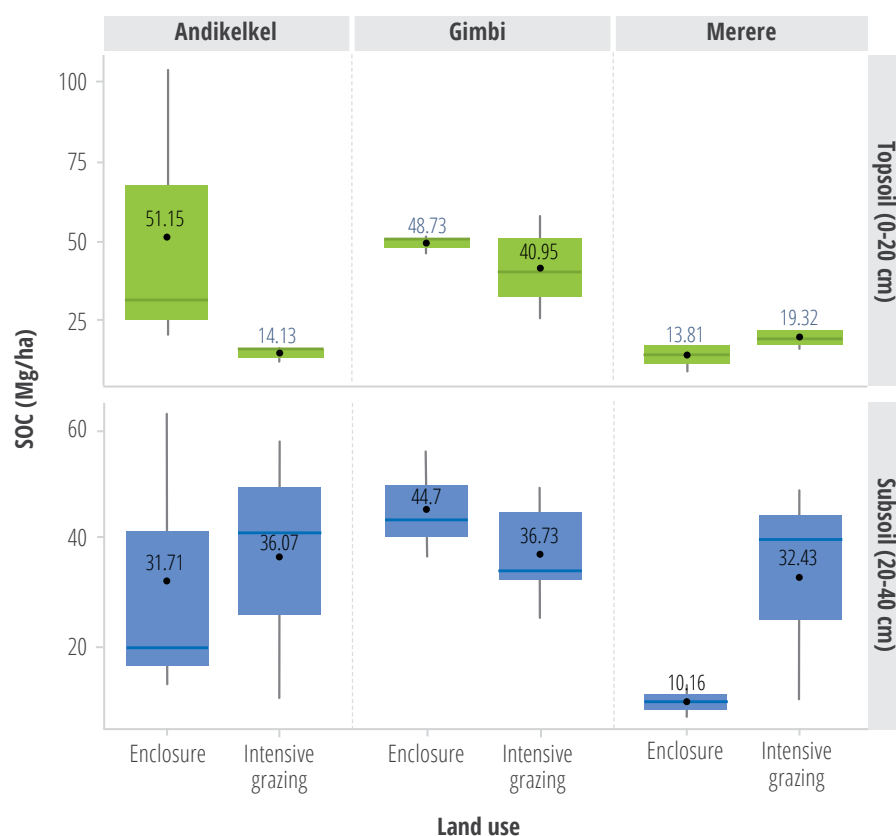


Figure 21 Soil carbon stocks of top and subsoil in response to land enclosure (animal exclusion) in grazing systems in Andikelkel and Merere in Tigray and Gimbi in western Oromia.

Watershed management – India

In comparison to the humid tropical environments of Ethiopia and Kenya, soil C contents in the Indian watersheds located in a semi-arid environment were roughly tenfold lower. In addition, these lands have a significant amount of gravel/large stones (16–76%). Still, a significant difference in topsoil C content was observed between the restored and the control watersheds (Figure 22). No such difference was found in the subsoil. The average topsoil C content of soil < 2 mm in the restored watershed was 5.9 g/kg, while the unprotected watershed was 4.6 g/kg representing an increase of 28% of SOC content in 19 years or a 0.015% increase per year. In addition, the minimum and maximum C contents were higher in the restored watershed, even in the subsoil where no significant differences were found between both places.

Topsoil C stocks varied from 1.5 to 17.9 t/ha and 2.3 to 22.5 t/ha in the control and restored watershed, respectively (Figure 23). Although the stocks were comparably low, the average stock in the restored (9 t/ha) was higher than in the control watershed

(8.6 t/ha). In the protected watershed, greater C stocks (~22.5 t C/ha) were observed in the reforested area (native trees), and lower stocks (<8 t C/ha) were found mainly in the barren and open scrub summits, which could be the effect of C losses due to soil erosion in those areas with reduced protection of the soil's surface. In terms of average gains in C stocks, in response to the implementation of the range of soil conservation practices, these are 0.02 t C/ha or 22 t C for the entire watershed (1042 ha) on an annual basis. This is equivalent to a 0.25% stock increase per year, summing up to 5% in 19 years, i.e. 0.41 t C/ha or 427 t C for the entire watershed.

In conclusion, while total C sequestered in this semi-arid region of India is not stunningly large, our study nevertheless proves that soil C sequestration in this harsh environment is possible. While this may not make it the main driver for adoption of soil watershed conservation measures – tangible benefits for farmers are increased soil fertility, agricultural productivity and resilience – the State of Maharashtra alone has some

19.0 Mha of semi-arid land. If each hectare of these lands sequestered 0.41 t C, this would amount to 7.7 million tons of C that could be sequestered in semi-arid soils of Maharashtra. For the entire semi-arid land of

India (95.7 Mha), the amount would be 39 Mt C or 144 Mt CO₂eq, which is equivalent to about 12% of all of India’s emissions from land use² in 2010.

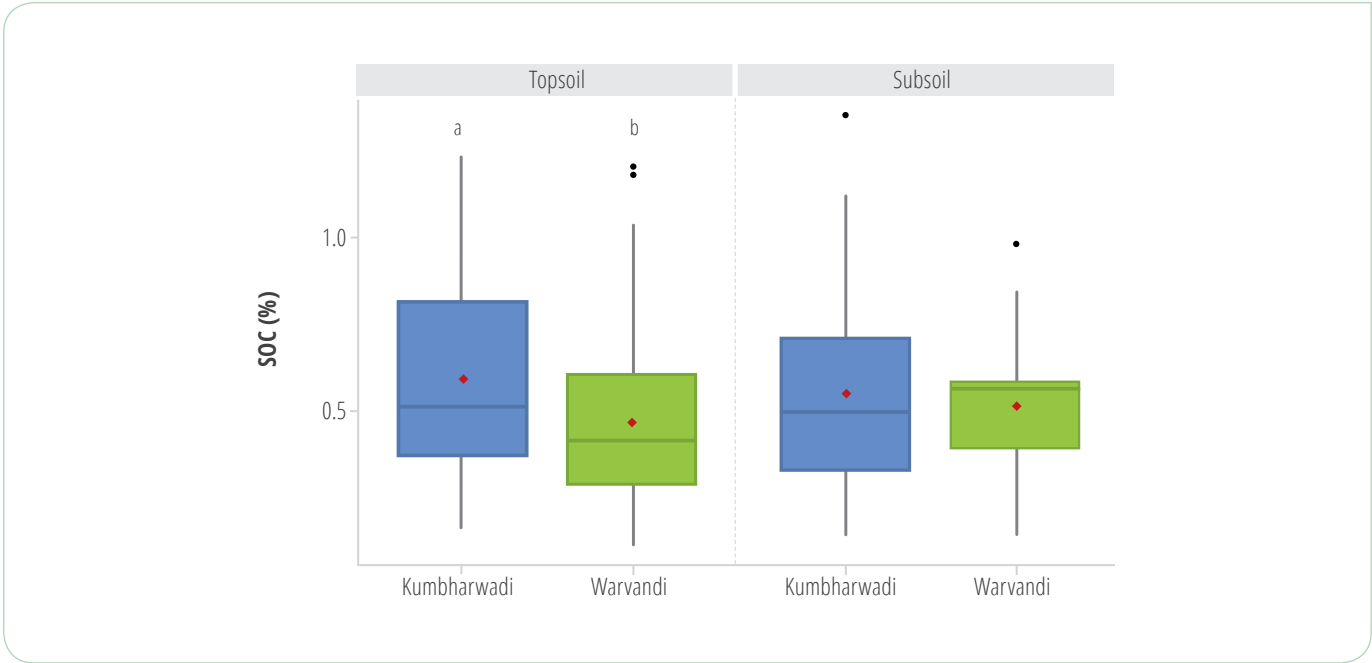


Figure 22 Soil organic carbon content comparison between a restored (Kumbharwadi) and unprotected watershed (Warvandi). Topsoil differences are significant at P < 0.01.

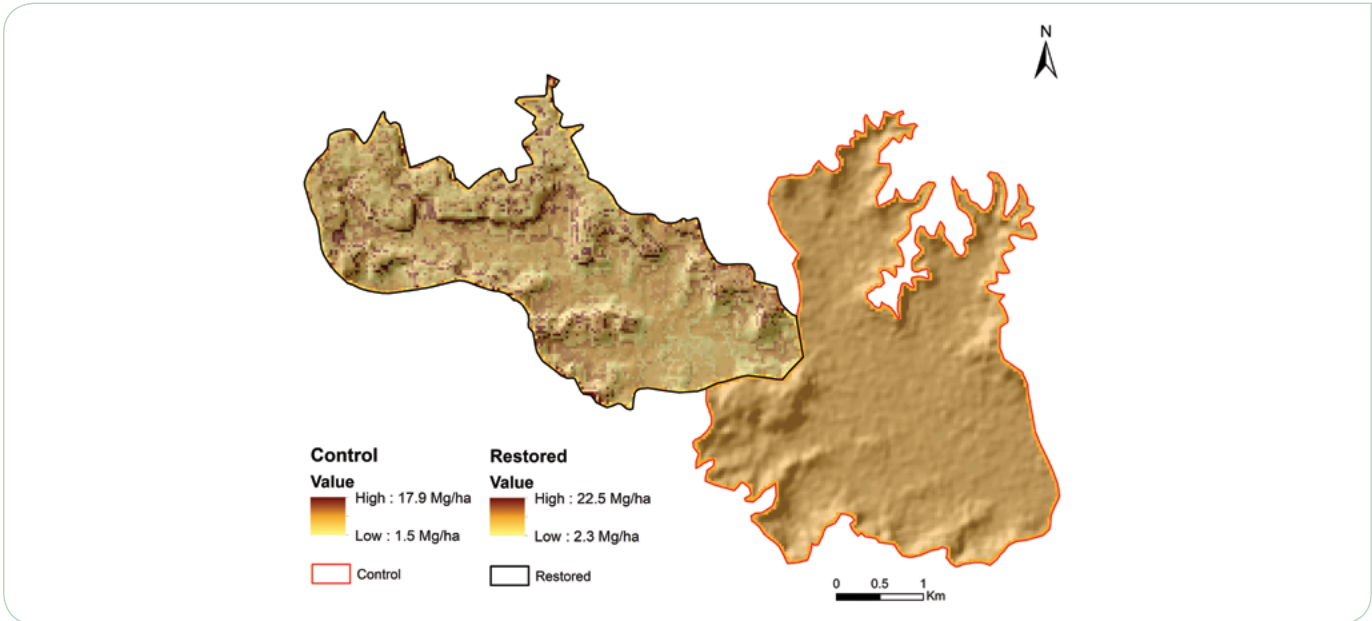


Figure 23 Topsoil organic carbon stocks at Kumbharwadi (restored) and Warvandi (control) watershed in India.

2 Using FAOSTAT data. Emissions include those from enteric fermentation, manure management, rice cultivation, synthetic fertilizer use, manure applied to soils, manure left on pasture, crop residues management, cultivation of organic soils, burning of crop residues, and burning of savanna. See www.fao.org/faostat/en/#data for details. According to these data, India is the world’s fourth largest emitter of GHG from land use, contributing 9% to the global total of such emissions.

Soil carbon and agronomic performance – evidence from CIAT’s long-term trials

Soil carbon dynamics

Detailed results on the soil C dynamics in CIAT’s western Kenya long-term trials have been published in an international journal publication entitled “Reducing losses but failing to sequester carbon in soils – the case of conservation agriculture and integrated soil fertility management in the humid tropical agro-ecosystem of western Kenya” (Sommer et al., 2018). Some major results and further considerations are summarized here.

To our surprise, neither of the ISFM (tested in the INM3 trial) or CA treatments (tested in CT1) were found to sequester SOC in the long term. Instead, SOC decreased significantly over time, in all but very few tested treatments. Losses ranged between 0.11 and 0.37 t C/ha per year in the CA long-term trial and 0.21 and 0.96 t C/ha/yr in the ISFM long-term trial. However, the ‘best-bet’ CA and ISFM treatments could avoid losses if compared against conventional farmer practices. Adopting zero tillage *and* residue retention could avoid SOC losses of on average 0.13 t C/ha/yr. Application of 4 t/ha/season of manure avoided losses of on average 0.26 t C/ha/yr.

The only ISFM treatment in which SOC levels were maintained was the one that included Tephrosia in rotation with maize (T-M), in combination with retention of maize stover residues (2 t/ha/yr), application of

manure and 30 kg of urea, two times 60 kg of phosphate and two times 60 kg of potash fertilizer per hectare and year. In CT1, three ‘true’ CA treatments maintained SOC levels, namely such where zero tillage was practiced, and crop residues retained. Overall, the long-term application of mineral N and P fertilizer did not mitigate SOC losses in both trials.

The initial SOC contents at the onset of the long-term trials differed: INM3 stocks at 0–15 cm were estimated at 39.9 t C/ha – equivalent to a C content of 24.2 g/kg – while in CT1, this was 34 t C/ha (≈ 20.8 g/kg), i.e. almost 6 t C/ha less. Both sites are very close to each other (< 1.6 km), have almost identical soil physical and chemical properties, and are exposed to the same climate. We assume that this initial difference in C is the effect of diverging land use history. According to the owners of the fields, INM3 had been under a grass-shrub fallow for an unknown length of time until 2003, while CT1 had been cultivated for three continuous years before the onset of the long-term trial. The setup of both trials comprised treatments that were identical, namely those under conventional tillage, no application of manure, continuous maize cultivation with 0, 30, 60 or 90 kg N/ha mineral fertilizer applied, and maize stover residues either retained or removed. Comparing the SOC dynamics of these treatments over time revealed that INM3 plots lost SOC faster than their CT1 analogues (Figure 24). Hence, it must be concluded that the initial soil status was responsible for the bulk of the SOC losses and less so the various tested agronomic management practices.

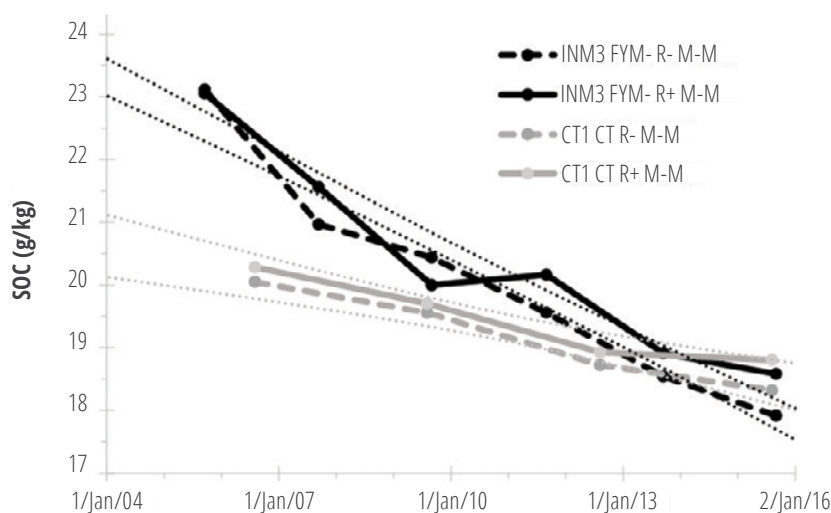


Figure 24 Changes of topsoil organic carbon of identical CT1 and INM3 treatments. Dotted thin curves are the lower and upper confidence interval of the linear regression of CT1 (N=128) and INM3 (N=192) data lumping together both residue levels.

In conclusion, our long-term trials teach us that we cannot predict with confidence that the adoption of certain improved land management practices in the tropical highlands of East Africa lead to true sequestration of soil C. It appears that the initial SOC status, which is a consequence of past land use, determines whether soils can gain C or whether adoption of improved soil management practices only slow down losses. This was one of the reasons for our team to look much more closely into SOC levels of various land use systems, and changes along a chronosequence of land use. The idea of this in-depth research was to find major determining factors that trigger SOC losses or enable to sequester C, such as soil properties (texture, pH), landscape position, etc. Results of these studies are presented later in this report.

In terms of climate change mitigation, what matters is the reduction in emissions. Avoiding losses of SOC contributes to reducing emissions and hence helps combating climate change. True sequestration is taking this idea a step further. Constituting a true C-sink, SOC sequestration qualifies for existing payments for environmental services, such as C offsetting schemes, while merely avoiding losses will most likely not. For

instance, global initiatives such as the well-known 4p1000 Initiative aim at implementing SOC sequestration for offsetting anthropogenic emissions, such as those from fossil fuel burning. Clearly, merely avoiding losses would not fulfil this target.

Agronomic performance

Agronomic performance was assessed using data from 26 seasons of CIAT’s CT1 long-term trial. Overall, practicing zero tillage (OT) reduced maize and soybean grain yields as compared to conventional tillage (CT), but differences were only significant if maize stover residues were removed as well (R-; Figure 25). Disaggregated by season, conventional tillage achieved higher yields than zero tillage in 11 of the 26 seasons. Also, although residue application did not have a significant effect overall, there was higher maize grain yield (+0.25 t/ha) with than with no residue application under conservation tillage while no differences occurred under conventional tillage, and there were 10 seasons when residue application in CA had higher yield than with no residue application. Thus, practicing CA with residue application achieved the same maize (even additional soybean) yield as conventional tillage but removal of residue was undesirable.

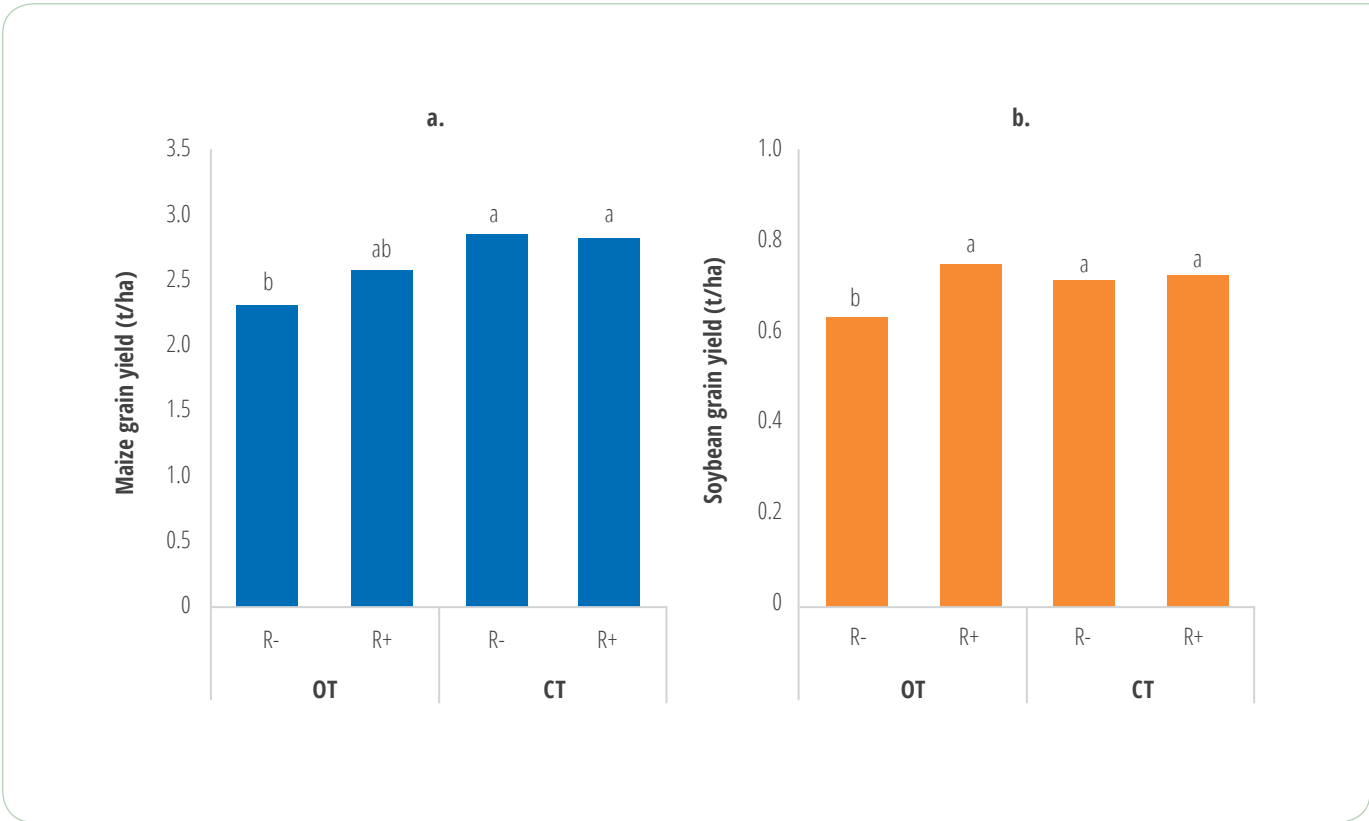


Figure 25 Maize (left) and soybean (right) yields observed under different tillage and residue management over 26 seasons in western Kenya. Bars with the same letter are not significantly different.

Economic analysis for the various tillage x residue x rotation x fertilizer combinations showed benefit-cost ratios (BCR) ranging from 0.92 to 1.84. At the same level of phosphate application, BCR increased with nitrogen (N) application up to 60 kg N/ha under continuous maize monocropping (M-M) and maize-soybean rotation (M-S) cropping systems. Four promising treatments with a BCR of at least 1.5 – selected also on basis of yield stability – include: (1) continuous maize with 60 kg/ha phosphate (P60) and 60 kg/ha N (N60) added, (2) continuous maize with P60 and N90, and (3) a maize-soybean rotation (P60 N30), and (4) one of the conventional tillage treatments, i.e. continuous maize without residues with 60N and 60P. However, the conventional tillage treatment is not appropriate considering its higher variable costs and lower net benefits than in conservation tillage.

Does soil organic carbon affect yields?

A covariate statistical analysis (four seasons of available C data) revealed that soil C had no effect on maize productivity in 2006 and 2015. However, SOC affected maize yields in 2009 and in 2012 in some selected treatments. In both seasons, correlations between yield and SOC were low ($R^2=0.18$ in 2009 and $R^2=0.04$ in 2012; data not shown). But, zooming into individual tillage practices, a strong correlation between yield and SOC was observed under reduced tillage during the short rains 2009 cropping season, while the correlation was still poor under conventional tillage (Figure 26). This 2009 season also had high overall maize yields of 3.7 t/ha unlike the 1.6 t/ha in 2012. Although it can be argued that SOC-yield relationships vary by seasons and are weak altogether given the superior overlaying effect of rainfall, zero tillage and residue retention supporting C sequestration do pay for farmers given the superior economic and yield stability performance.

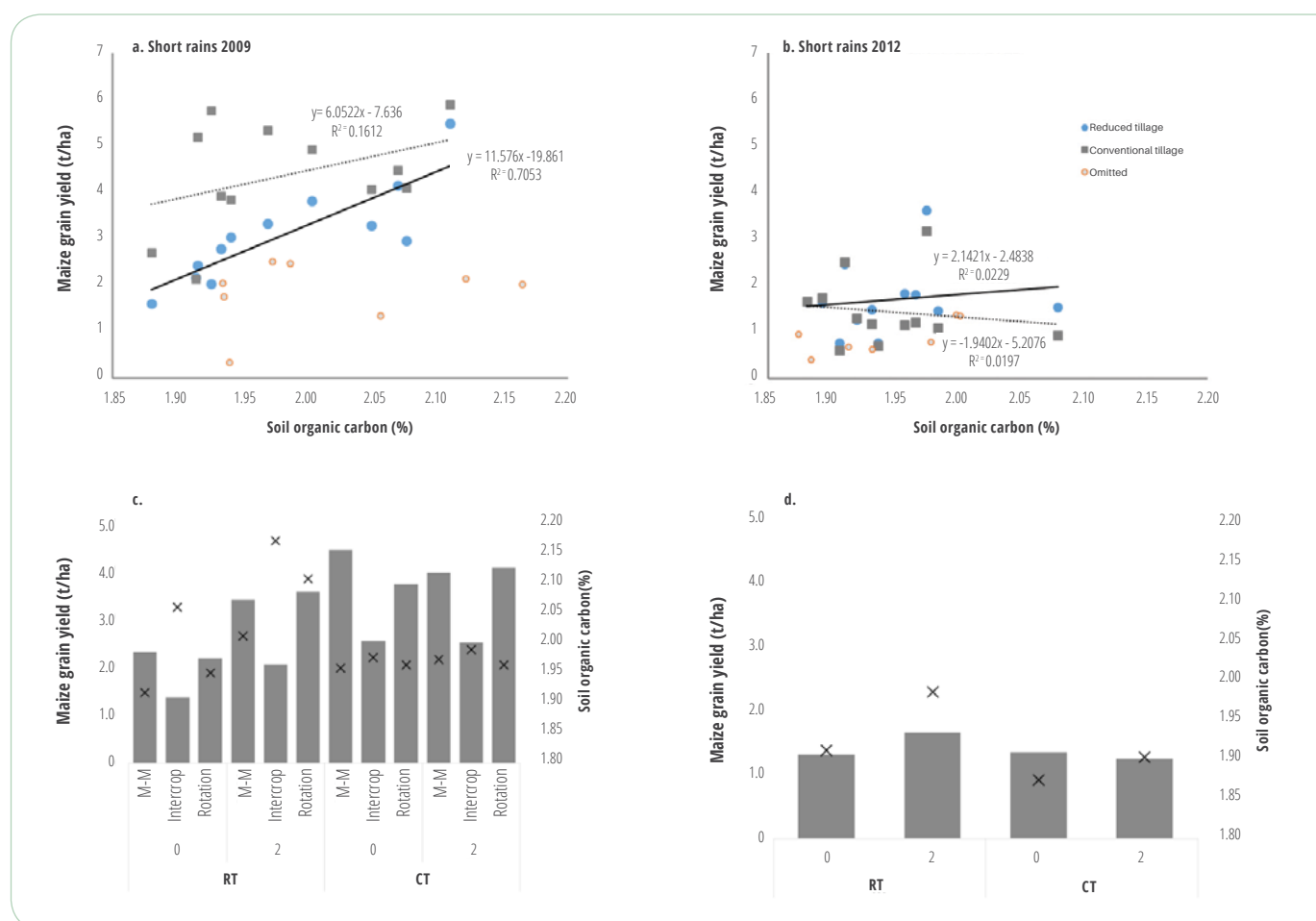


Figure 26 Relationships between maize grain yield and soil organic carbon (SOC) in 2009 (a) and 2012 (b), and treatment specific yield and SOC data for 2009 (c) and 2012 (d). RT=reduced/zero tillage, CT=conventional tillage; “omitted” in (a) and (b) refer to maize-soybean intercropping and zero P treatments, which were not included in the correlations. The numbers 0 and 2 below the X-axis in figures (c) and (d) indicate amounts of crop residue applied in t/ha.



Photo: K. Trautmann/CAAFS

Model-based assessment of critical levels of inputs required to rehabilitate soils

CIAT's western Kenya long-term trials showed losses of soil C over time even with the adoption of improved soil management practices, such as ISFM and CA (Sommer et al., 2018; see also Chapter *Soil carbon and agronomic performance – evidence from CIAT's long-term trials* in this report). To find out what it would take to avoid these losses and potentially even to sequester C, we engaged in a biophysical, model-based scenario exercise. We used the biophysical model CropSyst to assess the impact of increased manure application on the one hand, and crop residues retention on the other hand, for some selected ISFM treatments in CIAT's long-term trials. The model had been thoroughly calibrated earlier (Sommer et al., 2015; Sommer, 2017).

Sensitivity simulations were performed for Maize-Maize (M-M) and Maize-Tephrosia (M-T) rotations with manure addition and residue retention. The M-M rotation included treatments with 0, 30, 60 or 90 kg N/ha/season mineral fertilizer application, while the M-T rotation included only 0 or 30 kg N/ha/season. For treatments with manure addition, one standard ("STD") simulation was performed with 4 t/ha manure applied five days before planting every season as done in the field experiment. In addition to this simulation, we performed two sensitivity simulations with increased manure quantities, i.e. 6 t/ha ("FYM1") and 8 t/ha ("FYM2"). For addressing the impact of increased crop residue retention, we simulated the STD simulation, in which – as was done in reality – 2 t/ha of maize stover were

retained in the field after harvest every season. This is approximately 30% of the entire maize stover produced. For the first sensitivity simulation ("RES1"), this amount was increased to 50% of the aboveground biomass, and for the second simulation ("RES2"), 70% was retained in the field. Sensitivity simulations were furthermore performed in treatments that included a combination of both farm yard manure application *and* residues retention. In this case, for the FYM1 and FYM2 sensitivity simulations the amount of applied manure was increased (6 and 8 t/ha/season), while the amount of retained crop residues was as in the STD simulation (2 t/ha/season). For the RES1 and RES2 sensitivity simulations, the amount of crop residues was increased (50% and 70% of aboveground biomass), while the applied manure was as in the STD simulation (4 t/ha/season).

Despite increasing manure and crop residues, analysis of the temporal evolution of soil C for the upper 40 cm revealed losses of soil C for most of the sensitivity simulations (see an example in Figure 27). As expected, the losses decreased over time with additional C inputs. Simulated soil C stocks at year 2014 could be maintained at 2004 levels when as much as 8 t/ha of manure were applied and 2 t/ha of crop residues retained, irrespectively of the amount of mineral N applied (green lines in Figure 27), only in the treatment with both manure addition and residues retention.

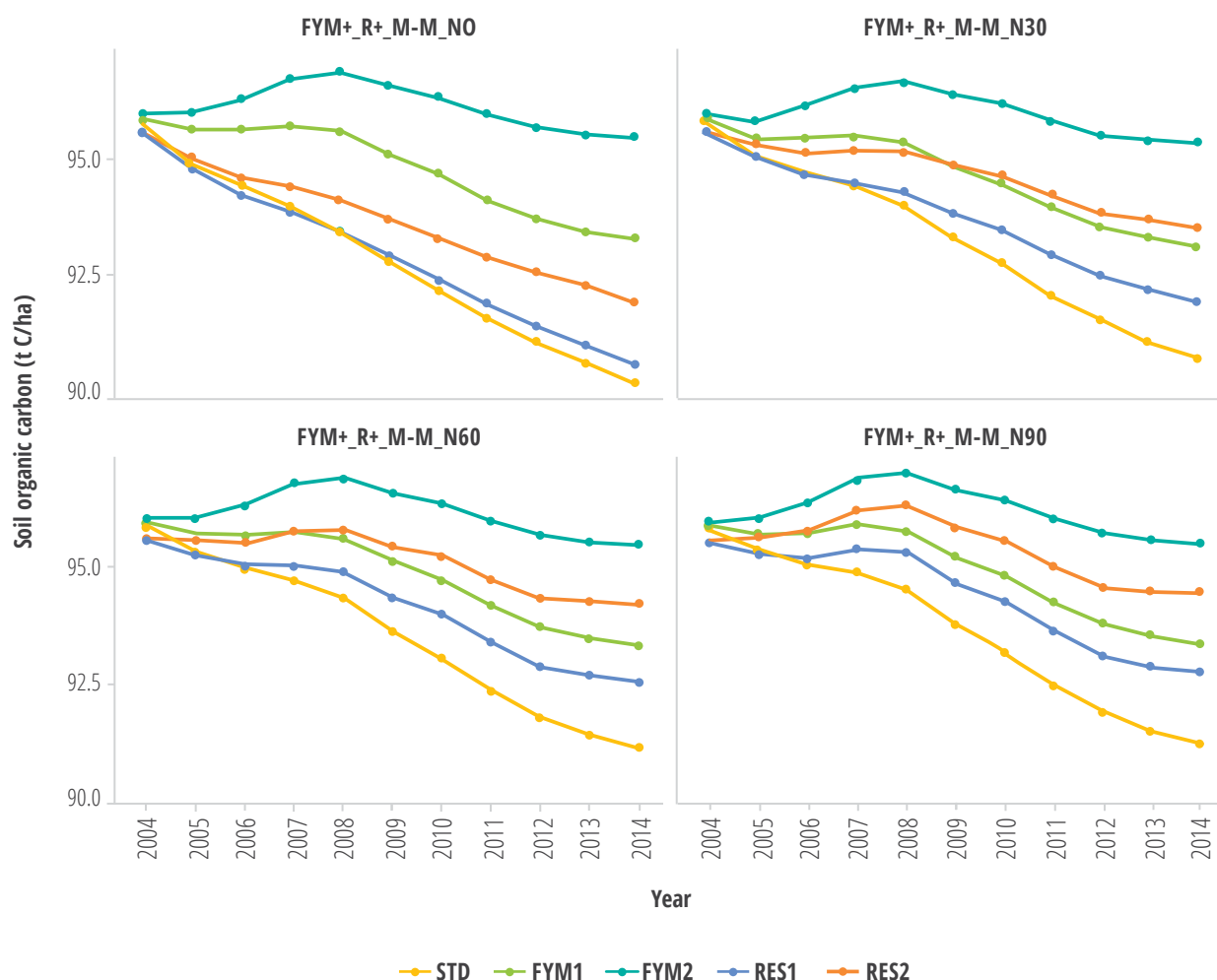


Figure 27 Temporal responses of soil C in the upper 40 cm in treatments with manure application and residue retention. The STD simulation comprises 4 t/ha farm yard manure (FYM) application and 2 t/ha residue (RES) retention per season. In the FYM1 simulation, 6 t/ha of FYM were applied and 2 t C/ha residues retained per season, while in the FYM2 simulation, this was 8 t C/ha FYM and 2 t/ha residue per season. In the RES1 simulation, 50% (2.12 to 3.29 t/ha) of crop residues were retained and 4 t C/ha of FYM applied per season, while this was 70% (2.95 to 4.51 t/ha) of crop residues and 4 t C/ha of FYM in the RES2 simulation. Note that the four plots distinguish treatment based on the amounts of mineral nitrogen fertilizer applied (0 to 90 kg N/ha/season).

The annual losses of soil C ranged from 0.5 to 1 t C/ha per year in the STD simulation. Adding more manure decreased this loss to below 0.1 t C/ha/yr for the treatments that received 8 t FYM and in which residues were retained (Figure 28a). As a result, the increased inputs of organic matter (and hence C) via FYM avoided

soil C losses of between 0.2 to 0.3 t C/ha/yr and 0.4 to 0.5 t C/ha/yr for the FYM1 and FYM2 simulations, respectively (Figure 28b). Furthermore, adding more FYM also slightly increased seasonal yields over the considered period (Appendices Figure A1).

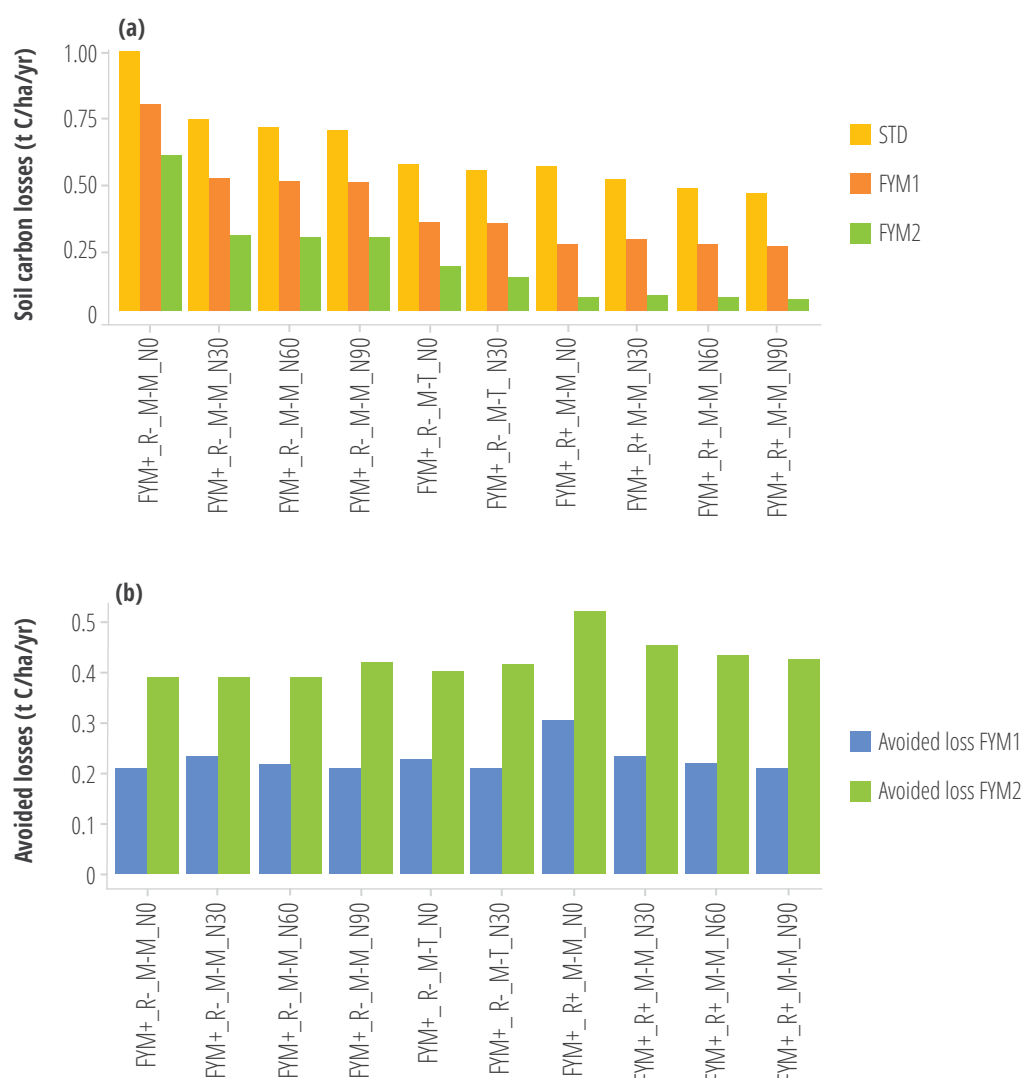


Figure 28 (a) Simulated annual soil carbon losses for the standard treatment (STD) with 4 t/ha farm yard manure application per season and for the sensitivity simulations with 6 t C/ha (FYM1) and 8 t/ha (FYM2) manure over the period 2004 to 2014. (b) Avoided soil carbon losses that can be achieved through additional manure application. Avoided losses are obtained by subtracting the losses in the sensitivity simulations (FYM1 and FYM2) from the losses in the standard treatment (STD).

Similar to the manure simulations, increased crop residue retention reduced losses of soil C (Figure 29a), with the avoided losses for the highest residue retention sensitivity simulation ranging between 0.1 to 0.35 t C/ha/yr (Figure 29b). However, in contrast to the FYM simulations, where extra manure increased yields, the increased crop residue retention did not always translate into increased maize yields (compare Figure A2 in Appendices). We simulated yield increases in a few treatments, but these increases were quite small and not statistically significant.

In summary, the above sensitivity simulations showed that increased organic matter inputs associated with manure application and crop residue retention resulted in less soil C being lost (“avoided losses”), with manure having a stronger effect than crop residue retention. Despite these high inputs, soil C losses were simulated for all treatments over the considered 11-year period, except for the one with highest inputs (8 t manure and 2 t residues). Hence, for a complete reversal of the decreasing soil C trend, at least 8 t/ha of manure would

be needed. This is an unrealistic amount that most smallholder farmers in western Kenya would be unable to source. Hence, to maintain carbon levels at or above about 20 g/kg (=2%), other means of conserving soils must be included into such “package”, for example, green manure cover cropping and minimum tillage. It must also

be noted that such research results must not be simply transferred to other agro-ecologies. For instance, a previous similar study for Ethiopia has shown that 3 t/ha manure and 50% retention of wheat straw is sufficient to stabilize soil carbon in farmers' fields in Gudo Beret Kebele of Amhara (Sommer et al., 2016).

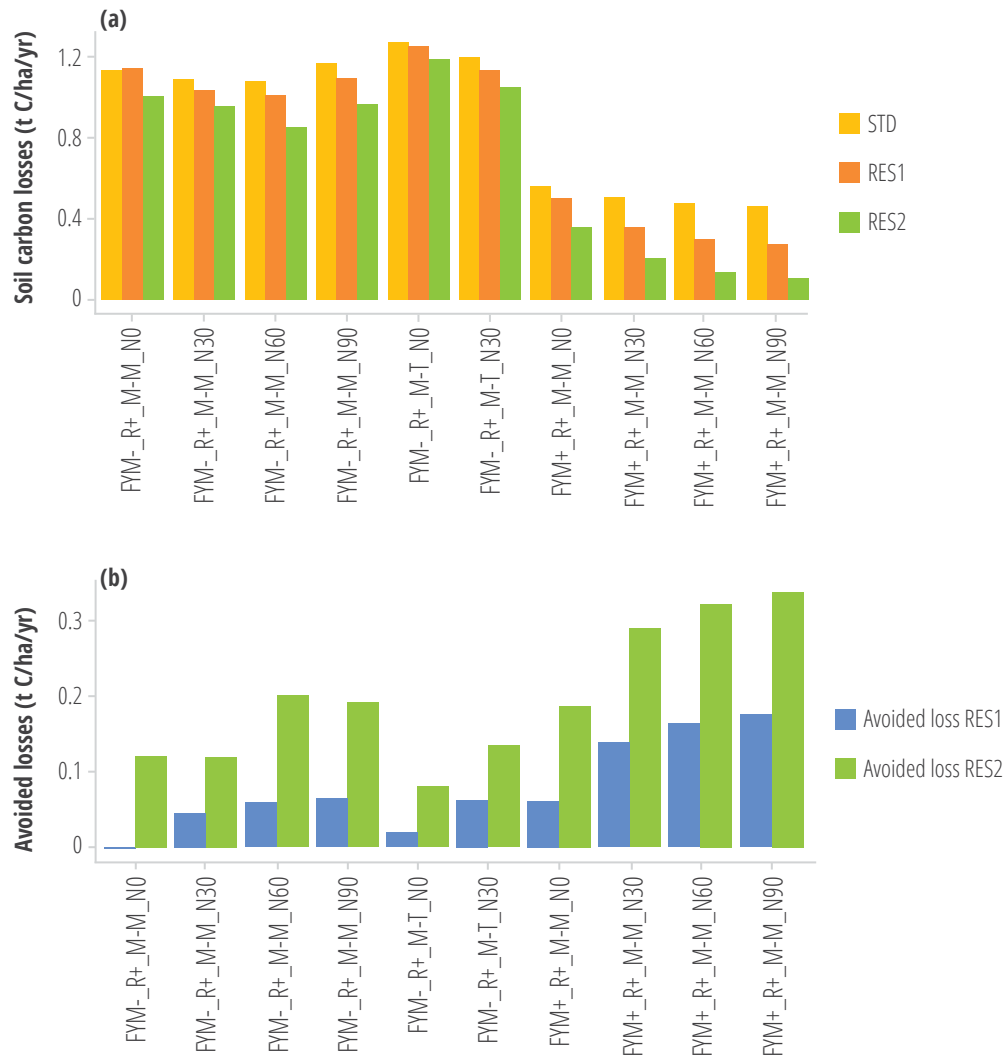


Figure 29 (a) Simulated annual soil carbon losses for the standard treatment (STD) with 2 t/ha/season maize stover residue retention and 50% (RES1) and 70% (RES2) residues retention over the period 2004 to 2014. Residues retained in the simulation ranged between 2.12 and 3.29 t/ha/season under RES1, between 2.95 and 4.51 t/ha/season under RES2. (b) Avoided soil carbon losses achieved through increased residue retention. The avoided losses were obtained by subtracting the losses in the sensitivity simulations (RES1 and RES2) from the losses in the standard treatment (STD).

Mapping and quantifying the potential impact of soil protection and rehabilitation on soil carbon

As shown earlier, soil C variation is driven by different factors acting simultaneously across the landscape. Hence, to quantify the impact of soil protection and rehabilitation interventions on soil C, we used a landscape approach based on digital soil mapping techniques, which combines the key drivers of SOC variation in a spatial model to produce continuous SOC stocks and texture maps at resolution of 30 m (Figure 30). We selected the Murugusi watershed in western Kenya, as this watershed is subject to soil protection and rehabilitation under GIZ Soil Program, and as soil samples had been collected and analysed for various properties, including SOC at much higher resolutions, namely at village level in accompanying CIAT project.

With a precision of 81% (21 t/ha), the current SOC stocks map shows a variation of 118 t C/ha and an average of 39 t C/ha. Higher SOC stocks (> 80 t C/ha) were found mainly in areas under tree cover (afforestation) above 1,720 m of altitude, which corresponded to only 2% of total watershed area (dark blue area in the East part of Figure 30). On the other hand, 63% of the watershed (mainly agricultural fields) had SOC stocks lower than the watershed average. The majority of watershed soils (73%) had a medium texture, but there were also fine-textured soils found mostly on the summits and shoulders (20%) and small areas with coarse soils mainly in valleys and footslopes (8%). Results presented earlier in this report indicated a significant potential of fine- and medium-textured soils to store C if adequate soil management, such as conservation agriculture (CA), is implemented. Since croplands represent 63% of total area of the Murugusi watershed and 92% of that is on fine- and medium-textured soils, we can expect that at least 58% of the entire watershed has potential to increase its soil C stocks if improved soil management practices were introduced.

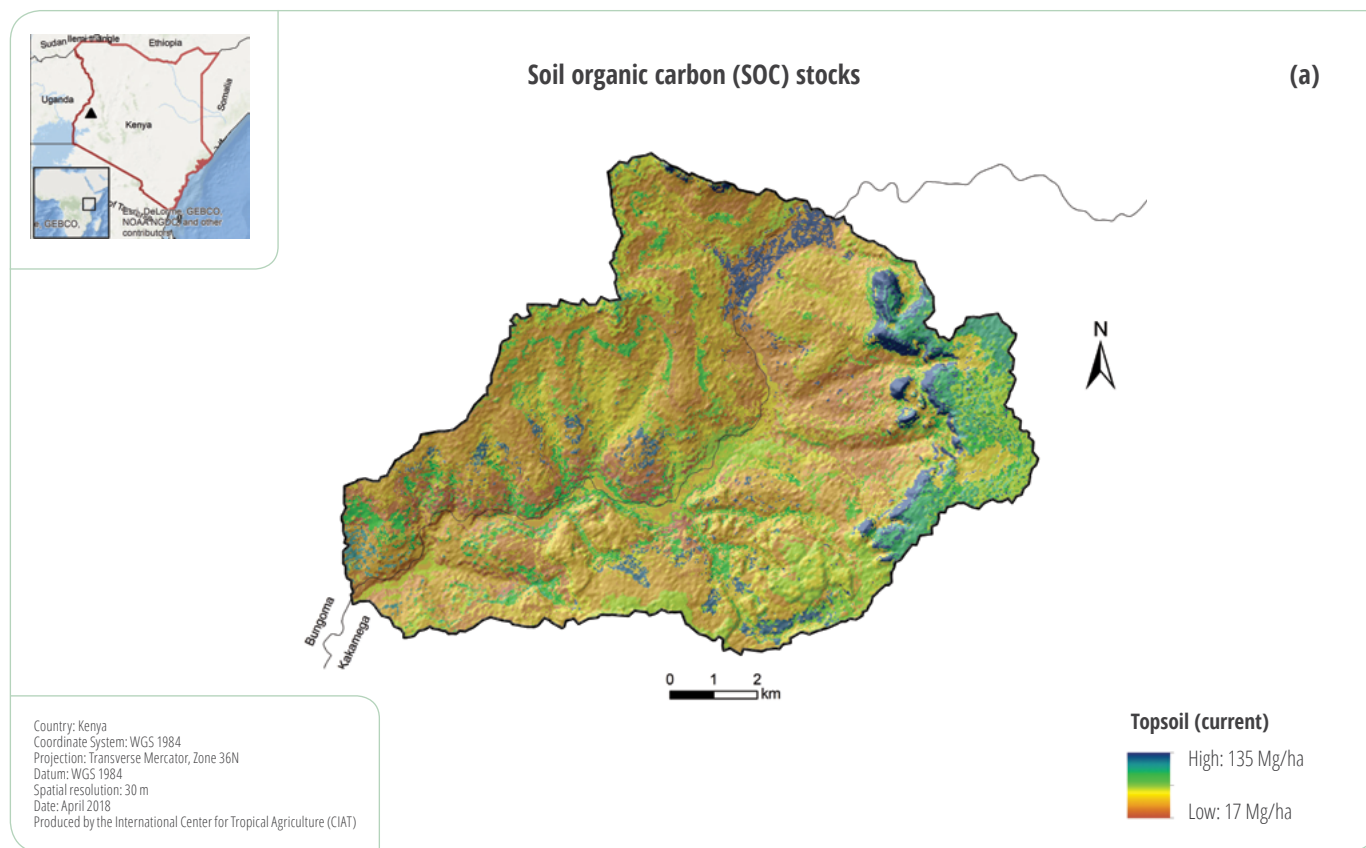


Figure 30a Spatial distribution of soil organic carbon stocks at the Murugusi watershed, western Kenya.

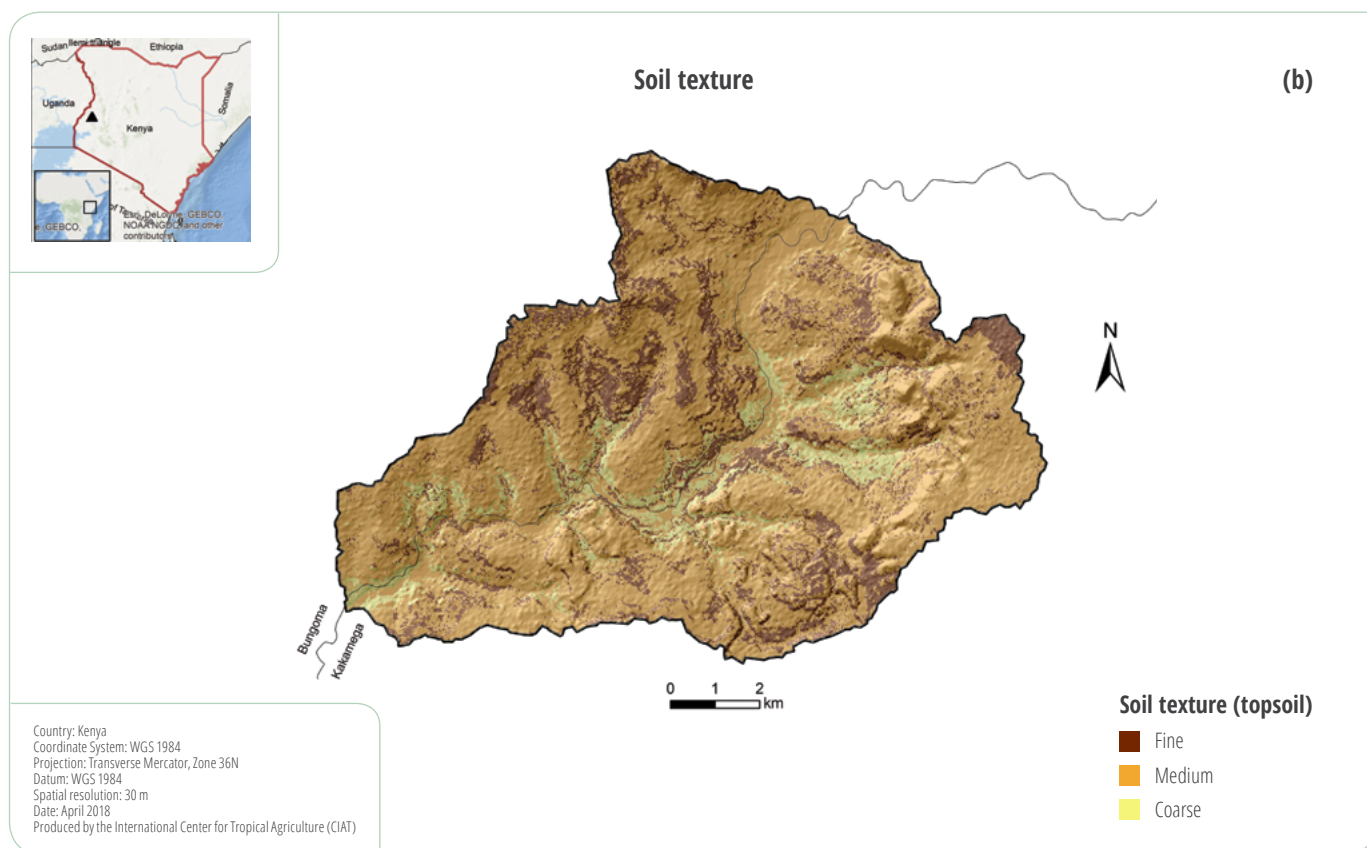


Figure 30b Spatial distribution of soil texture at the Murugusi watershed, western Kenya.

Following this assumption, we developed two landscape approaches, namely, (i) identify C saturation potential and deficits according to current SOC stocks and (ii) quantify the potential of CA to offset at least a certain fraction of these C deficits.

Soil organic carbon mineral saturation and deficit

Besides soil disturbance by agricultural management, temperature, moisture content and mineral compositions of soils affect the turnover of soil organic matter. The amount of clay and silt, but also clay mineralogy, has been identified to be a significant indicator of the total amount of C that soils can store. This type of mineral saturation concept builds on the fact that silt and clay particles act as stabilizing agents of SOC against microbial decomposition – the more so the more of these particles are present. The involved formation of organo-mineral complexes on the surface of mineral particles is regarded the quantitatively most important stabilization mechanism. The two other major

stabilization mechanisms are selective preservation due to recalcitrance of soil organic matter (SOM), and spatial inaccessibility of SOM (e.g. due to occlusion in soil aggregates). Yet, a SOC mineral saturation level does not necessarily constitute the ultimate upper limit of SOC contents in soils. SOC can, and does, also persist in more labile fractions (see POXC section on page 33).

To quantify the potential of SOC mineral saturation for the Murugusi watershed, we adjusted a statistical model using the entire soil dataset (N=664) collected in western Kenya and using the relationship between SOC and the sum of clay and silt content. A sigmoid type of curve³ was adjusted to describe the mineral saturation level based on these data, but excluding pristine forest sites (N=20) and a few outlier data of some other land use types, such as tree plantations, grassland and fallow (N=13), and land under annual crops (N=12), tea (N=5) or sugarcane (N=4) (Figure 31).

³ Rather than picking a linear trend, we assumed that this shape of curve would better represent the impact of an increased spatial overlap of mineral particles in the soil with increasing silt and clay contents – causing some spatial inaccessibility.

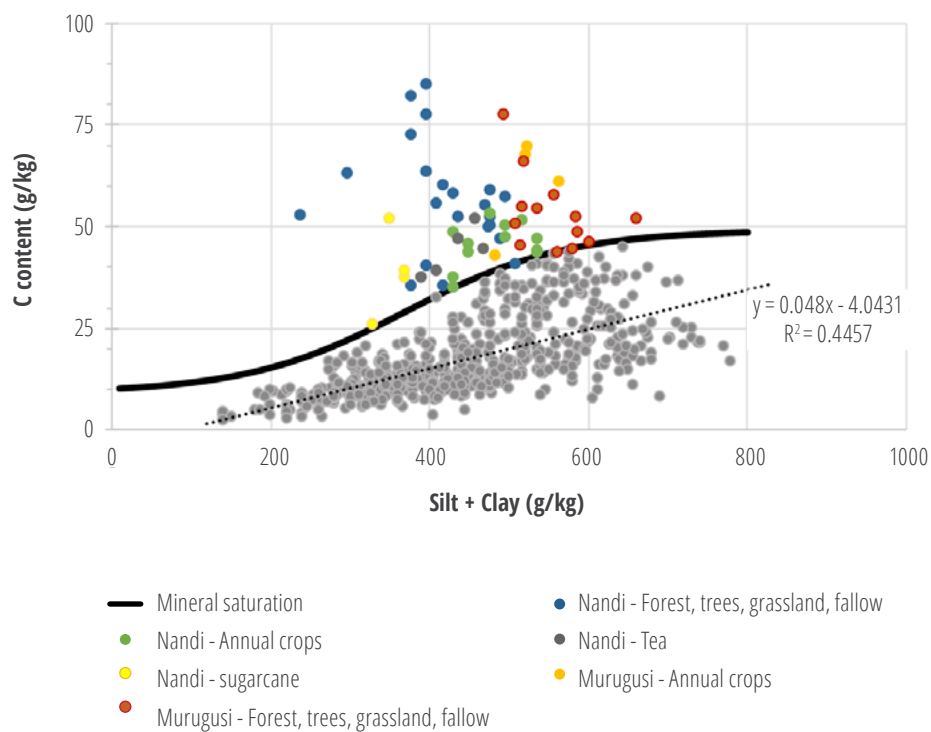


Figure 31 Soil organic carbon mineral saturation model for western Kenya. Coloured dots were excluded from the analysis.

The corresponding sigmoid equation was:

$$SOC \left(\frac{g}{kg} \right) = 9 + \frac{40}{1 + e^{-\frac{(SILT + CLAY) - 370}{100}}}$$

Accordingly, a pure sand (with no clay or silt) would still have a saturation level of approximately 10 g/kg C (= 1%), while the mineral saturation level of soils with little sand, i.e. some clay and silt-loam soils and silty-clay, silty-clay-loam and silt soils, would approach a saturation level of 49 g/kg C (= 4.9%).

This is certainly a very rough estimate of the SOC mineral saturation that is applicable to agricultural land and, for the time being and in the absence of other data sets, to western Kenya only, but does not include – intentionally! – pristine types of land uses, such as e.g. high-altitude grassland ecosystems or pristine forests.

This mineral saturation model was applied to the entire watershed using the digital soil maps of clay and silt (Figure 32). The saturation map of the Murugusi watershed confirms the potential of fine- and medium-textured soils to store up to 132 t C/ha in the upper 20 cm depth alone, mostly on summits and backslopes, and a minimum of 39 t C/ha in coarse(r) soils (Figure 32). The average saturation potential in the Murugusi watershed is 80 t C/ha in topsoil, which is more than double of the average currently found in the watershed. This means that C sequestration in soils in this type of agro-ecosystems is not constrained by an upper limit.

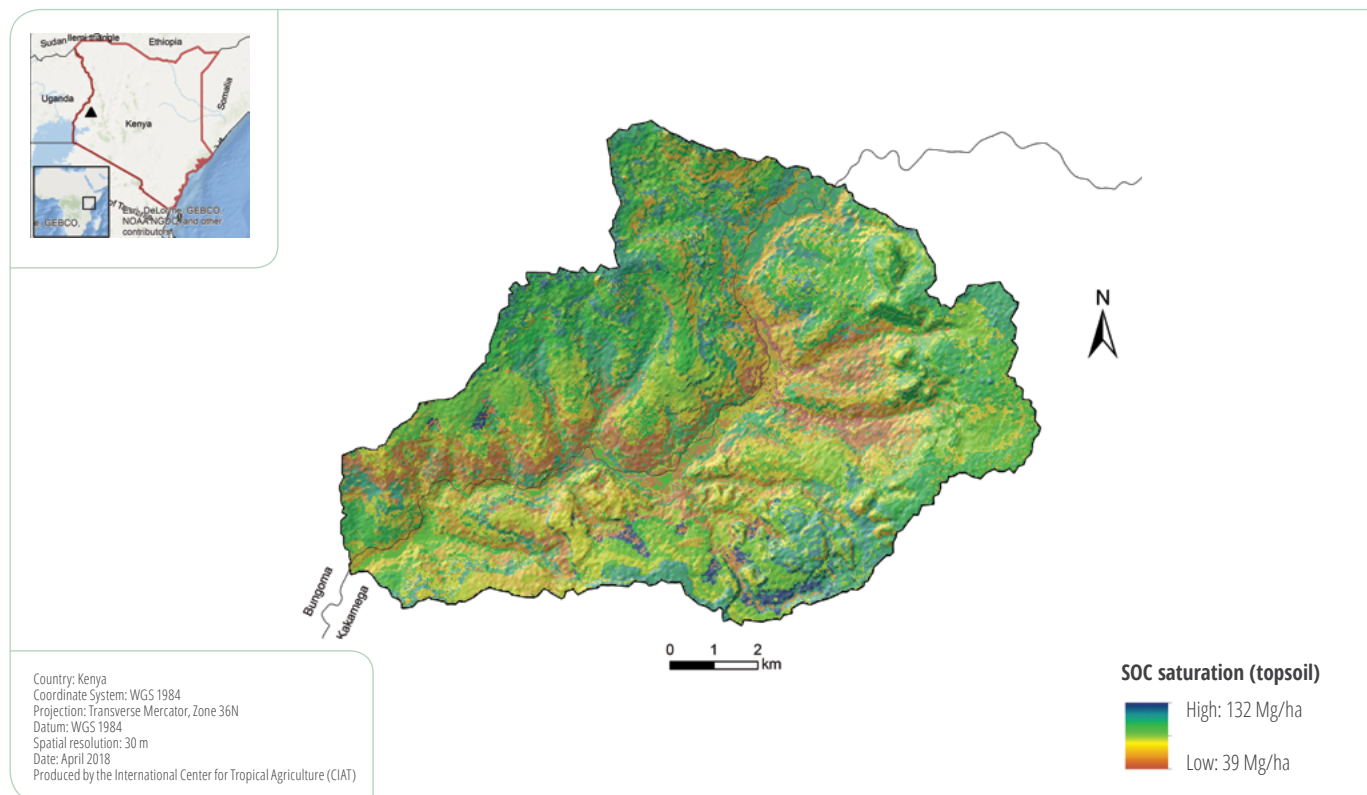


Figure 32 Soil organic carbon saturation map (Mg/ha) at the Murugusi watershed, western Kenya.

The SOC deficit in the watershed was determined by subtracting the current SOC stocks from the saturation map (Figure 33).

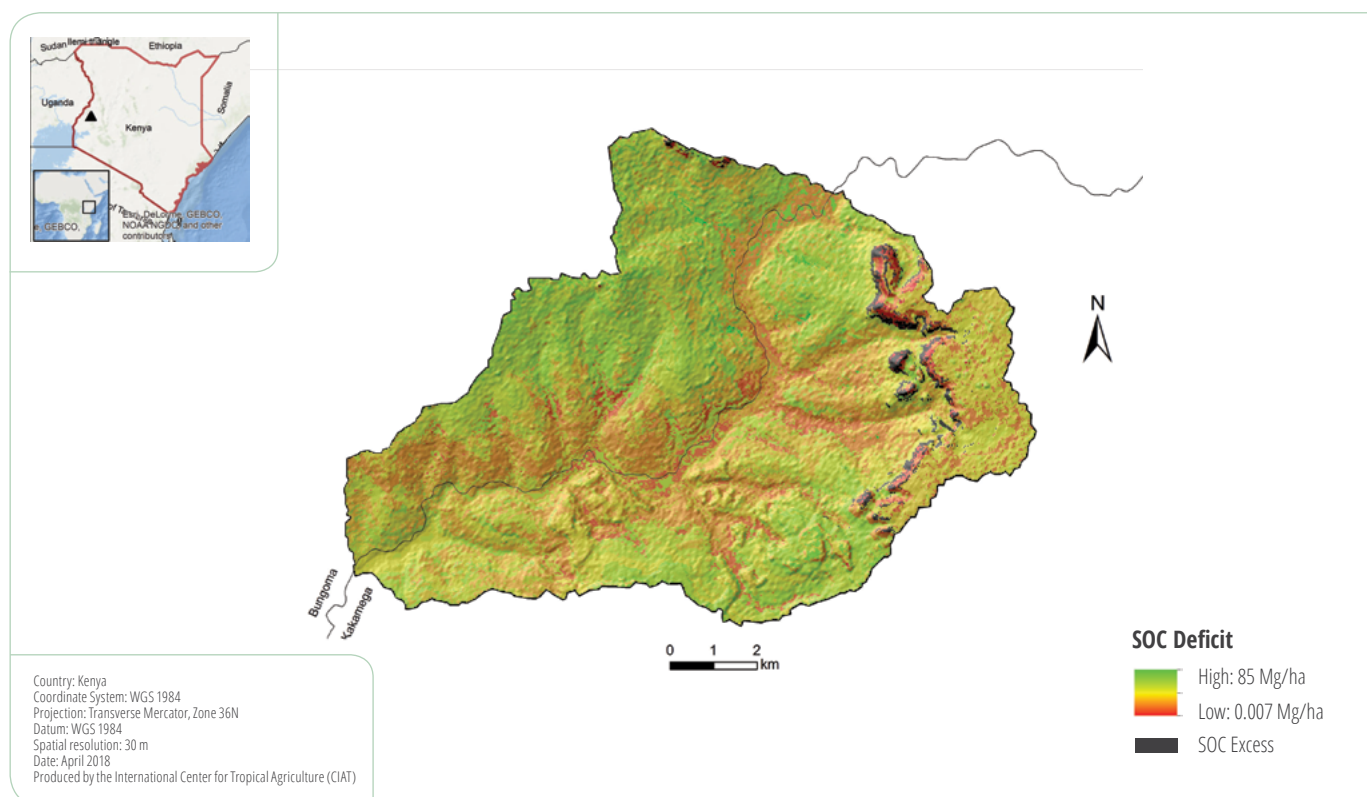


Figure 33 Soil organic carbon deficit/excess map (Mg/ha) of the Murugusi watershed, western Kenya.

Accordingly, the watershed had an average deficit of 43 t C/ha or 0.44 Mt C in total, and 63% (0.28 Mt C) of this deficit was under croplands. Given the fact that some – mostly forest areas – had a C-content that is above the determined saturation (see red dots in Figure 31), our model depicted these as SOC-excess areas, where land conversion to agriculture would thus imply a loss of C.

Potential of CA to increase SOC in croplands

As the previous chapters showed clearly: there is plenty of room for increasing SOC in the agricultural landscapes of western Kenya. To quantify the potential of CA to increase SOC in the watershed, the following pedotransfer function (PTF) that correlates current SOC stocks from CA farms in Bungoma with topography and soil texture was established:

$$SOC_{CA} = 4.0326291 + (0.0140678 * clay) + (-8.5706112 * relative\ slope\ position) \\ + (-0.0017999 * valley\ depth) + (0.0049244 * elevation) \\ + (-0.2270463 * wetness\ index); R^2 = 93\%$$

This PTF was then used to estimate the SOC stocks in the watershed assuming that CA would be implemented on all cropland. The required input parameters were the digitally mapped clay as well as topography variables derived from the DEM-30 m (Figure 34).

Adopting CA would increase SOC on 84% of all cropland area (Figure 35). On the remaining 16%, CA would not offset SOC deficits, but would incur losses of SOC.

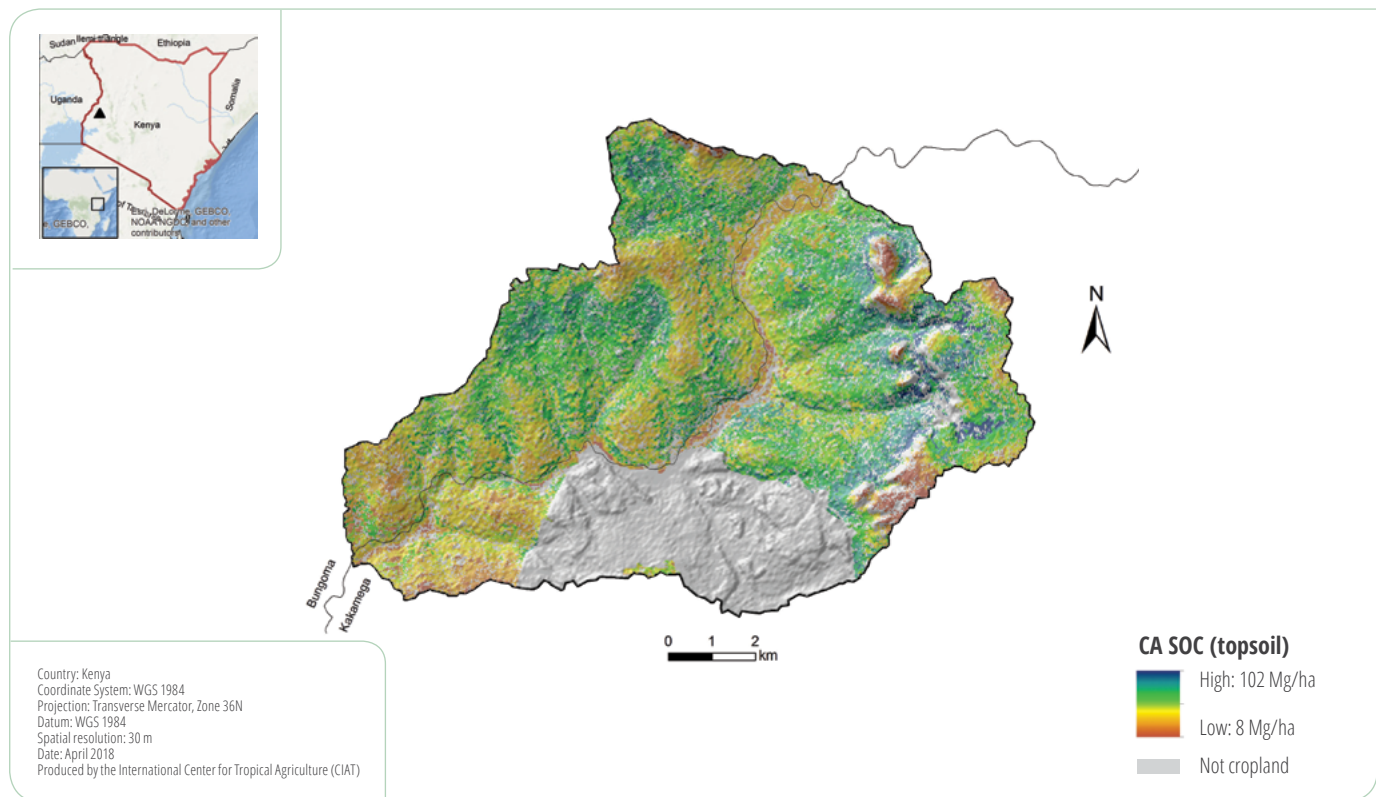


Figure 34 Soil organic carbon stocks (Mg/ha) in the Murugusi watershed, assuming that conservation agriculture (CA) is implemented on all cropland.

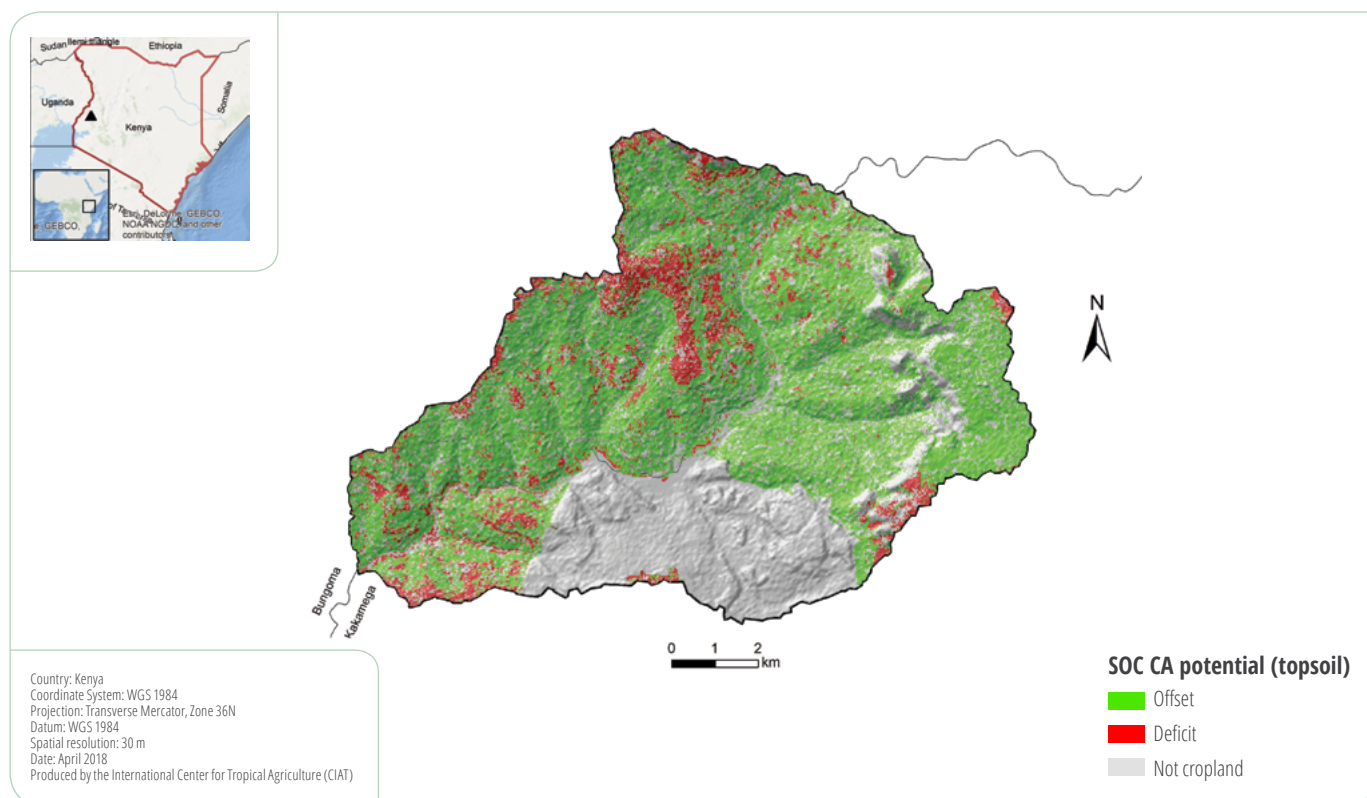


Figure 35 Soil organic carbon offset potential when conservation agriculture (CA) is implemented in croplands at the Murugusi watershed, western Kenya.

The potential of SOC sequestration of the Murugusi watershed is summarized in Table 2. The average SOC concentration figures in forest and cropland are very similar, which indicates that afforestation is not always the best option to store SOC as normally considered. The results also show that the watershed has potential to double its current SOC stocks until reach the saturation

limits especially on cropland. This opens an opportunity for well-managed agricultural systems to play a role as C sinks rather than sources as the example of CA, which demonstrates potential to minimize the saturation deficit by adding 131,000 tons of C to the current SOC content in the watershed.

Table 2 Soil carbon sequestration potential of the Murugusi watershed. Stocks are in 1000 t C/ha

LAND USE	AREA	AVG. SOC CONC.	CURRENT	CA	C-SATURATION	CA MINUS CURRENT	C-SATURATION MINUS CURRENT
	(ha)	(g/kg)	(1000 t C)				
Forest	3316	16.4	134	n.a.	268	n.a.	133
Cropland	6582	15.8	249	380	530	131	281
Total	10446	16	404		842	131	435
t C/ha			38		81	20	42
t CO ₂ eq/ha			141			73	154

Rapid indicators of soil health

We used the soil samples from the chronosequence sites in and around Nandi forest to determine whether certain indicators would allow for a rapid prediction of a general soil health/degradation status and the potential effect on C sequestration potentials. These samples had the advantage of precise information about length of land use – cross-checked by overlaying sampling location with historic satellite images – and other geomorphological characteristics.

Permanganate-oxidizable C (POXC)

The more labile or active fraction of SOC can be determined by oxidation of the soil with 0.02 mol/L potassium permanganate (Weil et al., 2003; Culman et al., 2012) and subsequent colorimetric quantification. We tested the hypothesis that more degraded soils have lower of such active, permanganate oxidizable (POX) C contents than healthier soils, e.g. those under pristine forest.

Indeed, there was a slight negative trend of POXC with years since start of cultivation for both soil depths (Figure 36). As expected, this impact was more notable in the top 20 cm than 20–40 cm depth.

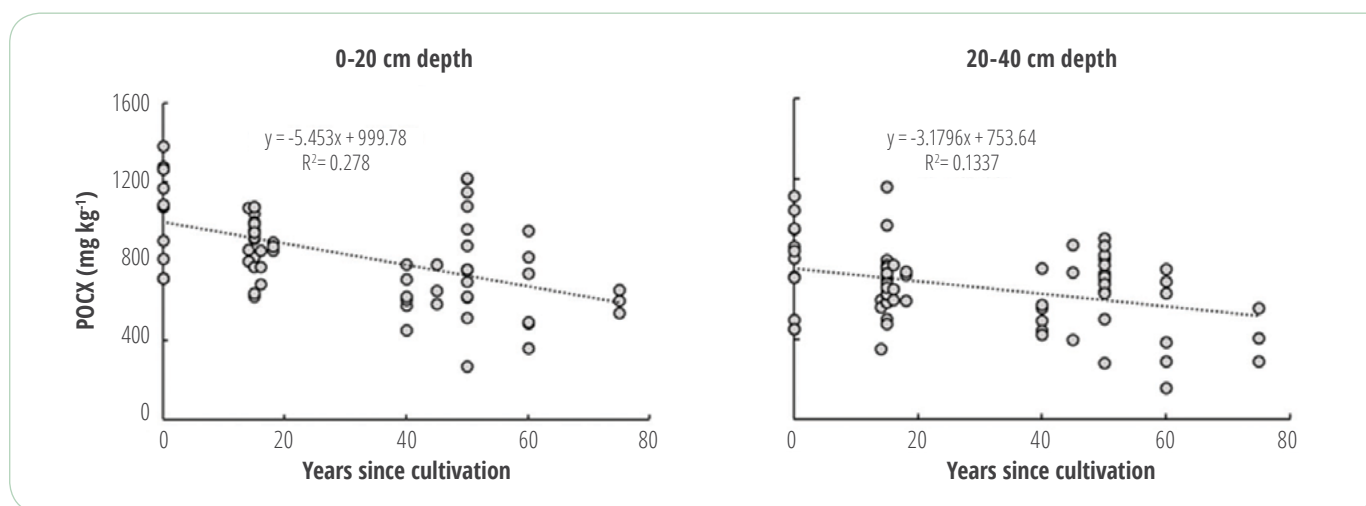


Figure 36 Impact of length of cultivation around Nandi forest on permanganate oxidizable (POX) C contents of topsoil (left) and subsoil (right) samples.

Yet, as total soil C showed the same decreasing trend (Figure 37 left), or in other words, as both variables were strongly correlated (Figure 37 right), POXC in fact did not bolster our understanding and prediction capacity of soil health changes in response to land use.

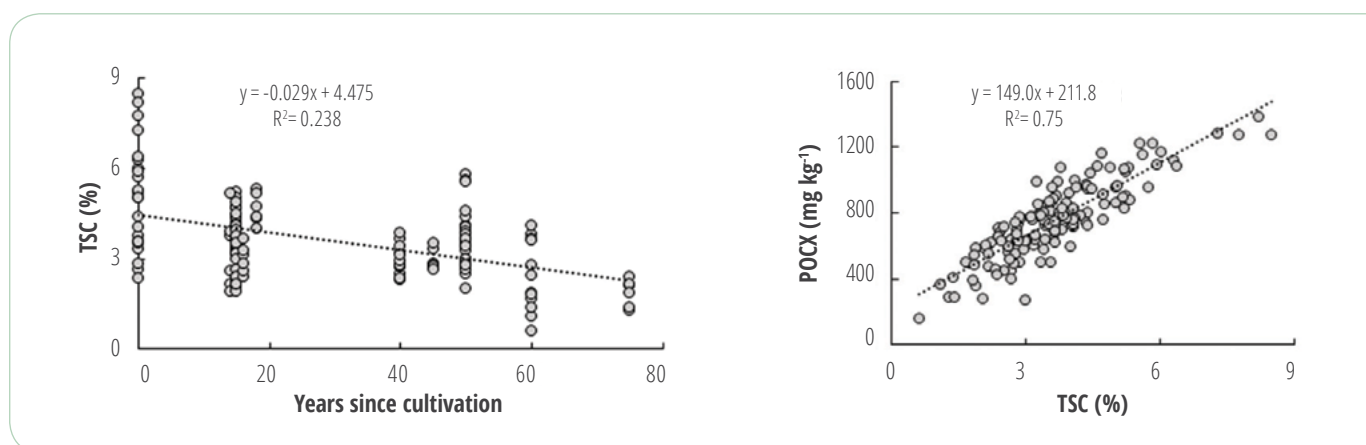


Figure 37 Impact of length of cultivation around Nandi forest on soil C contents (left), and correlation between POXC and soil total soil C (right); both top and subsoil combined; TSC = total soil carbon, which in the absence of inorganic carbon equals soil organic carbon.

Relating POXC to the clay content, revealed that pristine forest soils had higher POXC per unit clay (Figure 38). On the other hand, such difference was even more pronounced when comparing the SOC:clay ratio of

both land uses. This observation is consistent with the notion that forest soils have greater soil C saturation, and that POXC is a labile fraction that is not that strongly associated with the clay content.

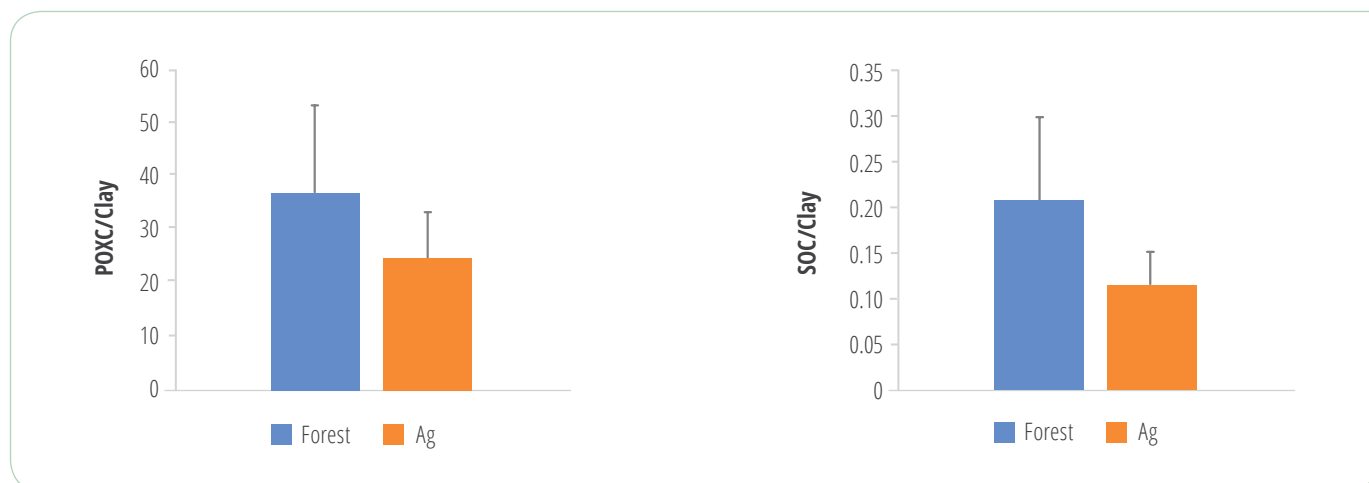


Figure 38 Ratios of POXC (left) and soil C (right) to clay content, distinguishing soil samples from pristine forest and agricultural land.

β-glucosidase activity

At enzyme level, β-glucosidase (BG) is involved in the decomposition of cellulose in soils. Some earlier scientific studies have shown that it has potential for monitoring biological soil quality (see e.g. Turner et al. 2002). Its determination in the lab involves assaying and colorimetric quantification.

The activity of BG increased weakly with time at 0–20 cm depth (Figure 39). BG activity was also only weakly related to soil C. A more conclusive indicator was the ratio or index of β-glucosidase to soil C ($\mu\text{mol pNP/g C/h}$), which increased significantly with the length of cultivation at 0–20 cm (Figure 40).

That β-glucosidase activity was associated with time since cultivation could indicate accelerated rates of C-cycling under cultivation (Margenot et al., 2017), supportive of the observation of losses of SOC with conversion of native forest to agricultural use. This indeed would allow for determining the soil biological degradation status with this indicator – which in fact is a combination of two variables (β-glucosidase activity and SOC); and both require a well-established lab. However, so far no threshold of what distinguishes healthy from degraded β-glucosidase:SOC ratios is available, which makes interpretation of data such as displayed in Figure 40 difficult.

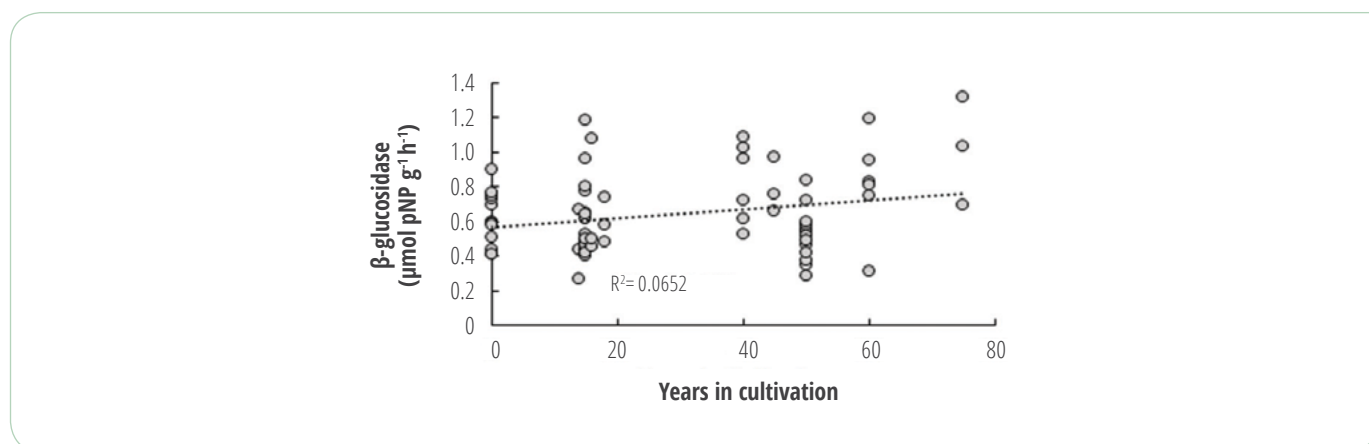


Figure 39 Impact of length of cultivation on β-glucosidase.

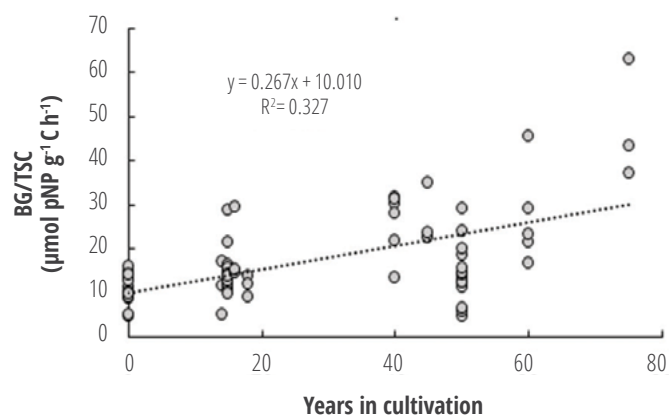


Figure 40 Impact of length of cultivation on the ratio of β -glucosidase to soil C.

Scopes of using infrared spectroscopy

In addition to the aforementioned – what we thought most promising soil health indicators – we examined the potential of diffuse reflectance infrared Fourier transform spectroscopy (DRIFTS) in the mid- (MIR) and near-infrared (NIR) light-spectra to predict soil health indicators.

DRIFTS is “an infrared spectroscopy technique used on powder [soil] samples with no preparation. ... The infrared light on a sample is reflected and transmitted at different amounts depending on the bulk properties of the material. The diffuse reflection is produced by the sample's rough surfaces' reflection of the light in all directions and is collected by use of an ellipsoid or paraboloid mirror.” (Source: Wikipedia.org).

Strong variation in agricultural type (annual vs. perennial) and clay content (14–49%) was expected to provide a challenging sample set to develop partial least squares (PLS) regression models to predict properties by infrared spectra alone.

MIR spectra showed clear differences between primary forest, young sites, and older sites (Figure 41). Spectra showed higher absorbance in the organic region (1800–1000 cm^{-1}) as well as the region of O-H and N-H compounds at 3400–3200 cm^{-1} and aliphatic C-H at 3000–2800 cm^{-1} for forest and young (<25 year) agricultural sites.

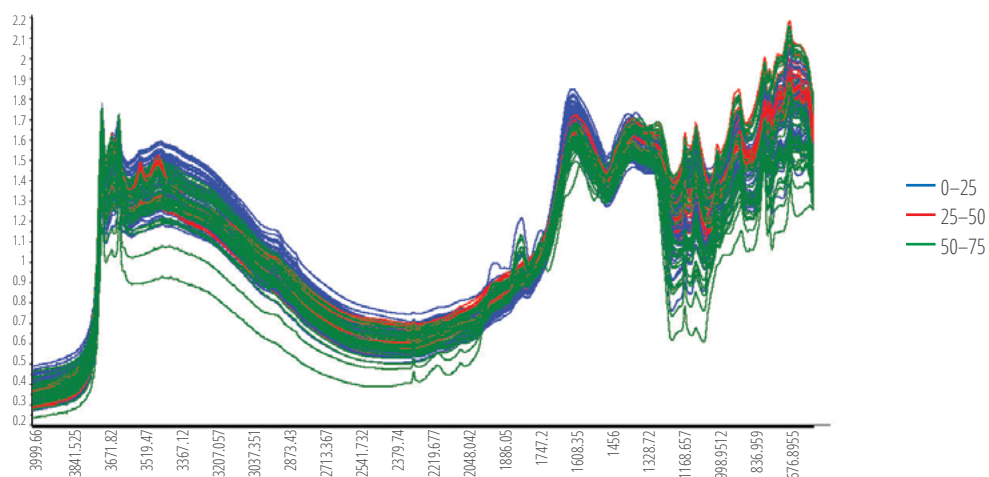


Figure 41 DRIFTS spectra of Nandi soil samples distinguished by years of land use (0–25, 25–50 and 50–75 years).

Thus the resulting PLS loading plot was able to distinguish clearly forest soils from all other sites highlighting their bio-chemical uniqueness (and similarity within) (Figure 42). This was in particular interesting, as forest and soils under agricultural land use around Nandi

did not differ in their soil texture, i.e. above all their clay content (and potential clay mineralogy), indicating that “management”-related impacts on soil chemical and physical properties are distinguishable by infrared spectroscopy.

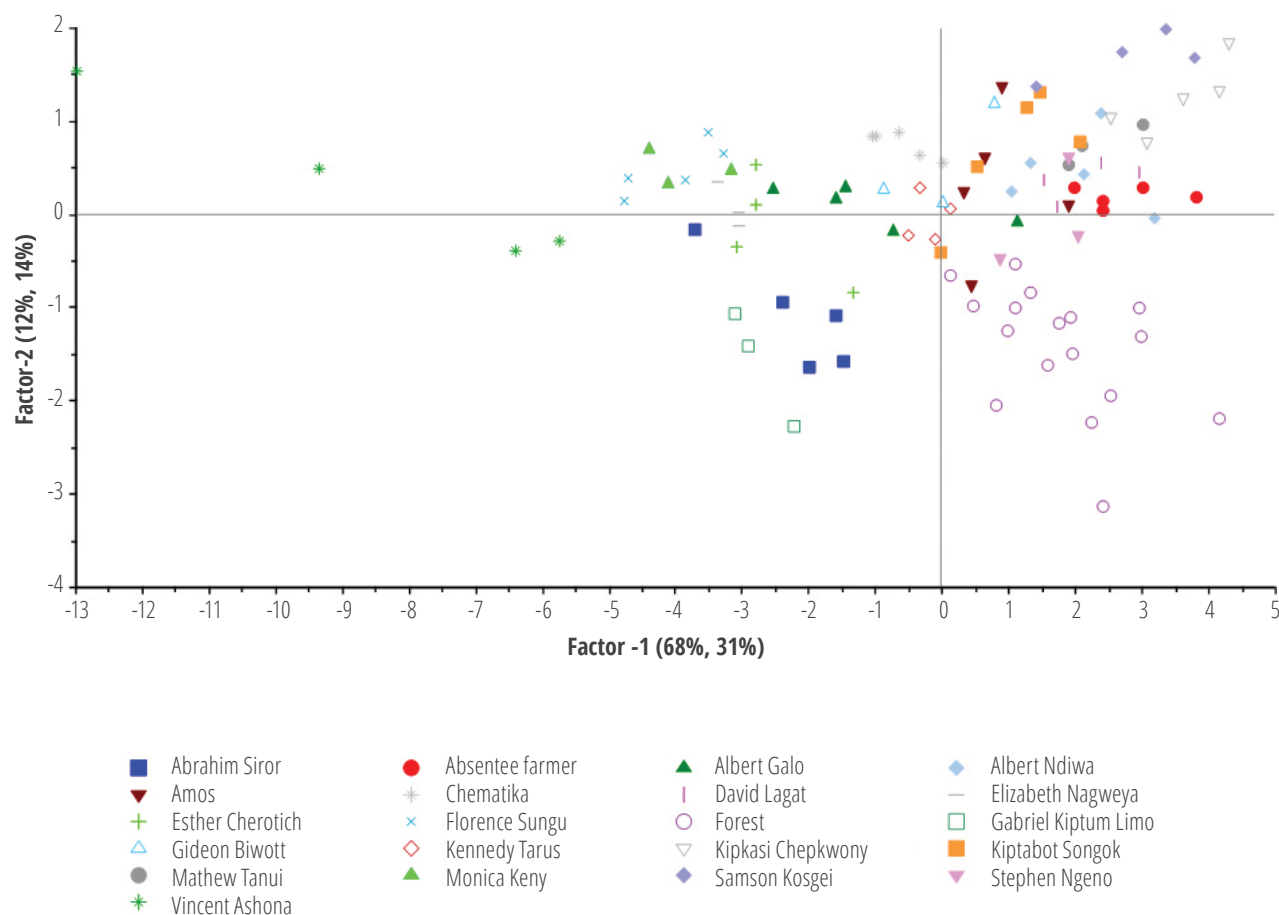


Figure 42 PLS loading plot scoring the first 2 factors of MIR (4000–400 cm^{-1} wave number) spectra of Nandi soil samples (distinguished here by owner of the farm on which these samples were taken). Factor 1 represents mainly the mineral signature, while Factor 2 includes some organic compounds.

The MIR spectroscopy (MIRS)-based PLS model allowed us to predict clay (Figure 43), silt, sand, soil C, soil N and C:N ratio with high accuracy.

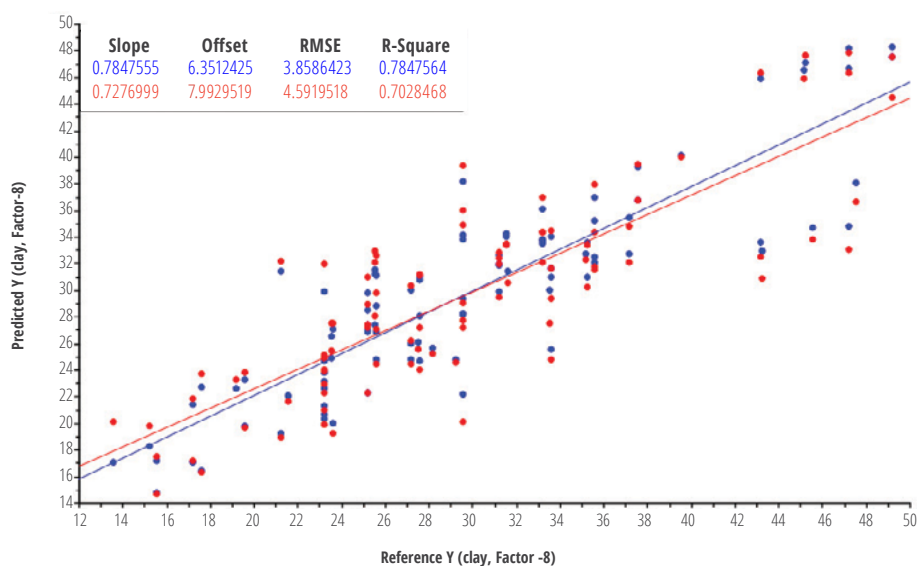


Figure 43 Prediction of clay content using mid-infrared spectroscopy. Blue dots and numbers = calibration, red dots and number = cross-validation.

Similarly, we could predict POXC with some surprisingly high level of accuracy (R^2 of cross-validation = 0.77; RMSE = 111 mg/kg). Absorbance bands that constituted the PLS model for POXC suggest direct detection of organic functional groups that constitute POXC as well as indirect detection via relationships with mineral functional groups.

It was then not surprising that MIRS would also pick up the ratio of β -glucosidase to soil C, the parameter most sensitive to time of cultivation across the chronosequence (Figure 24).

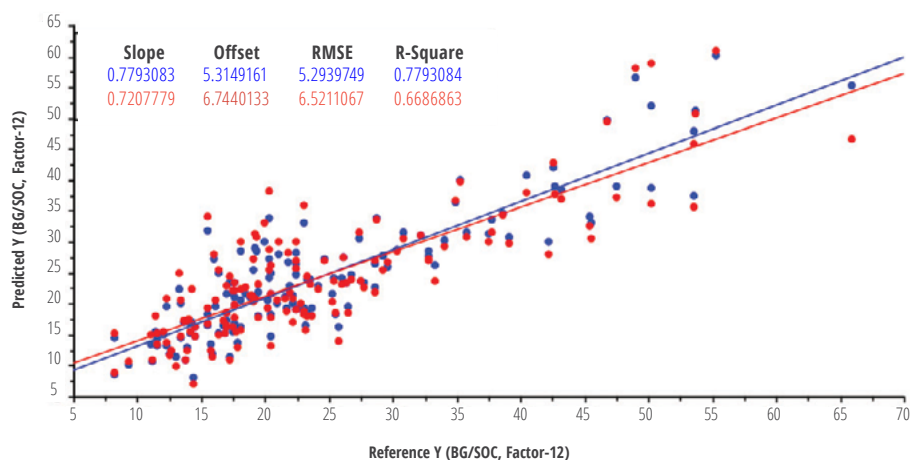


Figure 44 Prediction of permanganate oxidizable C (POXC) using mid-infrared spectroscopy.

Switching to NIR or MIR+NIR did not substantially change PLS predictions, with NIRS sometimes slightly less accurate than MIRS.



Photo: Neil Palmer/CIAT

Conclusion

Not surprisingly, elevation was a major factor affecting soil C in Kenya and Ethiopia, which is due to soil C turnover/microbial metabolism slowing down with decreasing temperatures. Subsequently, it was time since conversion from native vegetation (forest or alpine grass vegetation) that determined C stocks, followed by the impact of land use and soil texture, with light-textured, sandy soils providing less protection of organic matter against microbial breakdown than heavy-textured clay soils.

Massive losses of soil C in response to prolonged land use were quantified in Kenya and Ethiopia. In turn, these losses provide an opportunity to turn soil into C sinks by changing management practices. CA (Kenya – significant impact), integrated soil fertility and water management (Ethiopia – impact not significant but positive tendency) and land enclosure (Ethiopia – positive trend in two out of three cases) seem promising ways to increase soil C. In the case of CA, observed differences/impacts – if ultimately identifiable as C-sequestration – would allow offsetting other farm-management-related GHG emissions (CH_4 from livestock and N_2O from soils) and make these farms GHG/carbon neutral.

Soils of our long-term trials had C levels of above 2% (20 g/kg) before the onset of the trials in 2004. This was more than twice as high as average soil C contents observed in CA (and neighbored) fields in Bungoma. Practicing CA as compared to business as usual (CT R-) in our long-term trials avoided losses of on average 0.13 t C/ha/yr, while analogous observed differences in Bungoma amounted to 0.72 t C /ha/yr – a five times higher positive

impact. Whether or not CA led to true C sequestration in Bungoma cannot be revealed in the absence of repeated monitoring and data. In any case, it seems sound to assume that the potential to sequester C and the quantities achievable do depend on initial levels of soil C. Finding related C-content thresholds would allow us to predict and map soil sequestration hotspots, comparing thresholds against actual C contents – work in progress.

While infrared spectroscopy proved a valuable, fast and comparably cheap way of predicting a whole range of potentially suitable soil chemical variables and soil health indicators, it was the indicators themselves that showed limited “indication” of soil health and/or land degradation. The β -glucosidase-soil C ratio was the parameter most sensitive to time of cultivation. To make full use of this sensitivity, however, first of all, more universally applicable thresholds of that indicator would need to be found, then indeed allowing us to indicate critical soil health levels.

Extrapolating the observed positive impact of CA on soil C in Bungoma to the Murugusi watershed revealed that, if CA was practiced on all agricultural land in Murugusi, an approximate 131,000 tons of C (~20 t/ha cropland) could be sequestered in soils of this watershed. On the other hand, our estimates showed that the restored watershed, Kumbharwadi, in Maharashtra, India, merely sequestered 427 t C over 19 years (0.41 t C/ha). While the latter seems meagre and negligible, when extrapolated to the entire Indian semi-arid land, this would add up to about 39 million t C. Both are sizeable amounts worth trading on voluntary C markets as payments for environmental services and climate change mitigation, with achievable funds catalysing investments in soil and land restoration.

Appendices

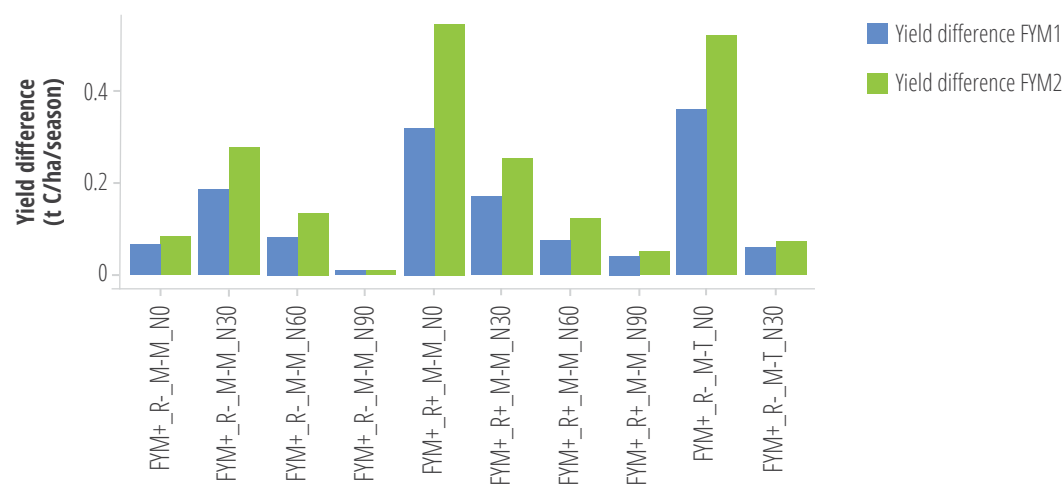


Figure A1 Increase in the yields per season resulting from the avoided losses in soil carbon for the farm yard manure application sensitivity simulations. The yield differences were obtained by subtracting the season yields of the standard (STD) stimulation from those of the sensitivity simulations (FYM1 and FYM2). The seasonal mean differences are significant with a p-value of 0.006 and 0.008 for FYM1 and FYM2, respectively.

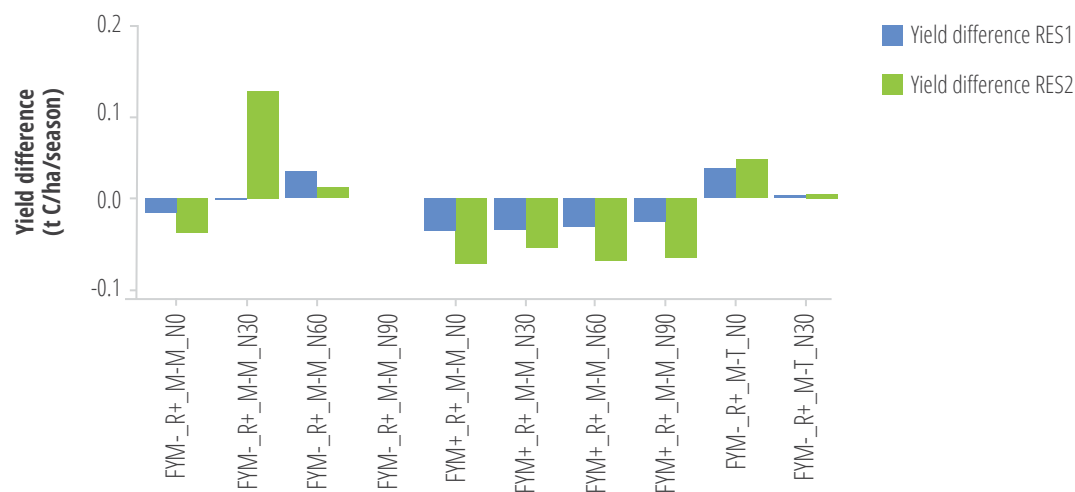


Figure A2 Yield differences per season resulting from the avoided losses in soil carbon for the residue retention sensitivity simulations. The yield differences were obtained by subtracting the season yields of the standard (STD) stimulation from those of the sensitivity simulations (RES1 and RES2). The seasonal mean differences are not significant with the p-values for both simulations being greater than 0.05.

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Headquarters and Regional Office for Latin America and the Caribbean

Km 17 Recta Cali-Palmira CP 763537
Apartado Aéreo 6713
Cali, Colombia
Phone: +57 2 4450000

CONTACT

Ruben Echeverría, Director General

Carolina Navarrete, Regional Director

✉ c.navarrete@cgiar.org

Regional Office for Africa

c/o ICIPE
Duduville Campus, Off Kasarani Road
P.O. Box 823-00621
Nairobi, Kenya
Phone: +254 0709134000
Fax: +254 20 8632001

CONTACT

Debisi Araba, Regional Director

✉ a.araba@cgiar.org

Regional Office for Asia

c/o Agricultural Genetics Institute (Vien Di Truyen Nong Nghiep),
Vietnam Academy of Agricultural Sciences (VAAS),
Pham Van Dong Street, Tu Liem
(opposite the Ministry of Security – Doi dien voi Bo Cong An)
Hanoi, Vietnam
Phone: +844 37576969

CONTACT

Dindo Campilan, Regional Director

✉ d.campilan@cgiar.org



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