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Drivers of soil organic carbon stocks at village scale in a sub-humid region of Zimbabwe

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A R T I C L E I N F O

Dataset link: Data for "Understanding drivers of soil organic carbon stocks at village scale in a sub-humid region of Zimbabwe" (Original data)

Keywords:
Land use
Homefield
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Clay content
sub-Saharan Africa

A B S T R A C T

Land use change caused by agriculture and inappropriate agricultural management cause soil organic carbon (SOC) loss. This study was conducted in a smallholder communal area of Zimbabwe with the following objectives: i) to quantify SOC stocks under contrasting land uses and soil types, and estimate landscape-level SOC stocks, ii) to assess the impact of historical agricultural management parctices on SOC in croplands (homefields vs outfields), and iii) to estimate temporal changes in SOC stocks due to land use change using field measurements and geospatial data (Africa Soil Information Service, AfSIS). SOC stocks were measured across three soil types and eight land uses (croplands, gardens, fallows, grasslands, vleis, shrublands, forests and tree plantations) at soil depths of 0–20 and 20–40 cm. Estimates from AfSIS were also used for comparison. SOC stocks were highest on black clay soils (66.9 ± 2.30 Mg C/ha), followed by red clay soils (36.1 ± 2.04 Mg C/ha) and sandy soils (25.5 ± 0.59 Mg C/ha). Among land uses, SOC stocks were highest in vleis (67.9 ± 3.55 Mg C/ha), followed by gardens (56.4 ± 2.34 Mg C/ha) and grasslands (53.1 ± 6.18 Mg C/ha). Croplands on sandy soils had the lowest stocks (22.7 ± 0.77 Mg C/ha). Distance from homestead had no significant effect on SOC stocks. SOC stocks estimated by AfSIS were systematically underestimated in vleis, grasslands and gardens, resulting in a 20 % underestimation of landscape SOC stocks. Landscape SOC stocks declined slightly (−0.2 %) from 2002 to 2023, though the change was not statistically significant. Our findings highlight that SOC stocks hotspots are concentrated in vleis, gardens and grasslands, mostly within communal grazing lands. Their conservation should therefore be a priority, emphasizing the need for collective management. On the other hand, restoration of degraded croplands could be enhanced by strenghtening linkages between cultivated fields and communal grazing lands through improved livestock management.

1. Introduction

Soil organic carbon (SOC) is instrumental in the global carbon cycle and in many functions related to soil fertility. It has a major influence on soil physical structure, nutrient retention, and water storage (Cotrufo and Lavallee, 2022). However, in many smallholder farming systems across sub-Saharan Africa (SSA), SOC levels are often depleted (Zingore et al., 2005; Cardinael et al., 2022; Laub et al., 2023). This depletion is primarily due to continuous cropping with inadequate nutrient inputs (Rurinda et al., 2013) and limited availability and use of organic

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resources (Rusinamhodzi et al., 2016). These challenges are exacerbated by the burden of climate change, which brings erratic and poorly distributed rainfall, higher temperatures and declining crop yields (Rufino et al., 2011), worsening food insecurity. With high poverty levels, many farmers have limited capacity to adopt new adaptation strategies (Zinyengere et al., 2013).

Increasing SOC levels is presumed to provide multiple benefits, including climate change mitigation, enhanced soil fertility leading to higher crop yields (Tittonell et al., 2010; Cardinael et al., 2022). This is particularly important for smallholder farmers who are negatively affected by large yield gaps that are associated with poor soil fertility (Chivenge et al., 2011; Oldfield et al., 2019), curtailing the achievement of sustainable development goals (SDGs), such as ending hunger and eradicating poverty (Dutta et al., 2020).

SOC has a complex structure, and it interacts with soil minerals in various ways (O'Rourke et al., 2015). Additionally, the amount of SOC that can be stored at any given time depends on several factors including, local climate, the type of land use and land management as well as other site-specific conditions (Lal, 2004). SOC stocks have high spatial variability, and the changes over time are usually small and difficult to measure accurately. Understanding the drivers of SOC change is critical for designing appropriate strategies to preserve or increase SOC levels across different scales (Feller et al., 2001; Xiao, 2015; Abegaz et al., 2020).

At the global scale, land use change is an important driver of SOC change (Beillouin et al., 2023). This is supported by Wiesmeier et al. (2019) as well as by Guo and Gifford (2002) who estimated SOC declines of 30 – 80 % within 30–50 years following conversion of natural lands (forests and grasslands) to croplands. This decline is attributed to lower C inputs in croplands compared to natural lands, coupled with an increase in decomposition because of higher temperatures and aeration, deterioration of aggregate protected soil organic matter as well as increased erosion. Land management also plays a crucial role at this scale, with systems that have higher crop diversity including deep rooting crops, perennial crops and cover crops maintaining higher SOC stocks (Wiesmeier et al., 2019). Other practices such as reduced tillage (Shumba et al., 2024), use of organic amendments (Fujisaki et al., 2018) and conversion of croplands to agroforestry have also been found to significantly improve SOC stocks (Cardinael et al., 2018). At a local scale, important drivers of SOC change include topography, parent material particularly as it relates to soil type and soil texture.

Although the importance of SOC maintenance and additional storage is acknowledged in SSA, detailed information on the specific drivers that influence these processes remains limited (Von Fromm et al., 2021). This is largely due to the limited availability of comprehensive studies (Hengl et al., 2017; Nenkam et al., 2024), as research has traditionally focused on temperate soils, with few studies addressing tropical soils (Ewing et al., 2022; Beillouin et al., 2023). Additionally, smallholder farming systems in SSA are highly heterogeneous due to diverse biophysical and socioeconomic factors. Historical management, such as limited use of organic inputs and mineral fertilizers have led in many places to the so-called "soil fertility gradients" typified by decreasing soil fertility with increasing distance from homesteads (Tittonell et al., 2007; Masvaya et al., 2010; Zingore et al., 2011). These complexities challenge the analysis of SOC drivers and their impact on SOC stocks (Tittonell et al., 2005; Giller et al., 2011; Dutta et al., 2020). Carbon losses at the landscape level have been reported, largely caused by the conversion of forests to agricultural croplands. While carbon stock estimates are made through soil sampling, these assessments face challenges such as inconsistencies due to limited range of land use types used in analysis (Olorunfemi et al., 2022). This is because the region's heterogeneous landscape makes it expensive to assess every land use type, resulting in only a few being evaluated. This limited data availability complicates efforts to extrapolate findings across the broader region.

Accurate region-wide data is essential for understanding and managing SOC and nutrient cycling in SSA. Recent soil nutrient maps at resolutions of 250 and 30 m (Hengl et al., 2015, 2021) provide readily available data. However, these global scale maps may not be sufficiently detailed for the small land parcels typical of SSA's smallholder farms (Chikowo et al., 2014; Ewing et al., 2021). For instance, in Zimbabwe, farms usually consist of one large field divided into smaller plots ranging between 0.1 – 0.5 ha (Zingore, 2006; Rusinamhodzi et al., 2013; Van Apeldoorn et al., 2014), with each plot managed differently based on resource endowment (Mtambanengwe and Mapfumo, 2005; Chikowo et al., 2014). The mismatch between predictions made using a model (e.g. as in geospatial mapping) and the measured values might have a substantial effect on the resulting management decisions (Berazneva et al., 2018; Djagba et al., 2022; Ewing et al., 2022; Rossiter et al., 2022). In addition, the inherent smoothing effect of machine learning models can obscure critical fine-scale variations which calls for refinement through data integration, local validation and robust ground-truthing (Rossiter et al., 2022). Accurate soil data are crucial for tailored management and nutrient recommendations. Therefore, further accuracy checks and refinement of the soil properties and nutrient maps are needed to ascertain their applicability to the highly heterogenous farming systems in SSA.

Given this context, the main objective of this study was to understand the drivers of SOC stocks in a case study in the sub-humid region of Zimbabwe. Specifically, we aimed to i) assess the impact of land use, soil type and texture on SOC stocks, ii) determine differences in SOC stocks as a function of historical cropland management between homefields and outfields (field types) iii) estimate temporal change in SOC stocks due to land use change at ward level (the smallest administrative unit in Zimbabwe), using both ground measurement, and AfSIS geospatial data.

2. Materials and methods

2.1. Study area

Murehwa (17°39′S, 31°47′E) is a smallholder farming district situated about 80 km northeast of the capital of Zimbabwe, Harare. The district has a population of approximately 205 442 people and an average of 54 people km^{-2} (ZimStat, 2022). Farmers in the area practice a mixed crop-livestock farming system. The crops that are usually grown include maize (*Zea mays* L.), groundnuts (*Arachis hypogaea* L.), cowpeas (*Vigna unguiculata* L.), sweet potatoes (*Ipomoea batatas* L.), and horticultural crops including tomatoes (*Solanum lycopersicum* L.) and other vegetables. Cattle used to be the predominant livestock in the area however, due to recent increase in diseases such as bovine theileriosis (*Theileria parva* L.) (Manyenyeka et al., 2021), many farmers have lost their cattle, and are mostly raising goats, and local chickens. Livestock, particularly cattle, graze freely in communal rangelands during the day and are tethered in kraals near homesteads overnight. Crop residues are used to feed cattle during the dry season, and manure is used to fertilize crops (Rufino et al., 2011; Zingore et al., 2007b). The district is located about 1300 m above sea level, in agroecological region II – a zone of high agricultural potential in both crop and livestock production (Mugandani et al., 2012). It receives an average annual rainfall of 750 – 1000 mm with a unimodal distribution from November to April. July is the driest month with only 2 mm of rainfall whilst January is the wettest month with 215 mm of rainfall on average. The average annual temperature is 24 °C, with October being the warmest month at around 30 °C and July the coldest month at approximately 14 °C (Zingore, 2006; Kafesu et al., 2018). The dominant soil type is granitic-derived sands (Lixisols) which have inherently low fertility. However, there are smaller sporadic areas with more fertile clay soils (Luvisols) resulting from dolerite intrusions (Zingore, 2006). In the low-lying areas, dark grey or black heavy clay soils (Vertisols) can be found, with a fertile topsoil horizon (Ivy, 1981; Nyamadzawo et al., 2015).

2.2. Farmer selection and soil sampling protocol

The district consists of 30 wards and this study was conducted in Ward 28. The total area of the ward is 6751 ha. Three villages, Chitemerere, Makombe and Manjonjo, were selected from this ward. Using a list of farm households in each village provided by the agricultural extension officer, 50 % of the households were randomly selected giving a total of 183 farm households. Soil samples were collected from all agricultural fields, including gardens and fields under fallow for each selected household (Fig. 1). Gardens represent plots primarily located in the low-lying areas usually near rivers and away from the homestead, commonly designated for growing vegetables. The fallow fields are areas where farmers have temporarily ceased cultivation for different reasons and varying periods of time with no additional management taking place. In our study, fallow fields had been uncultivated for 1 year to 15 years, with an average of 4 years. To describe the common lands based on the major land-use patterns, a participatory approach was employed, involving focus group discussions with key informants from each village. Common lands refer to land units which belong to the whole village, where users can obtain resources such as firewood, litter, and wild fruits. The common lands were identified as miombo woodlands, grasslands, vleis, and gumtree plantations. The miombo woodlands were comprised of either dense woodland where the tree canopy exceeds 2 m in height, and is identified as forests, and shrublands where the tree canopy is less than 2 m height and less dense. Vleis are grassy areas usually found in the low-lying areas and are seasonally waterlogged with few scattered trees (Nyamadzawo et al., 2015).

Soil sampling was carried out between June and July 2021. Soil samples were collected at two depths, 0–20 cm and 20–40 cm. In each farmer's field, the sampling for SOC measurements followed a zig-zag transect pattern, with 8–10 sub-samples being collected at 10 m distance using an auger. These sub-samples were then pooled to obtain one composite soil sample per field. Farmers' fields were small, and ranged from 0.01 to 1.6 ha, with an average size of 0.2 and 0.1 ha for croplands and gardens, respectively. Common land areas exceeding 1 km in length were sampled by taking one composite sample at every 100 m distance. At this location 10 sub-samples were collected within a 10 m radius to make the composite sample using an auger. A Garmin GPSMAP 66 s handheld unit was used to geo-reference the boundaries of each field, and the size of each field was recorded. For the common lands a geolocation was recorded at each point where a soil bulk density sample was collected. Additionally, description of the common land was recorded, specifying the type of ground cover and the presence of specific features such as rock outcrops and termite mounds.

One undisturbed core sample was collected from each field and common land area, at each of the two depths, 0–20 and 20–40 cm, using a volumetric cylinder (20 cm length × 5 cm diameter) to determine soil bulk density. A total of 671 georeferenced locations were sampled, yielding 1342 soil samples from two depth ranges: 0–20 and 20–40 cm: distributed as follows: 732 from croplands, 246 from gardens, 64 fallow fields and 300 samples from common lands (vleis, grasslands, shrublands, forests and plantations) (Fig. 2). Within the croplands, 626 soil samples were collected from sandy soils, followed by 92 from red clay soils and 14 from black clay soils. Furthermore, most samples were from homefields (527 samples) which are located close to the homestead. In Manjonjo village, field ownership was characterised by several small fields belonging to one farmer at varying distances from the homestead. This contrasted with Chitemerere village where famers usually had one large piece of land fenced within the homestead. In Makombe village, there was a mix of both types.

All soils were air dried and subsequently sieved through a 2 mm sieve. For bulk density samples, the fine and coarse fractions (greater than 2 mm) were weighed. Due to the high number of samples and limited oven space, a representative aliquot of 20 g from the fine fraction was oven dried at 105 °C for 24 h to determine the moisture content and the dry mass of the soil. Bulk density was determined by dividing the mass of the oven dry soil by the volume of the core used to collect the sample.

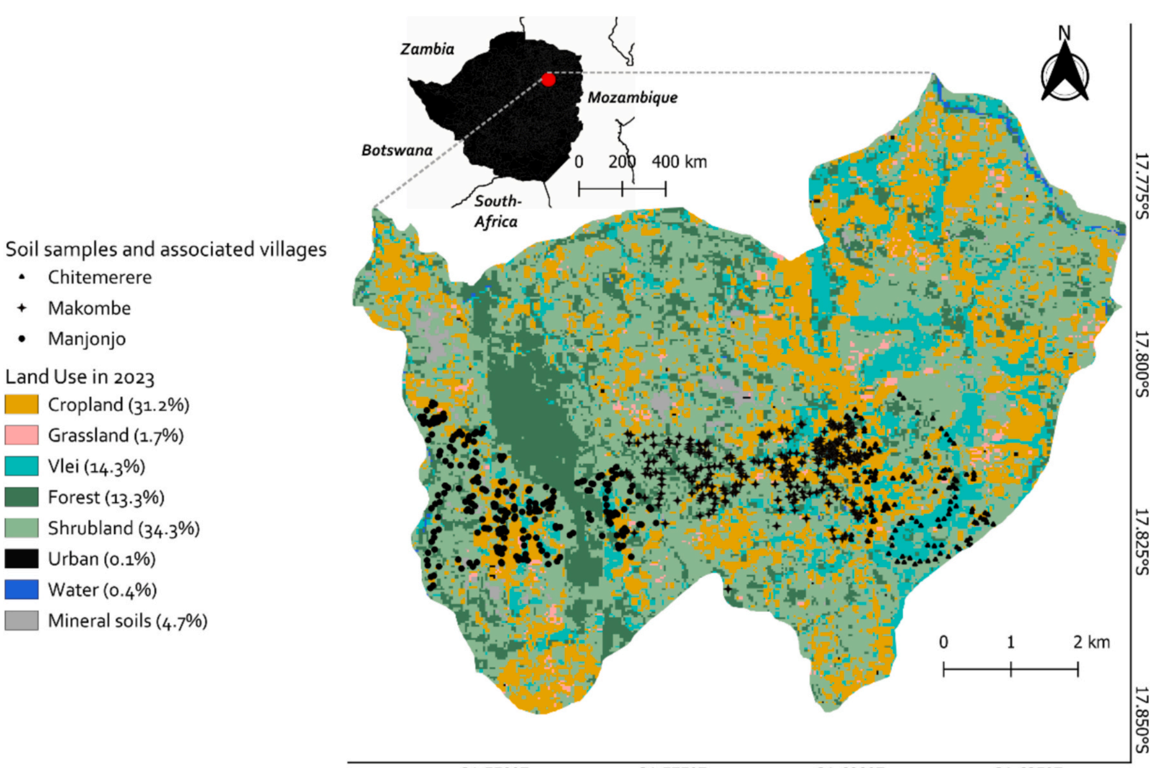

Fig. 1. Distribution of sampling locations across the study area based on land use and land cover maps derived from Landsat images at 30 m spatial resolution.

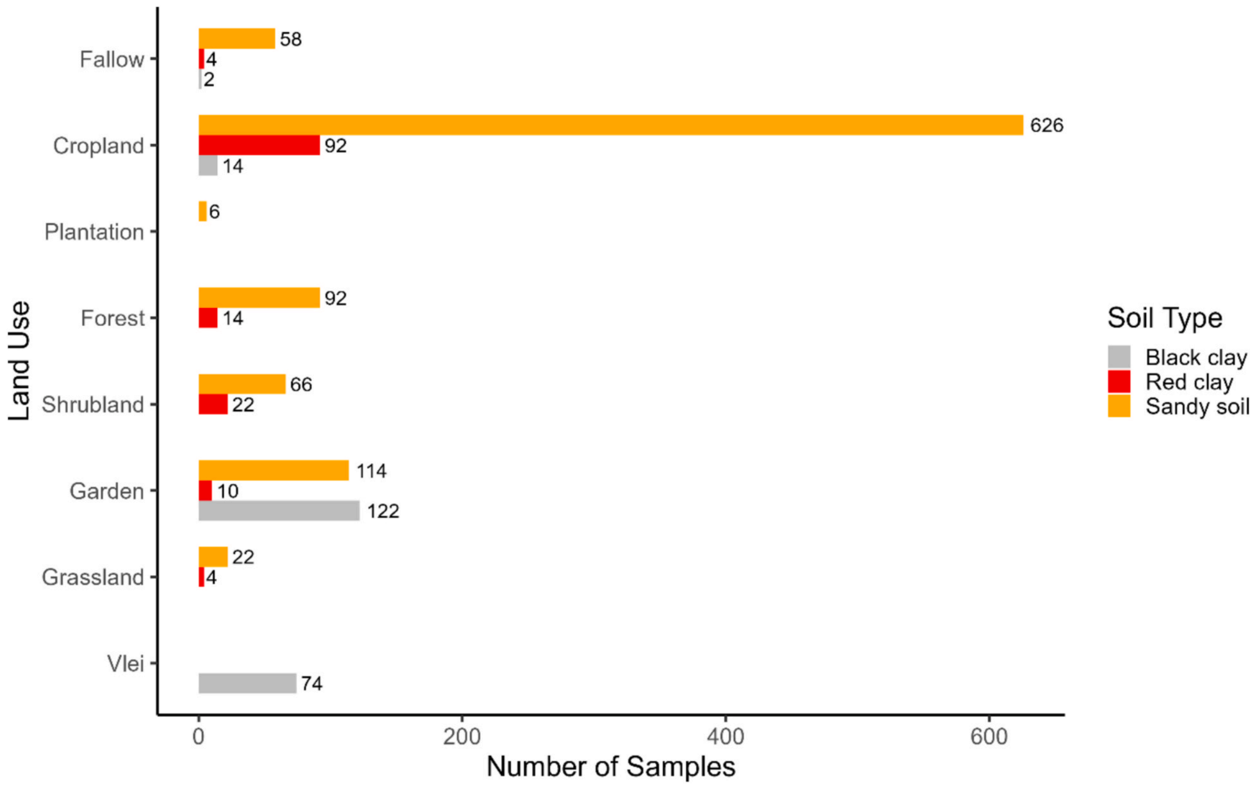

Fig. 2. Total number of soil samples (0–20 and 20–40 cm) as a function of land use and soil type.

2.3. Spectral acquisition and chemical analysis

Spectra were acquired at the laboratory of the French Agricultural Research Centre for International Development (CIRAD) in Saint Denis, La Réunion, on all soil samples ground to 200 μm. The MIR spectra were measured using an Agilent 4300 handheld FTIR spectrometer (Agilent Technologies, Santa Clara, CA). Spectral pre-processing was done to ensure the removal of any variations caused by light scattering and to enhance some features within the spectra (Wadoux et al., 2021). Firstly, smoothing was done using the Savitzky Golay filter with a window size of 11 and a polynomial order of 2 in the *signal* and *plyer* packages (Signal Developers, 2023) of R (R Core Team, 2023), then to correct for light scattering, Standard Normal Variate (SNV) was used and finally resampling was carried out at wavelength of 10 nm. Spectra were trimmed to remove the noise at the edges leaving the range between 800–4000 cm^{-1}. A subset of 230 soil samples, corresponding to 17 % of the total number of samples, was selected for laboratory analysis. This number of samples was determined by striking a balance between the cost of the soil analysis and the quantity required to obtain accurate estimates with spectroscopy. The selection was based on spectra similarity and the most representative spectra were chosen using the Kennard Stone algorithm as implemented in the Unscrambler X 10.5 Software (CAMO Software Inc., Oslo, Norway). Total carbon (corresponding to SOC in this case as soils are acidic and do not contain any carbonates) was determined by the Dumas elemental dry combustion method using an Elementar VarioMax Cube. Soil texture analysis was done using the hydrometer method following Gee and Bauder (1986). Following the laboratory analyses, two soil samples were disqualified due to being outliers (i.e. they had unrealistically high carbon and nitrogen values). Consequently, a total of 228 samples were used for the model building.

A multivariate feed forward artificial neural network (ANN) model was developed to predict SOC and soil texture. The measured values of the soil properties from the laboratory analyses used to fit the models were split into training and validation sets using k-fold cross-validation to assess prediction accuracy of the model predictions on unseen data. Ten approximately equal-sized folds were created. Each fold was used as a calibration set and the other nine sets as validation. The procedure was repeated until each of the ten folds had been used once as a validation set. For more details on model calibration see Nyawasha et al. (2024b). After successfully calibrating the model, it was used to make predictions on the rest of the dataset, i.e. on 1 112 soil samples. The RMSE and R^2 values for the successful model were 3.09 g C kg^{-1} and 0.89, 7 % and 0.77, 5 % and 0.73, 3 % and 0.57 for SOC, sand, clay and silt, respectively (Fig. S1) (Nyawasha et al., 2024b).

2.4. Soil data processing

Using the predicted soil fractions, soil texture classes were assigned based on the USDA classification system using the *soiltexture* package (Moeys, 2018) in R (R Core Team, 2023). Distance from the homestead was calculated using the *geosphere* package with the *distGeo* function (Hijmans, 2022). Based on these distances, fields were classified as homefields for areas within 50 m from homestead, midfields for those within 50 – 100 m and outfields for areas beyond 100 m (Zingore et al., 2007a). This classification was validated by cross-referencing with actual field classes given by the farmers during the field visits.

The SOC stocks were calculated using the following equation:

$$\begin{aligned} SOCstocks\left(Mg\ C\ ha^{-1}\right) = {} & SOCcontent\left(mg\ C\ g^{-1}\right) \\ & \times\ Bulkdensity\left(g\ cm^{-3}\right) \times (1 - coarsefraction) \\ & \times\ thickness(cm) \times 10 \end{aligned} \tag{1}$$

The equivalent soil mass approach is often recommended when comparing SOC stocks in an experiment established on a given soil type with different treatments to account for possible treatment changes in soil bulk density. Our study comprises, however, very different soil types with varying stoniness, making it very difficult to define a reference soil mass for the different soil types. The fixed depth approach was therefore preferred, as commonly done in studies at landscape level.

Total SOC concentration and bulk density from AfSIS at a 30 m spatial resolution were downloaded (Hengl et al., 2021) and stone content data was accessed from https://zenodo.org/records/4090927. The soil predicted property values were extracted from the AfSIS data using the coordinates corresponding to the centre of each sampled field. The AfSIS maps were available for 0–20 cm and 20–50 cm depth increments, so the comparison was made for the 0–20 cm depth only as this was the only depth overlapping with our samples. The SOC stocks were calculated using equation (1) above.

Recent land use and cover maps developed for ward 28 for 2002, 2007, 2013, 2018 and 2023 (Girod, 2023) were used to estimate SOC stocks per land use. These maps have been derived from Landsat images at 30 m spatial resolution and a ground database, using a pixel-based Random Forest classification algorithm. The maps are available on the CIRAD repository (Girod et al., 2024). Eight land use classes, i.e. croplands, forests, shrublands, grasslands, vleis, urban, mineral soils (representing rock outcrops) and water are considered. The global accuracy was 0.93 in 2002, 0.91 in 2007, and 0.90 for 2013, 2018 and 2023. Since it was difficult to differentiate other land uses such as fallow fields and gardens using the remote sensing data, these classes were excluded from the maps for this section of the analysis.

From each of the maps, the total area covered by each land use was calculated and this was subsequently used to determine its share of total area in the ward. The total area under each land use was multiplied by the average SOC stocks derived from either measured or AfSIS values for each land use in the previous section, to obtain the aggregated stocks at ward scale. This was done for each of the five years. This method assumes that SOC stocks were at equilibrium in each land use. With this assumption, changes in SOC stocks at landscape scale were driven solely by changes in the share of different land uses.

To analyse the annual percent change in SOC stocks, firstly we used two years, 2002 and 2023 and their corresponding aggregated SOC stocks as calculated by either the measured values or the AfSIS derived values. We specified the intermediary years (2002, 2007, 2013, 2018 and 2023) and used linear interpolation to estimate stocks for these years for each of the land uses as well as for the total landscape. We fitted a linear regression model to the data, extracting the coefficients to obtain the regression equation.

2.5. Statistical analyses

The data was analysed using linear mixed models to determine the variables that influence SOC stocks. We used the *lme4* package in R (Bates et al., 2015). Two models were created, one with all the land use types together and a second one using only croplands. The variable of interest, SOC concentration, bulk density or stock, was treated as a linear form of fixed and random effects. Several combinations of the fixed and random effects were tested, and the final best model was selected based on the lowest Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values. For the general model with all land use types, the fixed effects were land use, soil type, soil depth, and texture class, with soil type interaction with land use, soil type interaction with texture class, whilst the village, and field identity (ID) nested within sample ID were used as the random effects. For the model specific to croplands, the fixed effects were soil type, soil depth, texture class, field type and soil type interaction with field type, whilst the village and field identity (ID) nested within farmer ID were used as the random effects. P-values were calculated using the likelihood ratio tests of the full model with the fixed effect in question against the model without the fixed effect.

An analysis of variance (ANOVA) was carried out to determine the effects of different factors on SOC stocks. A *post-hoc* Least Significant difference (LSD) was done to investigate the pairwise differences using the *lsmeans* function in the *emmeans* package (Lenth, 2024) at 5 % significance level.

3. Results

3.1. Drivers of SOC stocks

The model with all the land use classes showed that soil type, land use, soil depth and texture class significantly ($p < 0.05$) influenced SOC stocks. Additionally, significant interactions were found between soil type and texture class and between soil type and land use (Table 1). The model with croplands showed significant effects of soil type, soil depth and texture class as well as a significant interaction between soil type and field type (Table 2). The field type (homefield vs midfield vs outfield) had no significant effect on SOC stocks; however, it showed an effect with interaction with soil type, driven by black clay soil (Fig. S2).

3.2. SOC concentration and bulk density across different land uses

Vleis, grasslands, and gardens had significantly higher SOC concentrations than other land uses, with average values of 14.20 ± 0.78, 12.10 ± 1.46 and 12.4 ± 0.47 g C kg^{-1} respectively. SOC concentrations in croplands and fallows were 4.77 ± 0.12 and 4.09 ± 0.33 g C kg^{-1} respectively, while shrublands had a SOC concentration of 4.72 ± 0.18 g C kg^{-1} (Fig. S3). Soil bulk density was generally below 1.5 g cm^{-3} across all land use types (Fig. S2). Specifically, vleis, grasslands and gardens had average bulk densities of 1.26 ± 0.02, 1.29 ± 0.05 and 1.27 ± 0.01 g cm^{-3} respectively. Both croplands and fallows had average bulk densities of 1.38 ± 0.01 and 1.40 ± 0.02 g cm^{-3} whereas bulk density in shrublands was 1.34 ± 0.01 g cm^{-3}. The model showed that soil type, land use, soil depth and texture class significantly ($p < 0.05$) influenced total C. Additionally, significant interactions were found between soil type and texture class and between soil type and land use (Table S1). Similarly, the model showed that land use, and soil texture class had significant effects on bulk density (Table S3).

3.3. SOC stocks under different land uses

SOC stocks at 0–40 cm were significantly higher on black clay 66.9 ± 2.30, followed by red clay 36.1 ± 2.04 and lastly sandy soil 25.5 ± 0.59. Across all soil types in the 0–40 cm layer, gardens had SOC stocks of 68.6 ± 3.16 Mg C ha^{-1} on black clay soils; 34.8 ± 1.60 Mg C ha^{-1} on red clay soils; and 22.0 ± 0.35 Mg C ha^{-1} on sandy soils. Across all soil types vleis had the highest SOC stocks, followed by gardens (56.4 ± 2.34 Mg C ha^{-1}) and then grasslands (53.1 ± 6.18 Mg C ha^{-1}). Vleis on black clay had 67.9 ± 3.55 Mg C ha^{-1}, with grasslands on sandy soil having 50.1 ± 6.24 Mg C ha^{-1}. In croplands, black clay had significantly

Table 1
Summary statistics of ANOVA for SOC stocks (Mg C/ha) under all land uses. The best linear mixed effect model had soil type, land use, soil texture class, soil depth, soil type interaction with land use and soil type interaction with soil texture class as fixed effects, with village, and field ID nested within sample identity (ID) as random effects. Variance and standard deviation (SD) of random effects, and chi-square (χ^2), degrees of freedom (df) and significance (P-value) of fixed effects are shown.

Random effect	Variance	SD	
Sample ID:Field ID	20.20	4.49	
Sample ID	8.54	2.92	
Village	0.0	0.0	
Residual	23.80	4.88	
Fixed effects	χ^2	**df**	**P-value**
Soil type	89.40	2	2.2e^{-16}
Land use	250.21	7	2.2e^{-16}
Soil texture class	108.28	4	2.2e^{-16}
Soil depth	365.70	1	2.2e^{-16}
Soil type:Land use	26.28	7	0.0004480
Soil type:soil texture class	23.15	6	0.0007471

Table 2
Summary statistics of ANOVA for SOC stocks (Mg C/ha) under croplands only. The linear mixed effect model had soil type, soil texture class, soil depth, soil type interaction with field type as fixed effects, with village and field identity (ID) nested within farmer ID as random effects. Variance and standard deviation (SD) of random effects, and chi-square (χ^2), degrees of freedom (df) and significance (P-value) of fixed effects are shown.

Random effect	Variance	SD	
Farmer ID:Field ID	5.51	2.34	
Farmer ID	2.93	1.71	
Village	0.61	0.78	
Residual	13.64	3.69	
Fixed effects	χ^2	df	P-value
Soil type	72.00	2	$2.2e^{-16}$
Soil depth	221.87	1	$2.2e^{-16}$
Soil texture class	51.30	4	$1.926e^{-10}$
Soil type:Field type	29.97	7	$9.630e^{-05}$

higher stocks (45.2 ± 6.35 Mg C ha^{-1}), and red clay (40.2.9 ± 2.72 Mg C ha^{-1}) than sand (22.0 ± 0.35 Mg C ha^{-1}). On shrublands and forests, SOC stocks were 26.7 ± 0.96 and 25.1 ± 1.50 Mg C ha^{-1} on red clay soils, and 22.2 ± 0.68 and 21.7 ± 0.68 Mg C ha^{-1} on sandy soils, respectively (Fig. 3). The clay + silt percentage had a significant effect on SOC concentration, particularly on black clay soils (Fig. S4) where there was an increase in SOC concentration with an increase in the clay + silt percentage.

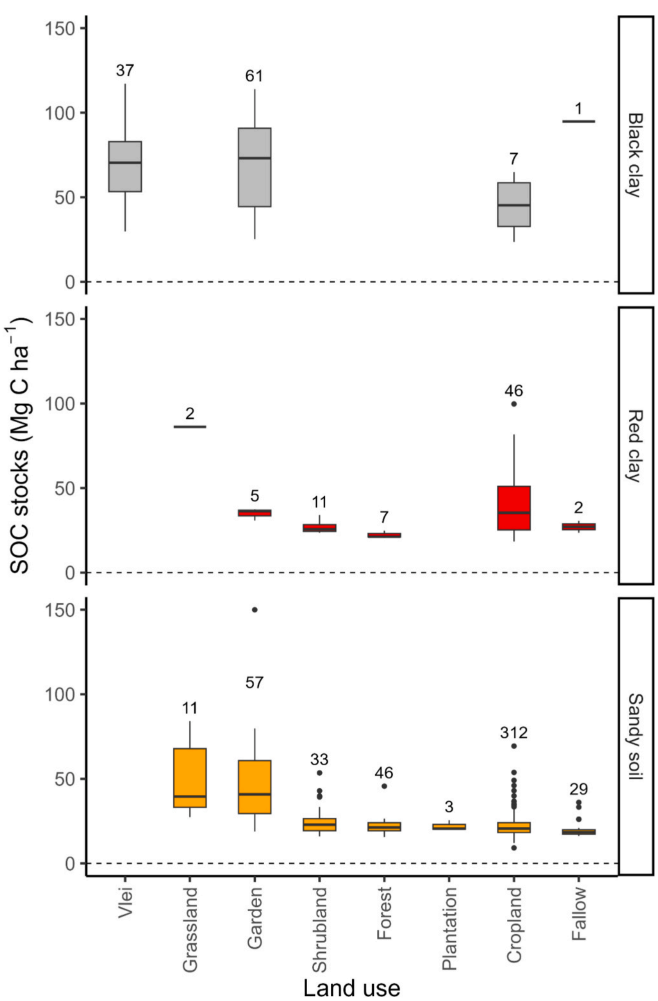

Fig. 3. SOC stocks (Mg C ha ^{1}) at 0–40 cm for the different land uses and soil types. The numbers above each boxplot represent the number of samples.

3.4. SOC stocks in croplands

Results from the linear mixed model indicate that soil type significantly influenced SOC stocks in croplands (Table 2). Black clay soils had a significantly higher SOC stock of 42.3 ± 3.47 Mg C ha^{-1} followed by red clay soils at 40.2 ± 1.42 Mg C ha^{-1} while sandy soils had a much lower stock of 22.0 ± 0.49 Mg C ha^{-1} (Fig. 4). A similar trend was observed for the soil texture classes, with the highest values for clay (52.8 ± 4.04 Mg C ha^{-1}), followed by sandy clay loam (45.7 ± 4.52 Mg C ha^{-1}), sandy loam (29.1 ± 1.02 Mg C ha^{-1}), sand 27.6 ± 2.86 and loamy sand (21.7 ± 0.58 Mg C ha^{-1}). There were no significant differences observed between field types (Fig. 4).

3.5. Comparison of measured and AfSIS SOC data

The measured SOC concentration in the 0–20 cm soil layer was more than double that of the AfSIS data in vleis (16.94 ± 0.57 vs 6.61 ± 0.57 g C kg^{-1}), grasslands (13.78 ± 0.96 vs 6.85 ± 0.96 g C kg^{-1}) and gardens (14.55 ± 0.31 vs 6.18 ± 0.31 g C kg^{-1}) (Fig. 5A). In contrast, the measured SOC concentration was slightly lower than the AfSIS values in croplands (5.56 ± 0.18 vs 5.95 ± 0.18 g C kg^{-1}), shrubland (5.26 ± 0.52 vs 6.63 ± 0.52 g C kg^{-1}) and fallow (4.40 ± 0.61 vs 5.65 ± 0.61 g C kg^{-1}). The mean soil bulk densities from AfSIS were systemically higher than the measured soil bulk densities regardless of land use with lowest ranging from 1.44 ± 0.01 to 1.48 ± 0.01 g cm^{-3} (Fig. 5B). In contrast, the lowest measured bulk density value was 1.21 ± 0.01 while the highest was 1.42 ± 0.02 g cm^{-3}, with gardens and vleis showing the lowest average value at 1.21 ± 0.01 and 1.24 ± 0.02 g cm^{-3} respectively. The range of variability for AfSIS was systemically low. The proportion of coarse fraction was greater in the AfSIS data compared to the measured values (Fig. S5).

The measured SOC stocks in the 0–20 cm soil layer were greater than those predicted by AfSIS (Fig. 5C) in vleis, (39.9 ± 1.10 vs 19.0 ± 1.08 Mg C ha^{-1}), grasslands (29.2 ± 1.90 vs 19.7 ± 1.83 Mg C ha^{-1}) and gardens (32.1 ± 0.62 vs 17.6 ± 0.60 Mg C ha^{-1}). In contrast, for the other land uses, the measured SOC stocks were significantly lower than those predicted by AfSIS, including croplands (14.5 ± 0.35 vs 17.0 ± 0.35 Mg C ha^{-1}), forest (12.9 ± 0.91 vs 18.7 ± 0.91 Mg C ha^{-1}) and shrublands (14.4 ± 1.0 vs 18.9 ± 1.0 Mg C ha^{-1}).

3.6. Change in SOC stocks with time at landscape scale

The four largest land uses by proportion of the total area as of 2023 are shrublands (0.46), croplands (0.24), forests (0.15) and vlei (0.13). Since 2002, the area of these land uses has been slightly fluctuating, with shrublands steadily increasing each year (Fig. 6). Forests and vleis remained largely unchanged. A similar pattern was observed for croplands peaking at 0.27 in 2008, whereas the other areas remained relatively stable (Fig. 6).

The total SOC stock computed from ground measurement for Ward 28 was above 150 000 Mg C, whereas for the total SOC stock estimated from AfSIS data was approximately 120 000 Mg C, indicating that AfSIS data underestimates total SOC stocks by 20 %. The measured total SOC stocks showed a declining trend from 2002 to 2023, although it was not significant (Fig. 7A). Conversely, the AfSIS total SOC stocks remained constant through the years from 2002 to 2023 (Fig. 7B).

4. Discussion

4.1. SOC stocks across different land uses

Our results indicate that soil type and land use are key indicators of SOC stocks in the study area. Specifically, black clay soils had significantly larger stocks than red clay soils, which in turn had significantly larger stocks than sandy soils. There was also a significant interaction between soil type and soil texture class as soils under sandy clay loam

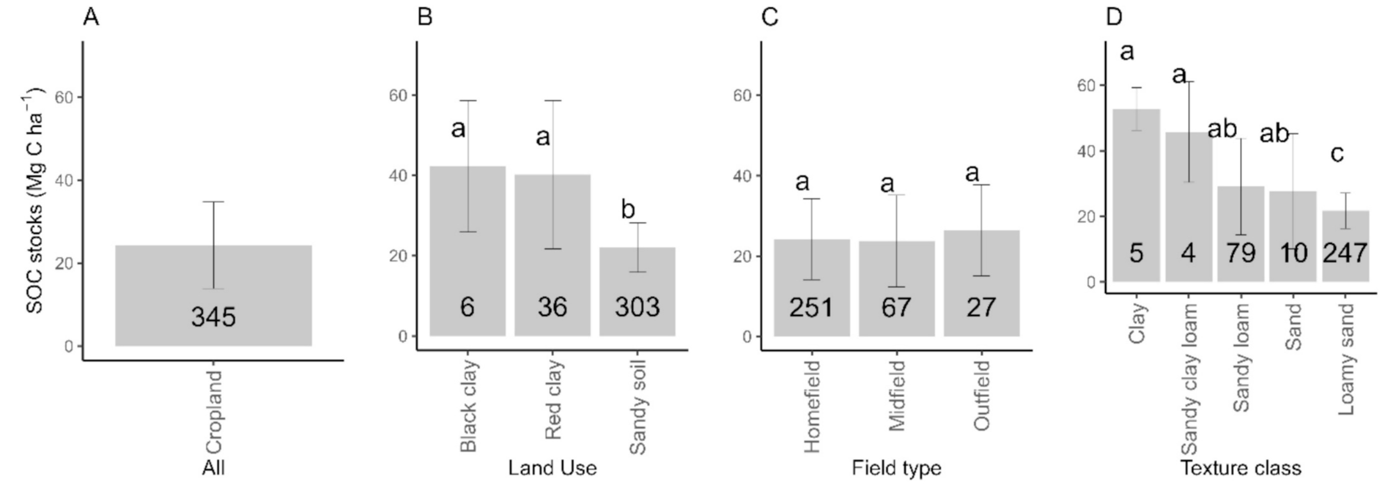

Fig. 4. Mean SOC stocks (Mg C ha ^{1}) at 0–40 cm in croplands for A), all samples, B) by soil type, C) by field type and D) by soil texture class. Numbers represent the number of samples; error bars show standard deviations. Different letters denote that values are significantly different.

had higher stocks than loamy sand texture class. Similar observations were made for soils in Senegal, were they reported that SOC stocks were significantly correlated with soil texture (Malou et al., 2021). This could be attributed to the higher clay content found in black and red soils compared to sandy soils. Clay content affects SOC stabilization by facilitating the binding of organic matter particles, resulting in the formation of soil aggregates (Six et al., 2002; Chivenge et al., 2007; Nyamadzawo et al., 2007; Nyamangara et al., 2014), and physical protection of organic matter by clays reduces the rate of SOM decomposition (Dalal and Chan, 2001; Six et al., 2002; Xiao, 2015).

An interaction between soil type and land use was evident, with vleis, grasslands and gardens having the highest SOC concentrations and stocks compared to croplands, forests and shrublands. Vleis are mainly located on black clay soils, often in lower-lying areas characterized as seasonal "grasslands", which typically have a higher clay content. Their location in lower positions allows them to act as a sink of organic carbon, where anoxic conditions lead to low rates of decomposition, thus ensuring the long-term persistence of SOC (Whitlow, 1985; Grant, 1995; Nyamadzawo et al., 2015). Grasslands and wetlands are known to hold large amounts of SOC, and their conversion should be avoided as much as possible to prevent further carbon emissions associated with the AFOLU sector (Goldstein et al., 2020; Beillouin et al., 2023). In gardens, in addition to clay content, management practices contribute to the higher stocks. SOC stocks in gardens located on sandy soils were similar to grasslands on sandy soils (Fig. 3), suggesting that effective management practices, such as the application of organic residues and manure probably also play a significant role in enhancing SOC stocks in gardens (Campbell et al., 1998). Gardens are essential for income generation and livelihoods, although they have been overlooked in many studies (Zingore et al., 2007b; Masvaya et al., 2010; Dunjana et al., 2012), with focus being placed on croplands. Due to the increasing uncertainties from erratic rains and frequent droughts linked to climate change many farmers are increasingly relying on gardens to cultivate maize and vegetables for household consumption and for sale (Nyamadzawo et al., 2015). Most gardens in our study are located near streams, where clay and nutrient accumulation occurs via sedimentation from erosion upslope (Zingore, 2006), or within homestead enclosures, close to water sources, allowing for continued access to water, which can boost productivity. Additionally, gardens are near the homestead and are fenced to keep livestock out, enabling the retention of crop residues to be used as manure for the next crop. We consistently observed high SOC stocks in gardens, regardless of soil type, highlighting the importance of management practices that could potentially be replicated to croplands. However, such management practices may not be possible for larger crop fields, as the volume of organic resources required may not be sufficient to build and maintain SOC stocks (Cardinael et al., 2022; Assogba et al., 2023).

In comparison to gardens and grasslands, SOC stocks were significantly lower in forests, shrublands and croplands, although soil type was an important factor in these differences. SOC stocks in croplands ranged between 14.4 – 20 Mg C ha $^{-1}$, and the majority of the croplands in the study area were on sandy soils (Nyamapfene, 1991; Nyamangara et al., 2014). These soils have been subject to continuous cropping with low external inputs contributing to the SOC depletion (Ramesh et al., 2019). Studies have shown that use of cattle manure, a key carbon source in these systems, has been on the decline for decades due to reduced cattle ownership (Mugwira and Murwira, 1997; Masvaya et al., 2010). This decline, also observed in this study, was attributed by farmers to frequent droughts and the higher incidence of disease mostly bovine theileriosis (Manyenyeka et al., 2021), resulting in limited manure availability. Low input use has a negative impact on SOC especially on these predominantly poor soils that dominate the study area (Cardinael et al., 2022; Falconnier et al., 2023). In tropical soils, carbon inputs have been found to be the strongest predictor of SOC increase (Fujisaki et al., 2018).

Surprisingly, croplands had higher or comparable SOC stocks to shrublands and forests. This could be attributed to limited ground cover in these natural areas, as farmers collect leaf litter from these lands for use as soil amendments in croplands. In this study, we observed minimal to no ground cover in forests and shrublands. Poor rainfall distribution and low crop productivity have caused a decline in residue availability. Many farmers are resorting to forests and shrublands for organic inputs to put in their gardens and croplands. One of the functions of woodlands has been providing leaf litter, with estimates reported at 0.5 t/ha per year (Campbell et al., 1998). Although forests are expected to hold more C than croplands, particularly as litter (Mujuru et al., 2013), frequent litter removal can lead to a decline in SOC. If this practice continues, it could have a significant effect on SOC stocks. Additionally, burning of grass biomass in forests, whether naturally or by human activity, can contribute to lower topsoil organic matter (Chidumayo and Kwibisa, 2003). We did not observe or collect data on burning effects, thus we cannot conclude that it contributed to low SOC stocks. It is important to note that SOC stocks in forests and shrublands found on sandy soils in our study (20.5 Mg C ha^{-1}) aligned with values found by other studies in the region (Ryan et al., 2011).

4.2. No SOC gradients with distance to homesteads in croplands

No SOC gradients were observed between the different field types in our study contrary to previous reports from this area (Zingore et al.,

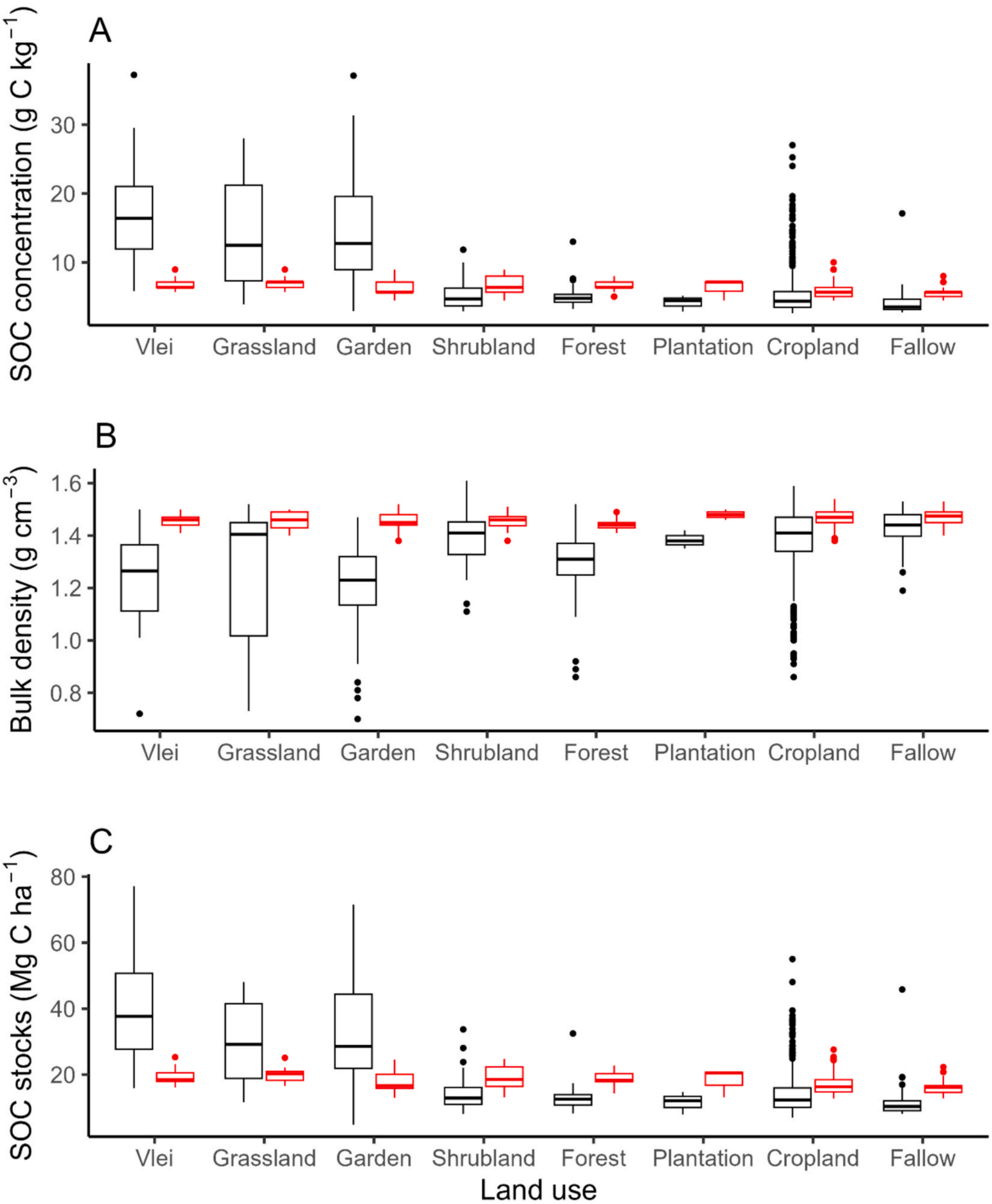

Fig. 5. Comparison of A) SOC concentration (g C kg^{-1}), B) soil bulk density (g cm^{-3}) and C) SOC stocks (Mg C ha ^{1}) in the 0–20 cm soil layer between measured (black) and AfSIS data (red).

2007b; Masvaya et al., 2010; Chikowo et al., 2014). It is important to highlight that in these studies, the authors looked at other soil parameters such as total nitrogen and cation exchange capacity in their assessment. Thus, the existence of a soil fertility gradient was attributed to the preferential application of scarce resources to fields closest to homesteads at the expense of outfields which are located further away. The preferential application of nutrient resources to homefields was also reported in Senegal (Malou et al., 2021) where it was shown that fields closest to the homestead received more organic amendments. Our results align with those of Namatsheve et al. (2021), who also found no soil fertility gradient between homefields and outfields, despite testing for other soil parameters other than SOC. These authors suggest that small land holdings may allow for more uniform application of resources across all fields and noted that some outfields were left fallow during some years, potentially helping to restore their fertility. Similarly, van Apeldoorn et al. (2014) also reported no SOC gradient at village scale in the same area, in contrast to what was previously reported in this area (Rufino et al., 2011; Zingore et al., 2011). Although they raised concerns about their methodology as a possible reason for this lack of gradient. Based on our findings, we would like to posit that there is general decline in available organic resources (cattle manure and crop residues), forcing a change in land management practices. In turn, farmers are leaving other fields fallow during some years which could restore their fertility. Consequently, farmers could also be focusing all their resources on homefields that are perceived to be “more fertile” such that this continuous cropping with limited resource input could be exacerbating nutrient decline in the homefields.

4.3. Temporal SOC change analysis

We found that the most important land uses by total area were shrublands, croplands, vleis and forests, with only marginal changes in

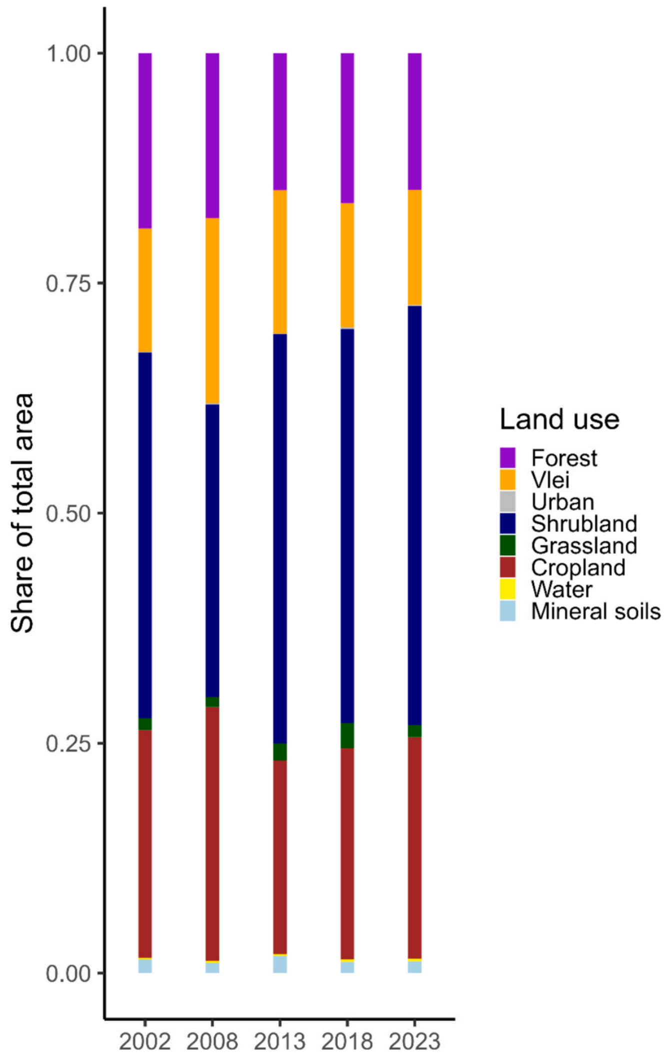

Fig. 6. Share of the area per major land use type for Murehwa district.

these land use areas over the course of 20 years. Notably, forest areas declined, with a corresponding increase in shrublands an observation confirmed by another study in the same area (Mataruse et al., 2021). Forest decline has been attributed to a combination of factors driven primarily by human activity and climate change. Heavy reliance on firewood for energy and use of branches and wooden poles for fencing off gardens has led to severe forest degradation. Moreover, with frequent droughts there's a reduction in soil moisture which can lead to death of natural forests (Mataruse et al., 2022). The transition from forests to shrublands represents a significant change in land area which can lead to alterations in the ecosystem dynamics. Land use change can have a significant impact in SOC accumulation since loss of forest cover can cause carbon losses (Beillouin et al., 2023). Shrublands have lower biomass and subsequently reduced carbon inputs which can impact SOC accumulation. Measurements of above ground carbon would have provided more insights to complement our findings, unfortunately this was beyond the scope of our study. The study of both could provide a more comprehensive understanding of the carbon dynamics, and subsequently allow an accurate evaluation of the sequestration potential of the area including both soils and biomass. This is critical since studies across southern Africa have shown that aboveground carbon is close to 30 % of the total carbon stored in an ecosystem (Frost, 1996; Ryan et al., 2011; Ribeiro et al., 2013). Although deforestation and burning have been found to remove nutrients from the system, luckily, most trees have been found to resprout from rootstocks after being cut or burnt (Chidumayo, 1997; Walker and Desanker, 2004). The total aggregated stocks showed a slight decline in value for the total landscape at ward scale, which could indicate a loss of SOC over time. However, this decline was not significant enough to result in variations of landscape stocks. High SOC stocks found in vleis and grasslands in the region should be preserved along with forests and shrublands that also contain large amounts of carbon in their biomass (Cook-Patton et al., 2021). Degraded croplands could be restored for example with agroforestry and conservation agriculture (Corbeels et al., 2019). In terms of climate change mitigation, changes in land use at landscape level can potentially undermine any efforts to enhance SOC in the croplands. Croplands form the major area, but with the lowest SOC stocks, therefore more sustainable farming practices that increase soil organic matter need to be adopted to enhance SOC stocks (Lal, 2004). In this context, a better integration of livestock with cropping systems seems crucial to enhance carbon and nutrient fluxes from grazing lands to croplands (Rufino et al., 2007).

4.4. Measured SOC stocks and AfSIS maps

Our findings in this study were consistent with other observations showing that data from digital soil maps tend to underestimate large SOC values whilst overestimating low ones (Gray et al., 2009; Mulder et al., 2016; Djagba et al., 2022). Measured stocks were largest under vleis, grasslands and gardens, and these values were underestimated by AfSIS geospatial data, whereas the SOC stocks for the other land uses with lower measured values were overestimated by AfSIS geospatial maps. This pattern was clear at the ward scale as total computed stocks from measured data were 20 % higher than those for AfSIS geospatial soil maps. In their study, Ewing et al. (2021) reported that AfSIS underestimated SOC stocks in Malawi, attributing this to the mismatch between remotely sensed resolution and sub-hectare scale of management in smallholder farming systems. We posit that the limited number of sampling points for tropical and wetland soils in Africa may also play a role in this discrepancy (Hengl et al., 2017; Djagba et al., 2022). Increasing sampling density could enhance accuracy in future assessments. Additionally, the environmental covariates used to prepare AfSIS maps might not match those of our study area, which could introduce inaccuracies (Djagba et al., 2022). In another study covering Kenya and Tanzania, Berazneva et al. (2018) found that AfSIS data showed less variation than measured soil data, although the data patterns were similar. In our study, the AfSIS mapped SOC stocks ranged between 16 – 19 Mg C ha $^{-1}$ whereas measured data showed more variation, especially between contrasting land uses like vleis and croplands. Despite this reduced variation, AfSIS remains valuable at larger spatial scales for planning and policy decisions. Given the high costs of soil surveys and analysis in heterogeneous smallholder farming systems across SSA, AfSIS maps provide an accessible resource to bridge data gaps.

These results highlight the critical influence of soil type and land use on SOC dynamics. However, it is crucial to acknowledge several limitations in the study that warrant further in-depth studies. Firstly, the use of measured SOC stocks per land use type from the field study to assess temporal dynamics of SOC stocks provides only a coarse estimation of the impact of land use change. Other factors, including soil type, climate and management, influence SOC dynamics and should be accounted for to accurately quantify the absolute change in SOC stocks at the landscape scale. Secondly, although our study demonstrated the importance of soil type and texture in SOC stocks distribution, it is important to mention that at landscape level, clayey soils are marginal, with sandy soils being dominant. This pattern aligns with observations across most of the smallholder farming communities in Zimbabwe (Nyamapfene, 1991; Van Apeldoorn et al., 2014). The absence of detailed soil type maps for the study area limits our ability to effectively incorporate this variable into the analysis. Other relevant factors, such as rainfall and elevation, could contribute to SOC variability, but given the very small study area (3 × 6 km), we assume these factors exert a minor influence

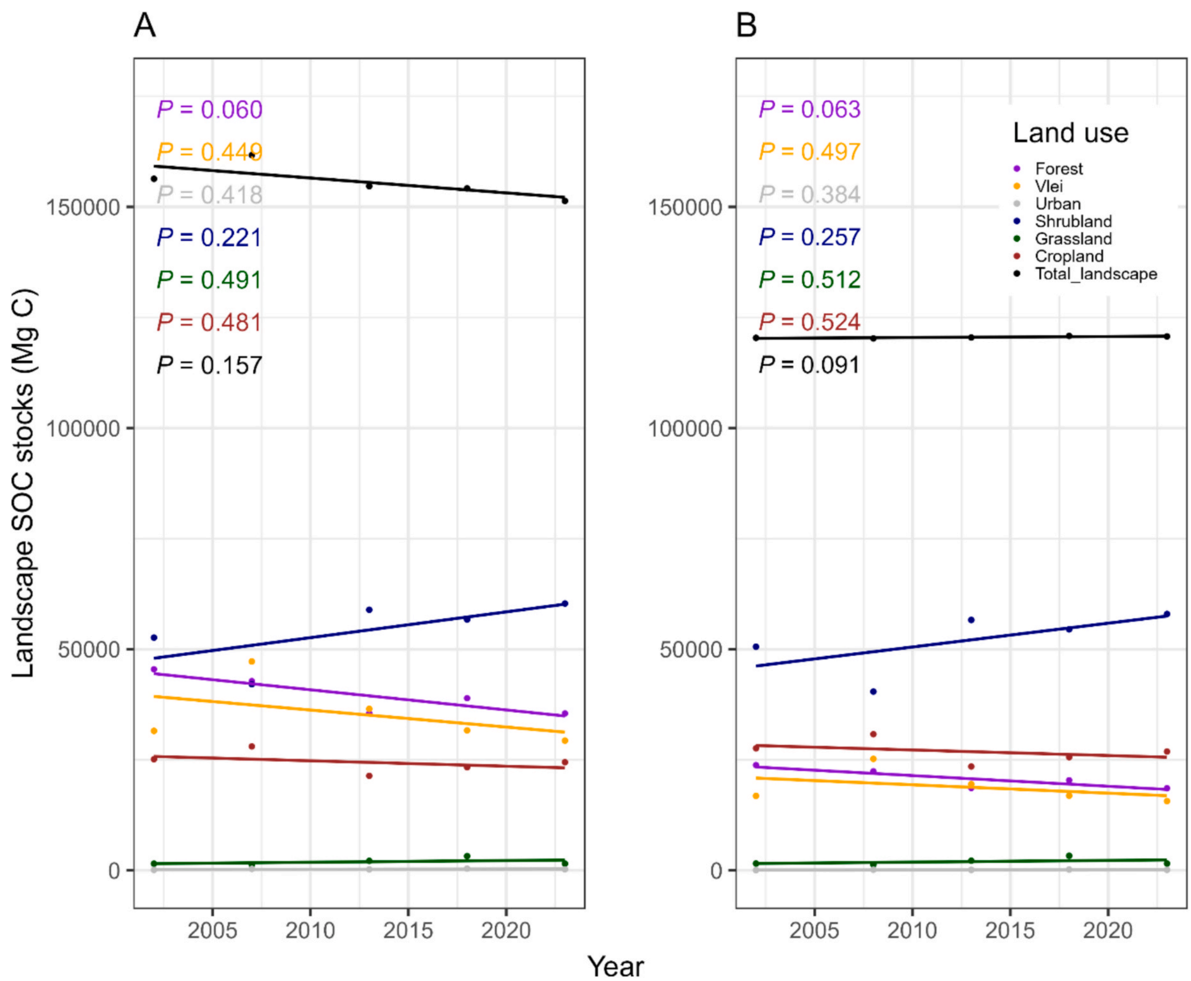

Fig. 7. Regression analysis results showing A) measured and B) AfSIS derived aggregated SOC stocks (Mg C) at 0–20 cm for Ward 28 in Murehwa district. P values were derived from the polynomial regression indicating the statistical significance of the relationship between stocks and year.

on SOC variability within the study boundaries. Overall, this study provides valuable insights into understanding SOC dynamics within smallholder farming areas.

5. Conclusion

We measured SOC stocks in a subhumid smallholder region of Zimbabwe across eight major land uses, croplands, vleis, grasslands, gardens, forests, shrublands, fallows, and plantations under three main soil types, black clay, red clay and sandy soils and two depths 0–20 and 20–40 cm. Furthermore, soil predicted property values for total SOC concentration, bulk density and stone content were also extracted from the AfSIS data for each sampled field and a comparison was made with the actual measured values. The main findings are:

- Stocks were significantly larger on black clay, followed by red clay and finally sandy soils. Clay content and texture class were key in explaining distribution of stocks as soils with high clay percent showed larger stocks.
- Vleis, gardens and grasslands were the land uses with significantly larger SOC stocks than the other land uses, across all the soil types.
- Gardens, whether on soils with high clay such as black soils or low clay as in sandy soils, had higher SOC stocks.
- A comparison of measured data against AfSIS geospatial data showed that the later underestimated larger SOC stocks from vleis, gardens and grasslands, however it overestimated the smaller stocks found under croplands, forests, shrublands, plantations and fallows. The AfSIS data underestimated by 20 % SOC stocks at landscape level and showed less variation than the measured data.

Overall, we conclude that soil type and land use are critical drivers of SOC stocks. Management practices used for gardens are very important in building and maintaining SOC for sandy soils which tend to be prone to rapid decomposition and loss of organic matter. Our study illustrates the necessity to acquire more field data in sub-Saharan Africa to reduce uncertainties associated with using geospatial data from AfSIS.

CRediT authorship contribution statement

Rumbidzai W. Nyawasha: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Gatien N. Falconnier:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Methodology, Investigation, Formal analysis, Conceptualization. **Pierre Todoroff:** Writing – review & editing, Supervision, Methodology, Investigation. **Alexandre M.J.-C. Wadoux:** Writing – review & editing, Visualization, Validation, Methodology, Investigation, Formal analysis, Conceptualization. **Regis Chikowo:** Writing – review & editing, Supervision, Project administration, Funding acquisition. **Adrien Coquereau:** Writing – review & editing, Formal analysis. **Louise Leroux:** Writing – review & editing, Visualization, Formal analysis. **Camille Jahel:** Writing – review & editing, Formal analysis. **Marc Corbeels:** Writing – review & editing, Writing – original draft, Supervision, Resources, Project administration, Funding acquisition. **Rémi**

Cardinael: Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: [At least one of the (co–)authors is a member of the editorial board of CATENA. Other authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.].

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.catena.2025.108843.

Data availability

Data for "Understanding drivers of soil organic carbon stocks at village scale in a sub-humid region of Zimbabwe" (Original data) ((Dataverse)) Nyawasha et al., (2024a).

References

Abegaz, A., Tamene, L., Abera, W., Yaekob, T., Hailu, H., Nyawira, S.S., Da, M., Sommer, R., 2020. Soil organic carbon dynamics along chrono-sequence land-use systems in the highlands of Ethiopia. Agric. Ecosyst. Environ. 300, 106997. https://doi.org/10.1016/j.agee.2020.106997.

Assogba, G.G.C., Berre, D., Adam, M., Descheemaeker, K., 2023. Can low-input agriculture in semi-arid Burkina Faso feed its soil, livestock and people? Eur. J. Agron. 151, 126983. https://doi.org/10.1016/j.eja.2023.126983.

Bates, D., Maechler, M., Bolker, B., Walker, S., 2015. Fitting Linear Mixed-Effects Models Using lme4. J. Stat. Softw. 67, 1–48. https://doi.org/10.18637/jss.v067.i01.

Beillouin, D., Corbeels, M., Demenois, J., Berre, D., Boyer, A., Fallot, A., Feder, F., Cardinael, R., 2023. A global meta-analysis of soil organic carbon in the Anthropocene. Nat. Commun. 14, 1–10. https://doi.org/10.1038/s41467-023-39338-z.

Berazneva, J., McBride, L., Sheahan, M., Güereña, D., 2018. Empirical assessment of subjective and objective soil fertility metrics in east Africa: Implications for researchers and policy makers. World Dev. 105, 367–382. https://doi.org/10.1016/j.worlddev.2017.12.009.

Campbell, B., Frost, P., Kirchmann, H., Swift, M., 1998. A Survey of Soil Fertility Management in Small-Scale Farming Systems in North Eastern Zimbabwe. J. Sustain. Agric. 11, 19–39.

Cardinael, R., Umulisa, V., Toudert, A., Olivier, A., Bockel, L., Bernoux, M., 2018. Revisiting IPCC Tier 1 coefficients for soil organic and biomass carbon storage in agroforestry systems. Environ. Res. Lett. 18, 124020. https://doi.org/10.1088/1748-9326/aafce0.

Cardinael, R., Guibert, H., Kouassi Brédoumy, S.T., Gigou, J., N'Goran, K.E., Corbeels, M., 2022. Sustaining maize yields and soil carbon following land clearing in the forest–savannah transition zone of West Africa: Results from a 20-year experiment. F. Crop. Res. 275. https://doi.org/10.1016/j.fcr.2021.108335.

Chidumayo, E.N., Kwibisa, L., 2003. Effects of deforestation on grass biomass and soil nutrient status in miombo woodland. Zambia. Agric. Ecosyst. Environ. 96, 97–105. https://doi.org/10.1016/S0167-8809(02)00229-3.

Chidumayo, E.N., 1997. Miombo ecology and management: An introduction. IT Publications in association with the Stockholm Environment Institute, London, U.K.

Chikowo, R., Zingore, S., Snapp, S., Johnston, A., 2014. Farm typologies, soil fertility variability and nutrient management in smallholder farming in Sub-Saharan Africa. Nutr. Cycl. Agroecosystems 100, 1–18. https://doi.org/10.1007/s10705-014-9632-y.

Chivenge, P.P., Murwira, H.K., Giller, K.E., Mapfumo, P., Six, J., 2007. Long-term impact of reduced tillage and residue management on soil carbon stabilization: Implications for conservation agriculture on contrasting soils. Soil Tillage Res. 94, 328–337. https://doi.org/10.1016/j.still.2006.08.006.

Chivenge, P., Vanlauwe, B., Six, J., 2011. Does the combined application of organic and mineral nutrient sources influence maize productivity? A meta-analysis. Plant Soil 342, 1–30. https://doi.org/10.1007/s11104-010-0626-5.

Cook-Patton, S.C., Drever, C.R., Griscom, B.W., Hamrick, K., Hardman, H., Kroeger, T., Pacheco, P., Raghav, S., Stevenson, M., Webb, C., Yeo, S., Ellis, P.W., 2021. Protect, manage and then restore lands for climate mitigation. Nat. Clim. Chang. 11, 1027–1034. https://doi.org/10.1038/s41558-021-01198-0.

Corbeels, M., Cardinael, R., Naudin, K., Guibert, H., Torquebiau, E., 2019. The 4 per 1000 goal and soil carbon storage under agroforestry and conservation agriculture systems in sub-Saharan Africa. Soil Tillage Res. 188, 16–26. https://doi.org/10.1016/j.still.2018.02.015.

Cotrufo, M.F., Lavallee, J.M., 2022. Chapter One - Soil organic matter formation, persistence, and functioning: A synthesis of current understanding to inform its conservation and regeneration, in: Sparks, Donald, L. (Ed.), Advances in Agronomy. Academic Press, pp. 1–66. Doi: 10.1016/bs.agron.2021.11.002.

Dalal, R., Chan, K.Y., 2001. Soil Organic Matter in Rained Cropping Systems of Australian Cereal Belt. Aust. J. Soil Res. 39, 435–464. https://doi.org/10.1071/SR99042.

Signal Developers, 2023. signal: Signal processing. http://r-forge.r-project.org/projects/signal/.

Djagba, F.J., Johnson, J.-M., Saito, K., 2022. Can soil fertility properties in rice fields in sub-Saharan Africa be predicted by digital soil information? A case study of AfSoilGrids250m. Geoderma Reg. 30, e00563. https://doi.org/10.1016/j.geodrs.2022.e00563.

Dunjana, N., Nyamugafata, P., Shumba, A., Nyamangara, J., Zingore, S., 2012. Effects of cattle manure on selected soil physical properties of smallholder farms on two soils of Murewa. Zimbabwe. Soil Use Manag. 28, 221–228. https://doi.org/10.1111/j.1475-2743.2012.00394.x.

Dutta, S., Chakraborty, S., Goswami, R., Banerjee, H., Majumdar, K., Li, B., Jat, M.L., 2020. Maize yield in smallholder agriculture system-An approach integrating socio-economic and crop management factors. PLoS One 15, 1–23. https://doi.org/10.1371/journal.pone.0229100.

Ewing, P.M., TerAvest, D., Tu, X., Snapp, S.S., 2021. Accessible, affordable, fine-scale estimates of soil carbon for sustainable management in sub-Saharan Africa. Soil Sci. Soc. Am. J. 85, 1814–1826. https://doi.org/10.1002/saj2.20263.

Ewing, P.M., Tu, X., Runck, B.C., Nord, A., Chikowo, R., Snapp, S.S., 2022. Smallholder farms have and can store more carbon than previously estimated. Glob. Chang. Biol. 00, 1–13. https://doi.org/10.1111/gcb.16551.

Falconnier, G.N., Cardinael, R., Corbeels, M., Baudron, F., Chivenge, P., Couëdel, A., Ripoche, A., Affholder, F., Naudin, K., Benaillon, E., Rusinamhodzi, L., Leroux, L., Vanlauwe, B., Giller, K.E., 2023. The input reduction principle of agroecology is wrong when it comes to mineral fertilizer use in sub-Saharan Africa. Outlook Agric. 52, 311–326. https://doi.org/10.1177/00307270231199795.

Feller, C., Albrecht, A., Blanchart, E., Cabidoche, Y.M., Chevallier, T., Hartmann, C., Eschenbrenner, V., Larre-Larrouy, M., Ndandou, J., 2001. Soil organic carbon sequestration in tropical areas. General considerations and analysis of some edaphic determinants for Lesser Antilles soils. Nutr. Cycl. Agroecosystems 61, 19–31.

Frost, P., 1996. The ecology of miombo woodlands, in: Campbell, B.M. (Ed.), The Miombo in Transition: Woodlands and Welfare in Africa. Center for International Forestry Research, Bogor, Indonesia, pp. 11–55.

Fujisaki, K., Chevallier, T., Chapuis-lardy, L., Albrecht, A., Raza, T., Masse, D., Badiane, Y., Chotte, J., 2018. Soil carbon stock changes in tropical croplands are mainly driven by carbon inputs: A synthesis. Agric. Ecosyst. Environ. 259, 147–158. https://doi.org/10.1016/j.agee.2017.12.008.

Gee, G.W., Bauder, J.W., 1986. Particle-size Analysis, in: Klute, A. (Ed.), Methods of Soil Analysis, Part 1. Physical and Mineralogical Methods-Agronomy. Agronomy Society of America/Soil Science Society of America, Madison, Wisconsin, pp. 384–411.

Giller, K.E., Tittonell, P., Rufino, M.C., Wijk, M.T. Van, Zingore, S., Mapfumo, P., Adjei-nsiah, S., Herrero, M., Chikowo, R., Corbeels, M., Rowe, E.C., Baijukya, F., Mwijage, A., Smith, J., Yeboah, E., Burg, W.J. Van Der, Sanogo, O.M., Misiko, M., Ridder, N. De, Karanja, S., Kaizzi, C., K, J., Mwale, M., Nwaga, D., Pacini, C., Vanlauwe, B., 2011. Communicating complexity : Integrated assessment of trade-offs concerning soil fertility management within African farming systems to support innovation and development. Agric. Syst. 104, 191–203. Doi: 10.1016/j.agsy.2010.07.002.

Girod, C., Coquereau, A., Nyawasha, R.W., Thanks, B., Jahel, C., Leroux, L., 2024. Land Use Maps of Murehwa District (Zimbabwe): Temporal Analysis from 2002 to 2023 Using Landsat Data. CIRAD Dataverse. https://doi.org/10.18167/DVN1/E0BP5I.

Girod, C., 2023. Landscape dynamic analysis using remote sensing in the district of Murewa in Zimbabwe. Agro ParisTech.

Goldstein, A., Turner, W.R., Spawn, S.A., Anderson-Teixeira, K.J., Cook-Patton, S., Fargione, J., Gibbs, H.K., Griscom, B., Hewson, J.H., Howard, J.F., Ledezma, J.C., Page, S., Koh, L.P., Rockström, J., Sanderman, J., Hole, D.G., 2020. Protecting irrecoverable carbon in Earth's ecosystems. Nat. Clim. Chang. 10, 287–295. https://doi.org/10.1038/s41558-020-0738-8.

Grant, P.M., 1995. Fertility of dambo soils and the related response of dambo soils to fertilizers and manure, in: Owen, R., Verbeek, K., Jackson, J., Steenhuls, T. (Eds.), Dambo Farming in Zimbabwe. University of Zimbabwe Publications, Harare, pp. 117–126.

Gray, J.M., Humphreys, G.S., Deckers, J.A., 2009. Relationships in soil distribution as revealed by a global soil database. Geoderma 309–323. https://doi.org/10.1016/j.geoderma.2009.02.012.
Guo, L.B., Gifford, R.M., 2002. Soil carbon stocks and land use change: A meta analysis. Glob. Chang. Biol. 8, 345–360. https://doi.org/10.1046/j.1354-1013.2002.00486.x.
Hengl, T., Heuvelink, G.B.M., Kempen, B., Leenaars, J.G.B., Walsh, M.G., Shepherd, K.D., Sila, A., MacMillan, R.A., De Jesus, J.M., Tamene, L., Tondoh, J.E., 2015. Mapping soil properties of Africa at 250 m resolution: Random forests significantly improve current predictions. PLoS One 10, e0125814. https://doi.org/10.1371/journal.pone.0125814.
Hengl, T., De Jesus, J.M., Heuvelink, G.B.M., Gonzalez, M.R., Kilibarda, M., Blagotić, A., Shangguan, W., Wright, M.N., Geng, X., Bauer-Marschallinger, B., Guevara, M.A., Vargas, R., MacMillan, R.A., Batjes, N.H., Leenaars, J.G.B., Ribeiro, E., Wheeler, I., Mantel, S., Kempen, B., 2017. SoilGrids250m: Global gridded soil information based on machine learning. PLoS One 12, :e0169748. https://doi.org/10.1371/journal.pone.0169748.
Hengl, T., Miller, M.A.E., Križan, J., Shepherd, K.D., Sila, A., Kilibarda, M., Antonijević, O., Glušica, L., Dobermann, A., Haefele, S.M., McGrath, S.P., Acquah, G.E., Collinson, J., Parente, L., Sheykhmousa, M., Saito, K., Johnson, J.M., Chamberlin, J., Silatsa, F.B.T., Yemefack, M., Wendt, J., MacMillan, R.A., Wheeler, I., Crouch, J., 2021. African soil properties and nutrients mapped at 30 m spatial resolution using two-scale ensemble machine learning. Sci. Rep. 11, 6130. https://doi.org/10.1038/s41598-021-85639-y.
Hijmans, R.J., 2022. geosphere: Spherical Trigonometry. https://cran.r-project.org/package=geosphere.
Ivy, P., 1981. A Guide to Soil Coding and Land Capability Classification: For Land Use Planners. Department of Conservation and Extension, Ministry of Agriculture, Zimbabwe, Harare, Zimbabwe.
Kafesu, N., Chikowo, R., Mazarura, U., Gwenzi, W., Snapp, S., 2018. Comparative fertilization effects on maize productivity under conservation and conventional tillage on sandy soils in a smallholder cropping system in Zimbabwe. F. Crop. Res. 218, 106–114. https://doi.org/10.1016/j.fcr.2018.01.014.
Lal, R., 2004. Agricultural activities and the global carbon cycle. Nutr. Cycl. Agroecosystems 70, 103–116. https://doi.org/10.1023/B:FRES.0000048480.24274.0f.
Laub, M., Corbeels, M., Couëdel, A., Ndungu, S.M., Mucheru-Muna, M.W., Mugendi, D., Necpalova, M., Waswa, W., Van De Broek, M., Vanlauwe, B., Six, J., 2023. Managing soil organic carbon in tropical agroecosystems: evidence from four long-term experiments in Kenya. Soil 9, 301–323. https://doi.org/10.5194/soil-9-301-2023.
Lenth, R.V., 2024. emmeans: Estimated Marginal Means, aka Least-Squares Means. https://cran.r-project.org/package=emmeans.
Malou, O.P., Moulin, P., Chevallier, T., Masse, D., Vayssières, J., Badiane-Ndour, N.Y., Tall, L., Thiam, A., Chapuis-Lardy, L., 2021. Estimates of carbon stocks in sandy soils cultivated under local management practices in Senegal's groundnut basin. Reg. Environ. Chang. 21. https://doi.org/10.1007/s10113-021-01790-2.
Manyenyeka, M., Munetsi, W., Munyaradzi, T., Marufu, C., Moregood, R., Eric, S., 2021. Spatio-temporal clustering and risk factor analysis of bovine theileriosis (Theileria parva) in Zimbabwe from 1995 to 2018. Transbound. Emerg. Dis. 00, 1–11. https://doi.org/10.1111/tbed.14081.
Masvaya, E.N., Nyamangara, J., Nyawasha, R.W., Zingore, S., Delve, R.J., Giller, K.E., 2010. Effect of farmer management strategies on spatial variability of soil fertility and crop nutrient uptake in contrasting agro-ecological zones in Zimbabwe. Nutr. Cycl. Agroecosystems 88, 111–120. https://doi.org/10.1007/s10705-009-9262-y.
Mataruse, P.T., Nyikahadzoi, K., Fallot, A., 2021. Social-ecologically Driven Threats to the Climate Mitigation Potential of Forests: A Case of Murehwa District, in: Nyikahadzoi, K., Mhlanga, L. (Eds.), Climate Change Impact, Adaptation and Mitigation in Zimbabwe Case Studies From Zimbabwe's Urban and Rural Areas. Konrad Adenauer Stiftung, Harare, Zimbabwe.
Mataruse, P.T., Nyikahadzoi, K., Fallot, A., 2022. Smallholder farmers' perceptions of the natural and anthropogenic drivers of deforestation and forest degradation: a case study of Murehwa. Zimbabwe. Trans. r. Soc. South Africa 1–10. https://doi.org/10.1080/0035919X.2022.2152507.
Moeys, J., 2018. soiltexture: Functions for Soil Texture Plot, Classification and Transformation. https://cran.r-project.org/package=soiltexture.
Mtambanengwe, F., Mapfumo, P., 2005. Organic matter management as an underlying cause for soil fertility gradients on smallholder farms in Zimbabwe. Nutr. Cycl. Agroecosystems 73, 227–243. https://doi.org/10.1007/s10705-005-2652-x.
Mugandani, R., Wuta, M., Makarau, A., Chipindu, B., 2012. Re-classification of agro-ecological regions of Zimbabwe in conformity with climate variability and change. African Crop Sci. J. 20, 361–369.
Mugwira, L.M., Murwira, H.K., 1997. Use of cattle manure to improve soil fertility in Zimbabwe: past, current research and future needs. (No. working paper No 2), Network Research Results.
Mujuru, L., Mureva, A., Velthorst, E.J., Hoosbeek, M.R., 2013. Land use and management effects on soil organic matter fractions in Rhodic Ferralsols and Haplic Arenosols in Bindura and Shamva districts of Zimbabwe. Geoderma 209–210, 262–272. https://doi.org/10.1016/j.geoderma.2013.06.025.
Mulder, V.L., Lacoste, M., Richer-de-Forges, A.C., Arrouays, D., 2016. Global Soil Map France: high-resolution spatial modelling the soils of France up to two meter depth. Sci. Total Environ. 1352–1369. https://doi.org/10.1016/j. scitotenv.2016.07.066.
Namatsheve, T., Chikowo, R., Corbeels, M., Mouquet-rivier, C., 2021. Maize-cowpea intercropping as an ecological intensification option for low input systems in sub-humid Zimbabwe: Productivity, biological N2-fixation and grain mineral content. F. Crop. Res. 263, 108052. https://doi.org/10.1016/j.fcr.2020.108052.
Nenkam, A.M., Wadoux, A.-M.-J.-C., Minasny, B., Silatsa, F.B.T., Yemefack, M., Ugbaje, S.U., Akpa, S., van Zijl, G., Bouasria, A., Bouslihim, Y., Chabala, L.M., Ali, A., Mcbratney, A.B., 2024. Applications and challenges of digital soil mapping in Africa. Geoderma 449, 117007. https://doi.org/10.1016/j.geoderma.2024.117007.
Nyamadzawo, G., Chikowo, R., Nyamugafata, P., Giller, K.E., 2007. Improved legume tree fallows and tillage effects on structural stability and infiltration rates of a kaolinitic sandy soil from central Zimbabwe. Soil Tillage Res. 96, 182–194. https://doi.org/10.1016/j.still.2007.06.008.
Nyamadzawo, G., Wuta, M., Nyamangara, J., Nyamugafata, P., Chirinda, N., 2015. Optimizing dambo (seasonal wetland) cultivation for climate change adaptation and sustainable crop production in the smallholder farming areas of Zimbabwe. Int. J. Agric. Sustain. 13, 23–39. https://doi.org/10.1080/14735903.2013.863450.
Nyamangara, J., Marondedze, A., Masvaya, E.N., Mawodza, T., Nyawasha, R., Nyengerai, K., Tirivavi, R., Nyamugafata, P., Wuta, M., 2014. Influence of basin-based conservation agriculture on selected soil quality parameters under smallholder farming in Zimbabwe. Soil Use Manag. 30, 550–559. https://doi.org/10.1111/sum.12149.
Nyamapfene, K., 1991. Soils of Zimbabwe. Nehanda Publishers, Harare, Zimbabwe.
Nyawasha, R.W., Falconnier, G.N., Todoroff, P., Wadoux, A.-M.-J.-C., Chikowo, R., Coquereau, A., Leroux, L., Jahel, C., Corbeels, M., Cardinael, R., 2024a. Data for "Drivers of soil organic carbon stocks at village scale in a sub-humid region of Zimbabwe. CIRAD Dataverse. https://doi.org/10.18167/DVN1/KVKWFL.
Nyawasha, R.W., Wadoux, A.-M.-J.-C., Todoroff, P., Chikowo, R., Falconnier, G.N., Lagorsse, M., Corbeels, M., Cardinael, R., 2024b. Multivariate regional deep learning prediction of soil properties from near-infrared, mid-infrared and their combined spectra. Geoderma Reg. 37, e00805. https://doi.org/10.1016/j.geodrs.2024.e00805.
O'Rourke, S.M., Angers, D.A., Holden, N.M., Mcbratney, A.B., 2015. Soil organic carbon across scales. Glob. Chang. Biol. 21, 3561–3574. https://doi.org/10.1111/gcb.12959.
Oldfield, E.E., Bradford, M.A., Wood, S.A., 2019. Global meta-analysis of the relationship between soil organic matter and crop yields. SOIL 5, 15–32. https://doi.org/10.5194/soil-5-15-2019.
Olorunfemi, I.E., Olufayo, A.A., Fasinmirin, J.T., Komolafe, A.A., 2022. Dynamics of land use land cover and its impact on carbon stocks in Sub-Saharan Africa: an overview. Environ. Dev. Sustain. 21, 40–76. https://doi.org/10.1007/s10668-021-01484-z.
R Core Team, 2023. R: A language and environment for statistical computing. R Foundation for Statistical Computing. https://www.r-project.org.
Ramesh, T., Bolan, N.S., Kirkham, M.B., Wijesekara, H., Kanchikerimath, M., Srinivasa Rao, C., Sandeep, S., Rinklebe, J., Ok, Y.S., Choudhury, B.U., Wang, H., Tang, C., Wang, X., Song, Z., Freeman, O.W., 2019. Soil organic carbon dynamics: Impact of land use changes and management practices: A review. Adv. Agron. 156, 1–107. https://doi.org/10.1016/bs.agron.2019.02.001.
Ribeiro, N.S., Matos, C.N., Moura, I.R., Washington-Allen, R.A., Ribeiro, A.I., 2013. Monitoring vegetation dynamics and carbon stock density in miombo woodlands. Carbon Balance Manag. 8, 1–9. https://doi.org/10.1186/1750-0680-8-11.
Rossiter, D.G., Poggio, L., Beaudette, D., Libohova, Z., 2022. How well does digital soil mapping represent soil geography? An investigation from the USA. Soil 8, 559–586. https://doi.org/10.5194/soil-8-559-2022.
Rufino, M.C., Tittonell, P., van Wijk, M.T., Castellanos-Navarrete, A., Delve, R.J., Ridder, N.D., Giller, K.E., 2007. Manure as a key resource within smallholder farming systems: Analysing farm-scale nutrient cycling efficiencies with the NUANCES framework. Livest. Sci. 112, 273–287. https://doi.org/10.1016/j.livsci.2007.09.011.
Rufino, M.C., Dury, J., Tittonell, P., Wijk, M.T.V., Herrero, M., Zingore, S., Mapfumo, P., Giller, K.E., 2011. Competing use of organic resources, climate variability and interactions at village scale in a communal area of NE Zimbabwe. Agric. Syst. 104, 175–190. https://doi.org/10.1016/j.agsy.2010.06.001.
Rurinda, J., Mapfumo, P., Wijk, M.T.V., Mtambanengwe, F., Rufino, M.C., Chikowo, R., Giller, K.E., 2013. Managing soil fertility to adapt to rainfall variability in smallholder cropping systems in Zimbabwe. F. Crop. Res. https://doi.org/10.1016/j.fcr.2013.08.012.
Rusinamhodzi, L., Corbeels, M., Zingore, S., Nyamangara, J., Giller, K.E., 2013. Pushing the envelope? Maize production intensification and the role of cattle manure in recovery of degraded soils in smallholder farming areas of Zimbabwe. F. Crop. Res. 147, 40–53. https://doi.org/10.1016/j.fcr.2013.03.014.
Rusinamhodzi, L., Corbeels, M., Giller, K.E., 2016. Diversity in crop residue management across an intensification gradient in southern Africa : System dynamics and crop productivity. F. Crop. Res. 185, 79–88. https://doi.org/10.1016/j.fcr.2015.10.007.
Ryan, C.M., Williams, M., Grace, J., 2011. Above- and belowground carbon stocks in a miombo woodland landscape of Mozambique. Biotropica 43, 423–432. https://doi.org/10.1111/j.1744-7429.2010.00713.x.
Shumba, A., Chikowo, R., Thierfelder, C., Corbeels, M., Six, J., Cardinael, R., 2024. Mulch application as the overarching factor explaining increase in soil organic carbon stocks under conservation agriculture in two 8-year-old experiments in Zimbabwe. Soil 10, 151–165. https://doi.org/10.5194/soil-10-151-2024.
Six, J., Conant, R.T., Paul, E.A., Paustian, K., 2002. Stabilization Mechanisms of Soil Organic Matter : Implications for C- Saturation of Soils Stabilization mechanisms of soil organic matter : Implications for C-saturation of soils. Doi: 10.1023/A.
Tittonell, P., Vanlauwe, B., Leffelaar, P.A., Rowe, E.C., Giller, K.E., 2005. Exploring diversity in soil fertility management of smallholder farms in western Kenya I. Heterogeneity at region and farm scale. Agric. Ecosyst. Environ. 110, 149–165. https://doi.org/10.1016/j.agee.2005.04.001.
Tittonell, P., Vanlauwe, B., de Ridder, N., Giller, K.E., 2007. Heterogeneity of crop productivity and resource use efficiency within smallholder Kenyan farms: Soil fertility gradients or management intensity gradients? Agric. Syst. 94, 376–390. https://doi.org/10.1016/j.agsy.2006.10.012.

Tittonell, P., Rufino, M.C., Janssen, B.H., Giller, K.E., 2010. Carbon and nutrient losses during manure storage under traditional and improved practices in smallholder crop-livestock systems-evidence from Kenya. Plant Soil 328, 253–269. https://doi.org/10.1007/s11104-009-0107-x.

Van Apeldoorn, D.F., Kempen, B., Bartholomeus, H.M., Rusinamhodzi, L., Zingore, S., Sonneveld, M.P.W., Kok, K., Giller, K.E., 2014. Analysing soil organic C gradients in a smallholder farming village of East Zimbabwe. Geoderma Reg. 2–3, 32–40. https://doi.org/10.1016/j.geodrs.2014.09.006.

Von Fromm, S.F., Hoyt, A.M., Lange, M., Acquah, G.E., Aynekulu, E., Berhe, A.A., Haefele, S.M., Mcgrath, S.P., Shepherd, K.D., Sila, A.M., Six, J., Towett, E.K., Trumbore, S.E., Vägen, T.G., Weullow, E., Winowiecki, L.A., Doetterl, S., 2021. Continental-scale controls on soil organic carbon across sub-Saharan Africa. Soil 7, 305–332. https://doi.org/10.5194/soil-7-305-2021.

Wadoux, A.M.J.-C., Malone, B., Minasny, B., Fajardo, M., McBratney, A.B., 2021. Soil Spectral Inference with R: Analysing Digital Soil Spectra Using the R Programming Environment, Springer International Publishing AG, Cham.

Walker, S.M., Desanker, P.V., 2004. The impact of land use on soil carbon in Miombo Woodlands of Malawi. For. Ecol. Manage. 203, 345–360. https://doi.org/10.1016/j.foreco.2004.08.004.

Whitlow, J.., 1985. Dambos in Zimbabwe: A review, in: Thomas, M.., Goudie, A.. (Eds.), Dambos: Small Channelless Valleys in the Tropics. Zeitschrift für Geomorphologie, Stuttgart: Borntraeger, pp. 115–146.

Wiesmeier, M., Urbanski, L., Hobley, E., Lang, B., von Lützow, M., Marin-Spiotta, E., van Wesemael, B., Rabot, E., Ließ, M., Garcia-Franco, N., Wollschläger, U., Vogel, H.J., Kögel-Knabner, I., 2019. Soil organic carbon storage as a key function of soils - A review of drivers and indicators at various scales. Geoderma. https://doi.org/10.1016/j.geoderma.2018.07.026.

Xiao, C., 2015. Soil Organic Carbon Storage (Sequestration) Principles and Management.

ZimStat, 2022. 2022 Population and Housing Census: Preliminary Report on Population Figures. Harare, Zimbabwe.

Zingore, S., Manyame, C., Nyamugafata, P., Giller, K.E., 2005. Long-term changes in organic matter of woodland soils cleared for arable cropping in Zimbabwe. Eur. J. Soil Sci. 56, 727–736. https://doi.org/10.1111/j.1365-2389.2005.00707.x.

Zingore, S., Murwira, H.K., Delve, R.J., Giller, K.E., 2007a. Soil type, management history and current resource allocation: Three dimensions regulating variability in crop productivity on African smallholder farms. F. Crop. Res. 101, 296–305. https://doi.org/10.1016/j.fcr.2006.12.006.

Zingore, S., Murwira, H.K., Delve, R.J., Giller, K.E., 2007b. Influence of nutrient management strategies on variability of soil fertility, crop yields and nutrient balances on smallholder farms in Zimbabwe. Agric. Ecosyst. Environ. 119, 112–126. https://doi.org/10.1016/j.agee.2006.06.019.

Zingore, S., Tittonell, P., Corbeels, M., van Wijk, M.T., Giller, K.E., 2011. Managing soil fertility diversity to enhance resource use efficiencies in smallholder farming systems: A case from Murewa District. Zimbabwe. Nutr. Cycl. Agroecosystems 90, 87–103. https://doi.org/10.1007/s10705-010-9414-0.

Zingore, S., 2006. Exploring diversity within smallholder farming systems in Zimbabwe: Nutrient use efficiencies and resource management strategies for crop production. Wageningen University, Wageningen, Netherlands.

Zinyengere, N., Crespo, O., Hachigonta, S., 2013. Crop response to climate change in southern Africa : A comprehensive review. Glob. Planet. Change 111, 118–126. https://doi.org/10.1016/j.gloplacha.2013.08.010.