



A Bayesian approach to understand controls on total and labile soil carbon in cultivated soils of Central and Southern Malawi

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ABSTRACT

Soil degradation on cultivated lands of Sub-Saharan Africa is a threat to food security. Even so, drivers of soil C total and labile pools are little understood for smallholder farms. A unique opportunity to evaluate how environment conditions management drivers was afforded by a systematically representative on-farm study of 1108 cultivated plots in marginal to mesic environments across Central and Southern Malawi. Soil sample collection and analysis and surveys of farmer practice were conducted, and linked to remote-sensed data on environmental and spectral factors. Soil properties included the following ranges (mean values per site), soil clay (6.41% to 17.36%), pH (6.09 to 6.54), soil organic carbon (SOC) (6.31 g C kg soil⁻¹ to 16.17 g C kg soil⁻¹), and two labile soil C assays: permanganate oxidizable carbon (POXC) (291.5 mg C kg soil⁻¹ to 504.5 mg C kg soil⁻¹) and 24-h mineralizable C (Cmin) (28.71 mg C kg soil⁻¹ to 65.34 mg C kg soil⁻¹). Incorporation of domain specialists' expectation of uncertainty levels is key to carrying out a multiscale assessment of soil total and labile C status, thus a Bayesian linear regression approach was used for determining the influential drivers. Overall, the soil clay content is a strong predictor of SOC (0.479–0.517), POXC (0.139–0.266), and Cmin (0.125–0.223) at the 95% Bayesian credibility level from the Gibbs posterior samples. Vegetative cover, reflected by Normalized Difference Vegetation Index (NDVI), is also a dominant driver for SOC (0.234–0.329), POXC (0.163–0.285), and Cmin (0.249–0.38). Of the management practices studied, crop diversity, residue incorporation, and weed presence are all positive drivers for total soil C, whereas fertilizer N is not. At both regional and local scales, labile soil C pools (as reflected by POXC and Cmin) are not consistently responsive to management. The drivers of SOC are highly consistent, a strong indication of statistical robustness. This contributes to the understanding of patterns of carbon pools in intensively cultivated fields in Sub-Saharan Africa.

1. Introduction

Soil degradation is a growing concern in Sub-Saharan African (SSA) smallholder farming systems, as intensive production is becoming common (Tully et al., 2015). Understanding soil carbon dynamics on smallholder farmers' is important, particularly so in SSA where this sector contributes over 90% of the food production (Wiggins and Keats, 2013). A widespread challenge is that there is limited access to organic resources by smallholders, Soil Organic Carbon (SOC) status is often degraded and soils are highly heterogeneous (Snapp, 2022). There is a need for a better understanding of the environment and management practices drivers for SOC pools. A unique opportunity is afforded in

Malawi, where smallholder farm soil status has been monitored over time, at multiple scales, from mesic to marginal environments.

Malawi's agricultural production system is typical of the SSA maize belt that stretches across East and Southern Africa, and increasingly in West Africa (Blackie et al., 2019). Malawi relies on rain-fed agriculture produced largely by hand cultivation on smallholder farms (Mhango et al., 2013; Snapp et al., 1998). Intensification trends in SSA and vulnerabilities to sustainability challenges more broadly are represented by Malawi, which has high population density, limited resources, soil depletion, and climatic risks, for multiple challenges to food security (Funk et al., 2008; Mungai et al., 2016; Snapp et al., 2018). On-farm studies that assess soil stable and labile carbon pools in Malawi thus

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provide unique insights to the global understanding of SOC accrual and drivers on cultivated fields.

SOC is a critical component because of its role in supporting soil structural stability and nutrients in addition to its other ecosystem functions (Mponela et al., 2020). In 1998, Snapp (1998) documented the status of soil on Malawian smallholder farms (generally sands and sandy loam) and concluded that SOC is sufficient for structural stability with a threshold concentration value of $8 \text{ g C kg soil}^{-1}$. Mpeketula (2016) reported a SOC depletion in Malawi. Evaluating drivers of SOC change in smallholder farms requires understanding the impact of management practices. However, the methodological challenges and slow processes associated with SOC accrual are such that it is often difficult to detect how SOC responds to field management practices (Mpeketula and Snapp, 2019).

Soil analytical procedures that act as an indicator of labile soil C pools can provide insights into how management practices influence soil carbon status (Awale et al., 2013; Bongiorno et al., 2019; Culman et al., 2012; Culman et al., 2013). The labile carbon pools have been little studied in relationship to climate gradients and how they interact with management, and hardly at all on smallholder farms in SSA (Murage et al., 2000; Ngwira et al., 2012). There are very few practical examples with empirical values from on-farm study sites. Chamberlin et al., (2021) found poor fertilizer response in soils with a deficiency in the labile SOC fraction, as indicated by permanganate oxidizable carbon (POXC). This is one indicator of labile C calculated from the oxidation–reduction process (Bongiorno et al., 2019). Fine et al., (2017) reported POXC as the best single predictor under the context of determining expected difference across the Northeast, Mid-Atlantic, and Midwest U.S. Yet, Wade et al., (2020) pointed out the high variability of POXC values, particularly for low SOC soils and other methodological challenges. Mineralizable Carbon (Cmin) is widely used to assess the biologically labile SOC fraction and reflects microbial activity (Awale et al., 2013).

Environmental factors, including temperature and precipitation, are usually viewed as the dominant predictor of total and labile C at the regional level across landscapes, as they limit the biomass accumulation, weathering, and erosion (Burke et al., 1989; Hontoria et al., 1999; Johnson et al., 2011). Akpa et al., (2016) evaluated several models to estimate SOC in Nigeria and found that soil type, climate, vegetation indices, and terrain attributes are important proxies. Researchers have found Normalized Difference Vegetation Index (NDVI), reflecting the vegetative cover, as a predictor for SOC at multiple temporal and spatial scales (Akpa et al., 2016; Kunkel et al., 2011; Page et al., 2013; Venter et al., 2021; Yang et al., 2020; Zhang et al., 2019). For cultivated fields, however, environmental factors are insufficient for understanding the SOC variation due to the importance of anthropogenic management (Calvo de Anta et al., 2020). Understanding the drivers in tropical cultivated fields will benefit modelers in selecting parameters for SOC prediction. There are some studies focused on the labile C variation across precipitation gradient, while limited information on environmental and management controls in Malawian smallholder farm soils and tropical cultivated fields (Ngwira et al., 2012). Regional scale assessments of labile C across precipitation gradients are needed to understand environmental controls and management, especially for Malawi, which faces land degradation and climatic risks to a high degree.

In SSA, farm practices that influence soil C are conditioned by the scarcity of organic resources. Crop residue retention can act as a mulch that provides physical protection to the surface layer, improves soil aggregate stability, and increases the abundance of soil fauna. Thus, it has been widely promoted to benefit crop yield and long-term soil quality (Ghuman and Sur, 2001; Ngwira et al., 2013; TerAvest et al., 2015; Titttonell et al., 2015). However, limited crop residues are used as a soil amendment due to moderate crop growth and alternate uses, including the need for livestock feed, and fuel (Titttonell et al., 2015). There is limited understanding of farmer practices' influence on

cultivated field SOC at the regional scale. Chivenge et al., (2011) pointed out that organic input is key to improving SOC on smallholder farms, particularly those on sandy soils. In the Dedza and Ntcheu districts in Malawi, crop residue retention is a widespread management practice used by farmers, although they also carry out the burning of residues and removal for livestock feed (Mungai et al., 2016).

Another important farming practice besides crop residue retention, that influences soil carbon accrual is the biochemical diversity of residues. This is influenced by crop species choice and sole versus mixed cropping system arrangements. Spatial crop diversity, also referred to as intercropping, is a sustainable intensification practice that produces high grain yields per land area and, potentially, has soil fertility benefits (Snapp et al., 2010; TerAvest et al., 2015). Intercropping of legumes with cereals has been shown through the field and controlled environment studies to specifically enhance soil C and N pools, relative to sole crop management (Cong et al., 2015; Garland et al., 2017). However, there is a substantial research gap between the understanding of soil C determinants based on experimentation, and that based on geospatial characterization. Thus, prediction of SOC accrual is inadequate, particularly for the smallholder farming sector, where environmental context has not been investigated in relation to management practices, at regional and local scales.

Overall, there are many challenges to understanding long-term sustainability and SOC consequences of smallholder practices such as intercropping, fertilizer, weed, and residue management practices (TerAvest et al., 2015; Tully et al., 2015). Management of all sources of diversity, including weeds, may influence soil properties. In the limited studies of weeds' ecosystem services, weeds have been found to have a positive effect on soil nutrients, although they often suppress crop yield (Blaix et al., 2018). We know of no other study that quantifies the broad range of management practices implemented on smallholder fields, including crop diversity and weed presence, and that considers their influence on SOC. Farmers in Malawi utilize both sole and intercrop management practices (Bezner Kerr et al., 2019; Mungai et al., 2016), providing an opportunity to evaluate soil C variation and the potential impact of management practices, within the context of tropical agroecosystems. As labile SOC pools are expected to be highly responsive to management, often more so than stable SOC (Culman et al., 2012; Ngwira et al., 2012), a further research gap addressed is that of predicting labile SOC patterns on cultivated fields.

Thus, to better understand drivers for variation of stable and labile carbon pools, we integrated Bayesian analyses of statistical models to analyze the climate-induced and management-induced variables. The Bayesian approach fills the gap of identifying sensitive drivers as this method accommodates the domain specialists' expectation of uncertainty levels, as illustrated in a recent study utilizing Bayesian models to interpret maize yield predictors in an agricultural survey (Wang et al., 2019). The natural probabilistic interpretation of Bayesian outputs, aided by cutting-edge computational methods, is typically much more detailed than classical analyses, holding stronger predictive power, especially for datasets of moderate size (Dunson, 2001; Neufcourt et al., 2018), and it systematically avoids misinterpretations of p values (McShane and Gal, 2017; Wang et al., 2019).

The objectives of this study were to 1) quantify the environment and management drivers on African smallholder farms, leveraging purposive, stratified sampling of fields across Central and Southern Malawi; 2) evaluate environmental and field management drivers that influence stable and labile C pools; and 3) identify practices that are generally associated with relatively high SOC status, at the regional and local scale. We hypothesized that (i) labile C indicators would be more sensitive to management practices than SOC, and (ii) the magnitude of environmental and management controls of SOC would vary at regional and local scales.

2. Materials and methods

2.1. Overall site description

Malawi ($9^{\circ}45'17''$ S, $32^{\circ}35'35''$ E) is a landlocked country bordered by Tanzania, Zambia, and Mozambique, and occupies 118,484 km² in Southeastern Africa. Malawi has an overall tropical climate and a sub-tropical climate at high latitude. The hot and wet season lasts from November to April, and the cool and dry season lasts from May to October. The mean annual temperature ranges from 18 °C to 27 °C, and the mean annual precipitation ranges from 725 mm to 2500 mm in Malawi. Maize is the dominant crop planted in the country and also contributes to the profit of smallholder farmers and the main calories intake for households.

In 2016, seven Extension Planning Areas (EPAs) in Malawi were selected based on a range of agricultural potential and representing a variety of biophysical characterizations (Li et al., 2017; Mungai et al., 2016). Golomoti and Mtakataka EPAs are located adjacent to each other and were grouped into one study site that is referred to throughout as Golomoti. This resulted in seven EPAs being represented, located in Central and Southern Malawi (Fig. 1). Linthipe was the only site classified as high agricultural potential (Mungai et al., 2016). Kandeu, Nsipe, Nyambi, and Nsanama were classified as medium agricultural potential sites. Golomoti and Mtubwi were classified as low agricultural

potential sites. A total of 614 households from seven EPAs were randomly selected for the study, with farmers asked to select two plots per household where maize was commonly grown, as described previously (Burke et al., 2020). Soil classes of the focal plots were summarized in Table A1 based on the SoilGrids250m (Hengl et al., 2017).

2.2. Soil fertility Panel survey

A farm management practice survey of the 614 households and a soil survey of two plots per household (total 1108 plots) were carried out in September and October 2016. This survey was part of the Africa RISING Panel Survey project that documented, through a questionnaire, household socio-economic characteristics while also documenting plot management practices employed, and rating of weed presence. Enumerators physically visited the plots with the farmer for the plot-specific questions, to enhance the quality of data by asking specifics about their plot management. The survey instrument and implementation protocols were supervised by MSU IRB Human Subjects Board, including following consent protocols, close supervision of enumerators by our research team, local language translations, and visual aids for specific questions.

Livestock variety and quantity were asked at the household level and then used to calculate household Tropical Livestock Units (TLUs) (Hockett and Richardson, 2018). For each household, a wealth score was

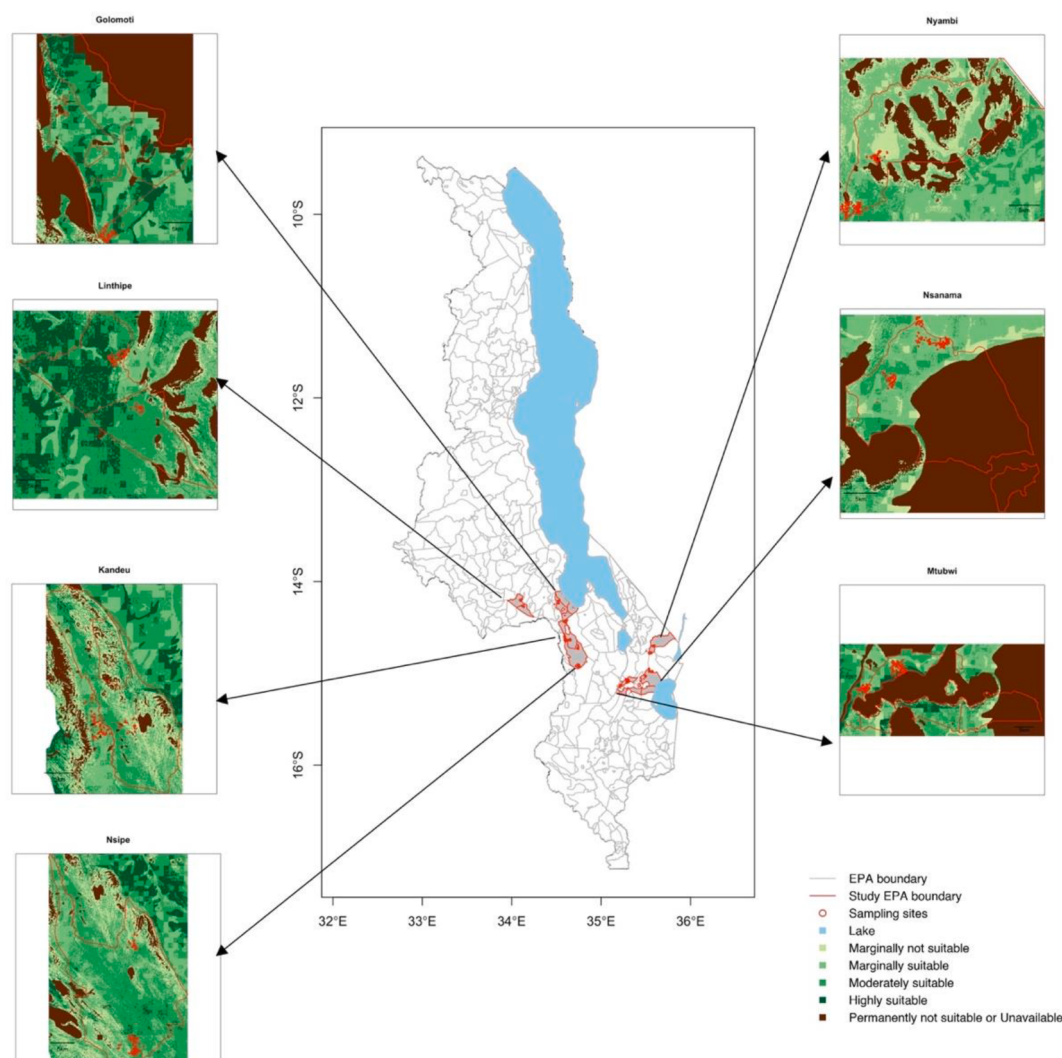


Fig. 1. Location of farm sampling sites surveyed ($n = 1108$) and agricultural potential (Li et al., 2017) characteristics of Extension Planning Areas in Central and Southern Malawi. For more information, <http://globalchangescience.org/eastafricanode/>.

calculated based on the asset indicators, employing the principal components analysis described in (Córdova, 2008).

The survey was conducted on two primary plots per household, which were rain-fed maize-based cropping systems. Most of the focal plots were under 2 acres and the mean focal plot size per study site ranged from 0.45 to 0.83 acres (Table 2). Enumerators were asked about the slope of the plot with a visual aid, the fertilizer use, manure, and compost use, residue management, crop diversity, and weed presence for the plots. The slope was assessed at each plot by categorized at four levels in the survey with a visual aid: nearly level, gentle, moderately steep, and steep. Nitrogen (N) rate in kg ha^{-1} of mineral fertilizer applied in each plot was calculated based on the type and application amount after converting from local units. Survey questions related to compost and manure use on study plots allowed farmers to answer regarding amounts and types of organic amendments based on local language terminology. Compost and manure amendments were further grouped into a single binary indicator of yes or no for data analysis due to the low application amount found in the explanatory analysis. Residue management was determined by categorizing the practices recorded into three groups: removal, burning, and incorporation. For assessing determinants of soil total and labile C, plot management data from the year 2016 was used.

Crop diversity, the crop numbers per plot, was collected from 2016 in Central Malawi and 2017 in Southern Malawi. For assessing determinants of soil total and labile C, we used the crop diversity data collected around the time of the soil sampling exercise in the year 2016. For Central Malawi, Golomoti, Linthip, Kande, and Nsipe, 2016 data was used; for Southern Malawi, Nyambi, Nsanama, and Mtubwi, 2017 data was used (as 2016 data was not available). Data on weed presence at crop harvest was collected and used as an indicator of endogenous weediness of a plot. Enumerators were asked to rate weed cover at six random locations per plot, at four levels of weediness: zero weed presence, weeds cover soil equivalent to less than bare soil, equal to, or more of the area (photos were used to calibrate). The data were summarized into a range of 0–18 to quantify weed intensity per plot.

2.3. Remote sensing data

Geographical coordinates of each plot were collected and used to obtain the remote sensing data of Mean Annual Temperature (MAT), Mean Annual Precipitation (MAP), Normalized Difference Vegetation Index (NDVI), and elevation. National Aeronautics and Space Administration (NASA) Moderate Resolution Imaging Spectroradiometer (MODIS) Land Surface Temperature (LST—MOD11A2) database was used to calculate the 10-year mean annual temperature from 2006–2016, and the mean growing season temperature for the year of 2016. Climate Hazards InfraRed Precipitation with Station (CHIRPS) database, recognized as the only comprehensive precipitation data source available for Malawi, was used to calculate the 10-year average precipitation from 2006 to 2016, and the growing season precipitation of 2016. Ten-year growing season NDVI from 2006 to 2016 and single growing season were calculated based on the MODIS Vegetation Indices (MODIS13Q1). Elevation data was derived from Shuttle Radar Topography Mission (SRTM) Digital Elevation Model at 90 m resolution.

2.4. Soil sampling and analyses

Soil sampling was conducted in October 2016, during the Malawian dry season before planting through a random sampling approach in each plot. The soil was sampled at 0–20 cm depth with a 5-cm diameter auger. The soil samples were mixed, air-dried, passed through a 2 mm sieve, and double-packaged before shipping to Michigan State University laboratory and analyzed for pH, texture (Burt et al., 1993), SOC, POXC (Culman et al., 2012), and Cmin (Culman et al., 2013).

Soil pH was measured in a one-to-two parts soil water solution with a standard pH meter. Textures of the samples were determined by the

micro-pipette method described in (Burt et al., 1993). Soil organic carbon was determined by dry combustion using Leco TruMac CN Analyzer (Leco Corporation, St. Joseph, MI). Permanganate Oxidizable Carbon was determined following the protocol by Culman et al., (2012) with two analytical reps and batches of eight samples, to minimize challenges with variability associated with this method. Two-and-a-half-gram soil samples were weighed and added to 50 mL centrifuge tubes with 2 mL of $0.2 \text{ mol L}^{-1} \text{ KMnO}_4$ and 18 mL of deionized (DI) water. The centrifuge tube was shaken for exactly 2 min at 240 rpm and settled for exactly 10 min. Then, 0.5 mL of the supernatant was mixed with 49.5 mL of DI water, transferred to a 96-well plate, and the absorbance was read with the BioTek Synergy Microplate reader at the wavelength of 550 nm.

Water Filled Pore Space (WFPS) was determined for each soil type, classified based on the soil texture, with 5 replications through a gravimetric method adjusted from Haney and Haney, (2010). Forty grams of soil were measured for volume, added to a 50 mL plastic beaker with drainage holes in the bottom, wetted by adding 30 mL DI water, mounted on a funnel, and allowed to drain. After 24 h, wet samples were weighed, oven-dried at 105°C for 24 h, and weighed again. WFPS for each soil type was calculated based on the wet soil weight, the oven-dried soil weight, and the volume. Carbon mineralization was determined using the rewetted method adjusted from Franzluebbers et al., (2000) as follows. Ten grams of air-dried soil samples were rewetted to 50% WFPS based on the soil type in a 100 mL beaker and incubated for 24 h in a 237 mL mason jar at 24°C in dark. The CO_2 concentration was measured by injecting 0.5 mL into LI-COR LI-820 infrared gas analyzer (LI-COR Biosciences, Lincoln, NE) at the time of sealing the jar and after 24 h. Carbon mineralization was determined by the difference of initial and 24 h CO_2 concentration.

2.5. Statistical analysis and data visualization

Fishers' Least Significant Difference (LSD) tests were used to assess the means of variables at EPAs at the 0.05 probability level with Bonferroni adjustment. The data was processed in the software R version 3.5.2. with *agricolae* package. Local village clusters were determined by the geographical locations of the sampling plots, as shown in Fig. A1 and in more detail at <http://globalchangescience.org/eastafricanode>. Inverse Distance Weighting (IDW) interpolation map of SOC at village level was performed for six village clusters. Visualization of sampling locations and IDW maps were graphed in R.

A Bayesian approach was employed to determine drivers of SOC, POXC, and Cmin at the regional level (across all sites) and at the local level (village clusters). All the statistical analyses of Bayesian linear regression were performed in Python software version 3.6.5 with package PyMC3 package version 3.8. Prior distributions were set within classes of weakly informative priors: normal distributions for the regression coefficients and the inverse-gamma distribution for each model's error term, with relatively wide prior uncertainty level (relatively large variances). Hyperparameters for these priors, particularly those determining distribution variances, were chosen according to the agronomists' prior interpretation of model uncertainty, in accordance with a systematic prior elicitation framework (Oakley and O'Hagan, 2019). In this framework, agronomist insights provide assurance regarding the order of magnitude of a regressor's influence on a response variable, and the prior variance for that regressor's coefficient can be set consistently with that level, or at a moderate integer multiple thereof (e.g. 2 or 3). The Bayesian analysis thus explores the posterior possibilities for the coefficient. The use of a multiple is considered a conservative approach, since in principle it may result in posterior credibility intervals which are slightly larger than needed. In practice, this conservative approach only lengthens the numerical methods for the Bayesian analysis slightly, while not resulting in notably larger uncertainty reports. We adopt this approach, since it comes at a very low additional computational cost, and a very low risk of reporting credibility intervals which are too wide. Two independent Monte-Carlo Markov Chains

(MCMC) were used as a way to check for adequate convergence with 10,000 iterations after burn-in with 500 samples, from a standard Gibbs sampler.

Equation (1) and equation (2) show the linear regression models used in the Bayesian framework in this study for regional scale and local scale, respectively:

$$Y_i = \alpha + \beta X_i + \sigma \epsilon_i \quad (1)$$

$$Y_{ij} = \alpha_j + \beta_j X_{ij} + \sigma \epsilon_{ij} \quad (2)$$

where in equation (1): for each plot i , the 4-dimensional vector Y_i is formed of the 3 possible responses SOC (g C kg soil⁻¹), POXC (mg C kg soil⁻¹), and Cmin (mg C kg soil⁻¹) of plot i ; the 3-dimensional vector α is the set of three y-intercepts; X_i is a p -dimensional vector that include all p predictors (explanatory variables MAT, NVDI, slope, clay, pH, N rate from fertilizer, compost adoption, residue management, crop diversity, weed presence, and tropical livestock unit; when all predictors are included in the model, $p = 11$); β is the 3-by- p -dimensional matrix of regression coefficients; σ is a 3-dimensional vector of standard deviations; and ϵ_i is a 3-dimensional vector of Gaussian noise terms, whose components are assumed to be independent across all responses and all fields. In equation (2), the index j was introduced to the label the corresponding local village cluster; the same model structure was used for each village cluster as for the regional model of Eq. (1). For the data analysis, all variables in X and Y are standardized (their empirical means and standard deviations are computed across all i , and the variables are then scaled to result in variables with empirical mean = 0 and empirical standard deviation = 1). This allows an evaluation of the relative importance of each predictor in each model, by comparing the values of their corresponding β 's directly, since all standardized variables are at the same dimensionless scale, in addition to determining whether each predictor is significant by checking that its posterior 95% credible interval does not contain the value 0. These two checks are facilitated by direct visual inspection of the so-called forest-plots produced by the Python package. The distance of a credible interval to 0 is an indication of its regressor's significance beyond the 95% credibility level, the size of its overlap with 0 is an indication of how nearly significant it might be. The distance of the middle of a significant credible interval to 0 (its β 's posterior mean, indicated by a dot) is a way to measure the strength of a predictor.

The elevation was highly correlated with MAT and MAP (Table A2) and thus was not included in the Bayesian linear regression model analyses for climate and management. A relatively high correlation ($R = -0.69$, $p < 0.05$, Table A2) was found between the precipitation and temperature for the long-term 10-year average and the three growing seasons. While not necessarily of concern, such correlations can lead to collinearity problems in cases where both regressors are dominant predictors compared to other explanatory variables. This in turn can result in spurious conclusions if the regression with respect to one variable is not robust to the omission of the other. It can also adversely affect the significance of less dominant predictors. In our study, robustness was an issue when omitting temperature as a predictor. Specifically, the results from models including both MAP and MAT, and MAP only showed that the model was not robust to the influence of MAP when MAP was present (Figs. A2, A3). Thus, only the temperature was used in the model as a climatic indicator.

The robustness of the Bayesian linear regression was tested with reduced variables (Fig. A4). With the removal of three variables in the model, the results for the significance of drivers did not vary notably. Thus, the robustness of the model was confirmed to support our conclusion. We also tried classical, frequentist linear regression. We found that both methods used on the core models draw the same conclusion regarding the significance of each of the models' regressors. To be specific, we find that for any explanatory variable X whose regression coefficient β has a 95%-credibility interval in the Bayesian

analysis that does not contain the value 0, that same variable X has a regression coefficient β whose reported p -value in the frequentist analysis is < 0.05 . We also found that the Bayesian analysis is more robust in the sense that the significance of variables remained more often when some of the variables were removed from the model. Finally, the Bayesian output represents a safer and more efficient report on uncertainty (Neufcourt et al., 2018) because it provides full explanatory and predictive uncertainty profiles (posterior distributions) without relying on assumptions about the distribution of the observed data as a vector beyond the likelihood model, whereas the frequentist method provides reports only on means and variances of the regression coefficients, under more restrictive distributional assumptions on the data. Thus, we decide to use the Bayesian approach.

3. Results

3.1. Site characterization and common management practices by EPA

3.1.1. The environmental context of the study sites

The Linthipe site had the highest elevation and Mtubwi site had the lowest elevation. Mesic sites with sufficient rainfall (960–978 mm) include Nsipe, Nyambi, and Linthipe (Table 1). The marginal sites of Golomoti and Mtubwi had low precipitation, and were the hottest at 27.20 °C and 27.17 °C, respectively. The coolest sites were Nsipe (24.64 °C) and Linthipe (23.97 °C). Thus the widest range of environments among the seven sites, were represented by Golomoti, a hot and dry site near the lakeshore with generally coarse soils, while Linthipe was the most mesic, being cool, with sufficient and well-distributed moisture for maize production (Mungai et al., 2016). Long term NDVI of the 10 growing season from 2006 to 2016 was the highest at the Nsipe site (0.57) and the lowest at the Nsanama site (0.49) (Table 1). For growing season 2016, NDVI was highest Nsipe site and lowest in Nsanama site.

Slopes of the plots from the collected survey with visual aid were mainly nearly level or gentle (Table 1). Nsanama and Mtubwi sites had no plots with steep slopes. The Golomoti EPA had the highest percentage of nearly level for the plots (57.82%), and it was the only one with nearly level as the most dominant slope. All other EPAs were dominated by the gentle slope (41.13% to 63.43%). Both Nyambi and Mtubwi had the highest percentage of gentle slope for the plots (63%). The percent of moderately steep slopes ranged from 2.67 % to 12.67%. Nsipe EPA had the highest number of moderately steep percentages (12.67%). The steep slope plots made up 0% to 9% to the total.

3.1.2. Management practices by study sites

Overall, the range and intensify of farm management practices reported were consistent with an earlier survey of these farms, for the Central Malawi sites (Mungai et al., 2016). The only exception was compost use, which was substantially higher in this study (2016), at 46–60% of Central Malawi fields surveyed compared to 23 – 46% in a baseline survey conducted in this area in 2013. Across all 7 sites, 69 to 90% of the plots were fertilized (Table 2). Golomoti and Mtubwi both have the lowest percentage of plots with fertilizer use (69%). The average fertilizer N rate for each EPA was calculated based on the data from plots with fertilizer use. Fertilizer N rate was highest in the Nsipe (85 kg N ha⁻¹) and the Linthipe (84 kg N ha⁻¹), different from the two lowest sites of Mtubwi (54 kg N ha⁻¹) and Nsanama (47 kg N ha⁻¹). Compost application was moderately high, ranging from 36% to 60%, compared to high fertilizer application ranging from 69% to 90% (Table 2).

Crop management followed limited use of burning residues at 2 to 23%, and widespread use of intercrops (Table 2). Residue management of plots largely involved incorporation after crop harvest (71% – 93%), with burning residues being relatively high in only one location (Nyambi, at 23%). For the majority of plots, at least two crop species were grown. A wide range of crops per plot was observed in Central

Table 1

Environmental properties based on remote sensing and observed slope of surveyed farms (n = 1108) on surveyed farms at seven sites (Extension Planning Areas, EPAs) in Central and Southern Malawi. Precipitation and temperature are mean of 10 years from 2006 – 2016. NDVI data is mean of growing season from 11/1–4/30 of 2006–2016. The range is based on the minimum and maximum value in that area. The letters indicate the Least Significant Difference (LSD) test category with one-way ANOVA test (comparison is across a row).

	Golomoti n = 147	Linthipe n = 132	Kandeu n = 141	Nsipe n = 150	Nyambi n = 175	Nsanama n = 187	Mtubwi n = 176
Latitude	14.39° S	14.22° S	14.36° S	14.87° S	14.75° S	14.99° S	15.10° S
Longitude	34.58° E	34.11° E	34.62° E	34.74° E	35.56° E	34.53° E	35.27° E
Elevation (m)	549.41e	1235.09a	908.43b	919.48b	817.84c	663.48d	514.85f
Precipitation (mean, mm)	782.21f	959.54b	939.91c	978.30a	965.92ab	858.49e	903.9d
Precipitation (range, mm)	754	925	912	937	936	850	844
Precipitation 2016 GS ^a	641.86f	850.11a	733.65c	731.91c	759.92b	655.14e	665.42d
Temperature (mean, °C)	27.20a	23.97f	25.05d	24.64e	25.35c	26.23b	27.17a
Temperature (range, °C)	25.24	23.20	24.82	24.02	24.97	25.92	26.65
Temperature 2016 GS	30.41a	26.99f	28.25d	27.38e	28.28d	29.79c	30.03b
NDVI (mean)	0.54cd	0.53d	0.55bc	0.57a	0.52e	0.49f	0.53b
NDVI (range)	0.46	0.46	0.47	0.51	0.44	0.39	0.48
NDVI 2016 GS	0.49c	0.46e	0.47d	0.54a	0.49c	0.46e	0.51b
Slope							
Nearly Level (%)	57.82	36.37	39.01	36.00	23.43	46.52	28.41
Gentle (%)	30.61	58.33	41.13	48.67	63.43	50.80	63.07
Moderately steep (%)	10.88	3.79	11.35	12.67	11.43	2.67	8.52
Steep (%)	0.68	1.52	8.51	2.67	1.71		

^a GS is growing season from 11/1 to 4/30 of that year.

Table 2

Farm management practices of plots (n = 1108) on surveyed farms at seven sites (Extension Planning Areas, EPAs) in Central and Southern Malawi. The letters indicate the Least Significant Difference (LSD) test category with one-way ANOVA test (comparison is across a row).

	Golomoti n = 147	Linthipe n = 132	Kandeu n = 141	Nsipe n = 150	Nyambi n = 175	Nsanama n = 187	Mtubwi n = 176
Wealth score	0.039 bc	−0.150c	0.331 a	0.243 ab	0.002 bc	0.249ab	−0.021c
Average plot size (acre)	0.63	0.45	0.68	0.49	0.62	0.59	0.83
Range of plot size (acre)	0.08–3.00	0.05–2.00	0.08–2.50	0.04–3.00	0.10–3.00	0.11–2.00	0.01–4.00
2016 Fertilizer Nitrogen							
Yes (%)	69	79	90	79	75	76	69
Mean at where applied (kg N ha ^{−1})	64abc	84a	81ab	85a	59abc	47c	54bc
2016 Compost							
2016 Yes (%)	46	56	60	49	39	45	36
2016 Residue Management							
Incorporated (%)	81	89	93	92	71	92	81
Removal (%)	1	7	1	1	6	6	9
Burning (%)	18	4	6	7	23	2	10
2016 Crop diversity							
Sole maize (%)	18.37	9.09	2.84	8.67	0.57	4.28	8.52
Range	1–5	1–5	1–5	1–5	1–3	1–3	1–3
No. per plot at when crop diversity > 1	2.53d	3.18a	3ab	2.83bc	2.88bc	2.73cd	2.67cd
Weeds (0–18) ^a							
Mean	9b	10ab	11a	11a	9b	7c	10ab
Median	6	8	10	11	7	6	9
Tropical Livestock Unit							
Yes (%)	76.87	81.82	66.67	81.33	68.57	64.17	54.55
Mean at when livestock present	0.63ab	0.46bc	0.93a	0.68ab	0.23c	0.19c	0.24c
Median	0.20	0.17	0.12	0.20	0.04	0.03	0.01
Max	6.60	2.60	9.33	6.50	1.22	1.00	1.55

^a Observations of weed presence at crop harvest of 2017.

Malawi (1 to 5) compared to Southern Malawi (1 to 3). Linthipe had the highest numbers of crops per plot (3.18). A sole maize cropping system made up 0.57% to 18.37% of all plots, with few sole maize plots in Southern Malawi. Mean weed presence at all sites was above 9, equivalent to 50% coverage of the ground at harvest (Table 2). Nsanama (6) and Golomoti (6) had a low median weed presence, whereas Nsipe had the highest median weed presence (11). In each EPA studied, the majority of households had livestock, which ranged from 54.55% to 81.82% (Table 2). However, the number of livestock were very low, with a mean tropical livestock unit that ranged from 0.19 (Nsanama) to 0.93 (Kandeu).

3.2. Characteristics of soil properties

Overall sites were slightly acid, with the highest pH at the hot and dry site of Golomoti (6.54) and the lowest at the cool and wet site of Linthipe (6.09) (Table 3). Linthipe also had the lowest percentage of sand (58.64%). Highest mean sand content was in Nsanama (82.62%), followed by Nyambi (72.53%) and Mtubwi (70.69%), the three sites located in Southern Malawi. Clay percentage means was highest in Linthipe (17.36%), followed by Nsipe (15.22%) and Kandeu (15.14%).

Mean of SOC ranged from 6.31 g C kg soil^{−1} to 16.17 g C kg soil^{−1} (Table 3). Linthipe site had both the highest SOC (16.17 g C kg soil^{−1}). The three sites with the highest sand percentage, Nyambi, Nsanama, and Mtubwi, also the three lowest SOC means. The mean POXC value was highest in Linthipe (504.52 mg C kg soil^{−1}), and lowest in Nsanama

Table 3

Mean soil properties of plots (n = 1108) on surveyed farms at seven sites (Extension Planning Areas, EPAs) in Central and Southern Malawi. The letters indicate the LSD test category with one-tail ANOVA test (comparison is across a row).

	Golomoti n = 147	Linthipe n = 132	Kandeu n = 141	Nsipe n = 150	Nyambi n = 175	Nsanama n = 187	Mtubwi n = 176
pH	6.54a	6.09d	6.13cd	6.33bc	6.19bcd	6.33bc	6.34b
Texture							
Sand (%)	69.20bcd	58.64e	67.58 cd	67.06d	72.53b	82.62a	70.69bc
Silt (%)	18.09bc	24.00a	17.27cd	17.72cd	15.80d	10.97e	19.91b
Clay (%)	12.71b	17.36a	15.14a	15.22a	11.67b	6.41d	9.41c
SOC (g C kg soil ⁻¹)	10.29c	16.17a	12.39b	12.25b	8.07d	6.31e	8.97cd
Coefficient of variation	0.50	0.47	0.44	0.41	0.43	0.54	0.55
Skewness	2.69	0.57	0.85	0.78	1.93	1.87	2.93
POXC (mg C kg soil ⁻¹)	386.9bc	504.5a	432.3abc	479.6a	369.3c	291.5d	446.7ab
Coefficient of variation	0.42	0.41	0.52	0.52	0.52	0.69	0.64
Skewness	0.65	0.49	0.61	1.19	2.01	2.41	1.72
Cmin (mg C kg soil ⁻¹)	52.76b	44.96c	56.99b	65.34a	28.71d	39.25c	40.73c
Coefficient of variation	0.43	0.37	0.41	0.40	0.44	0.52	0.40
Skewness	0.78	1.03	0.78	1.00	1.75	1.52	0.68

(291.49 mg C kg soil⁻¹). This followed the pattern observed for SOC. However, Mtubwi site with low SOC, had relatively high POXC. Cmin value was highest in Nsipe site and lowest in Nyambi site, and generally followed the SOC status.

Soil organic carbon was correlated to POXC, with high Person's coefficient in three of the central sites, Golomoti, Linthipe and Kandeu (Table 4). However, SOC was not significantly associated with the Cmin at two sites, Linthipe and Nyambi. The two labile fractions, POXC and Cmin, were not correlated at the Nyambi and Mtubwi sites, whereas on other sites there was an association at low levels (0.19 to 0.47).

3.3. Regional drivers of soil properties

The regional analysis was conducted for all plots included in this study. Posterior results of the Bayesian regression analysis with 2 chains of 10, 000 iteration were shown in Fig. 2. The dependent variable is at 95% Bayesian credibility if the interval of the drivers (blue line) resides on one side of the value zero. The posterior result lines show the range of 95% Bayesian credible intervals, where the two lines depict the credibility intervals for the two chains, as a convenient visual gauge of convergence of the regression's computational method.

3.3.1. SOC

The dominant drivers of SOC were environmental and soil edaphic factors, including MAT, slope, NDVI, and clay content, where the latter two were highly positive drivers (Fig. 2a). The 10-year average MAT was negatively related to SOC, at medium magnitude (Fig. 2a, Table 4). The slope had a modest negative influence and soil pH had a modest positive association with SOC. Management practices' effects were identified, at a small magnitude (Table 5). These included weed presence, which was a larger determinant for SOC than residue management and crop diversity. The number of tropical livestock units per household was found to be negatively associated with SOC.

3.3.2. Labile carbon

The main determinants of POXC were identified as NDVI and clay, which were also important determinants of SOC (Fig. 2b). Soil pH was also significant at a small magnitude. The only significant management

practice indicator was crop diversity. However, environmental factors did not show an effect on POXC and only one management factor was influential in a positive way, that of crop diversity. Mineralizable C was also not associated with the climatic indicator, MAT. Yet, mineralizable C was more sensitive to drivers in the model compared to POXC (Fig. 2c). Four environmental variables and two management indicators were determinants of Cmin. Similar to the SOC, NDVI, soil pH, and clay percentage were positively related to Cmin. The N rate from fertilizer application was found to be positively associated with Cmin, while no significance was shown for SOC and POXC. Residue retention was also a positive driver for Cmin.

3.4. Local level drivers of soil properties

The climatic indicator, ten-year average MAT, was a dominant determinant of SOC at the regional level and associated with SOC variations at three local sites (Fig. 3 and Fig. 4). Clay content and NDVI showed markedly positive influences on SOC at several sites, and the magnitude was considerably larger than all other indicators in the local model.

At the Central Malawi sites, NDVI was a positive driver for SOC at varying magnitude for two local sites, but none of the management controls had shown influence on SOC except livestock ownership in the Linthipe cluster (Fig. 3). At the Golomoti cluster, the low agricultural potential site, NDVI did not show any influence on SOC variation. Soil organic carbon in plots at the Linthipe village cluster was highest compared to other clusters. At the Linthipe cluster, three main determinants in the order of large to small magnitude are clay content, NDVI, and livestock. Compared to the Golomoti and Linthipe village clusters, plots in Nsipe had more steeper slopes (Table 1). The slope was identified as a negative determinant for SOC at the Nsipe site. In addition, the Nsipe site was identified as the coolest site in this study (Table 1), thus temperature was a positive determinant for SOC besides NDVI and clay content. Crop diversity was also positively associated with SOC in Nsipe.

In Southern Malawi, a distinctly positive effect of clay on SOC was found at all sites (Fig. 4). Compost had a positive influence on SOC in Nyambi, where few plots were sole maize. Even within the same EPA,

Table 4

Pearson correlations between SOC, POXC, and Cmin by Extension Planning Areas in Central and Southern Malawi. Values with ***, **, and * indicate correlations are significant at the levels $p < 0.001$, $p < 0.01$, and $p < 0.05$, respectively.

	Golomoti n = 147	Linthipe n = 132	Kandeu n = 141	Nsipe n = 150	Nyambi n = 175	Nsanama n = 187	Mtubwi n = 176
SOC (g C kg soil ⁻¹) and POXC (mg C kg soil ⁻¹)	0.70***	0.86***	0.67***	0.31***	0.29***	0.43***	0.32***
SOC (g C kg soil ⁻¹) and Cmin (mg C kg soil ⁻¹)	0.36***	0.14	0.51***	0.40***	0.093	0.63***	0.51***
POXC (mg C kg soil ⁻¹) and Cmin (mg C kg soil ⁻¹)	0.37***	0.21*	0.47***	0.19*	0.026	0.27***	0.14

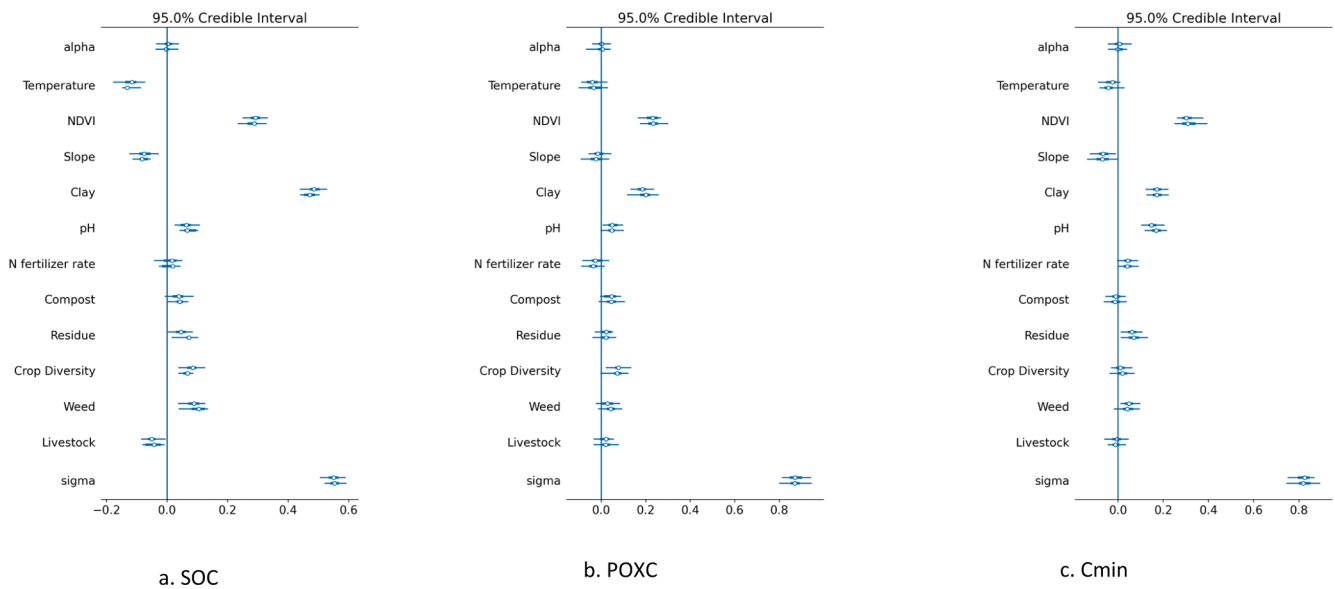


Fig. 2. Posterior results of Bayesian regression model with 2 chains of 10, 000 iterations explicit the 95% credible intervals associated with drivers of SOC, POXC, and Cmin across all plots ($n = 1108$) in Central and Southern Malawi.

Table 5

Bayesian statistics summary, significant variables are in bold with red indicate positive influence and black indicate negative influence. Values with * indicate 95% credible significant at the level of $p < 0.05$.

	SOC		POXC		Cmin	
	Mean (sd)	95% Credible interval	Mean (sd)	95% Credible interval	Mean (sd)	95% Credible interval
alpha	0.001 (0.02)	(-0.036, 0.038)	0 (0.025)	(-0.041, 0.046)	0.003 (0.026)	(-0.045, 0.052)
Temperature	-0.124 (0.024)	(-0.172, -0.086)*	-0.036 (0.037)	(-0.096, 0.029)	-0.035 (0.029)	(-0.084, 0.019)
NDVI	0.287 (0.026)	(0.234, 0.329)*	0.231 (0.034)	(0.163, 0.285)*	0.309 (0.036)	(0.249, 0.38)*
Slope	-0.078 (0.023)	(-0.122, -0.039)*	-0.016 (0.032)	(-0.07, 0.046)	-0.067 (0.033)	(-0.126, -0.003)*
Clay	0.479 (0.024)	(0.439, 0.517)*	0.189 (0.033)	(0.139, 0.266)*	0.172 (0.027)	(0.125, 0.223)*
pH	0.067 (0.023)	(0.03, 0.104)*	0.048 (0.027)	(0.006, 0.104)*	0.161 (0.028)	(0.117, 0.215)*
N fertilizer rate	0.01 (0.024)	(-0.027, 0.056)	-0.028 (0.032)	(-0.084, 0.032)	0.042 (0.024)	(0.001, 0.092)*
Compost	0.039 (0.023)	(-0.008, 0.081)	0.043 (0.031)	(-0.007, 0.094)	-0.012 (0.026)	(-0.058, 0.034)
Residue	0.058 (0.025)	(0.015, 0.103)*	0.018 (0.027)	(-0.039, 0.059)	0.066 (0.03)	(0.012, 0.122)*
Crop Diversity	0.072 (0.022)	(0.037, 0.115)*	0.074 (0.029)	(0.009, 0.126)*	0.015 (0.028)	(-0.029, 0.07)
Weed	0.093 (0.03)	(0.038, 0.136)*	0.035 (0.032)	(-0.02, 0.09)	0.045 (0.028)	(-0.002, 0.096)
Livestock	-0.047 (0.024)	(-0.082, -0.006)*	0.018 (0.028)	(-0.036, 0.071)	-0.006 (0.027)	(-0.051, 0.04)
sigma	0.552 (0.022)	(0.509, 0.59)	0.877 (0.038)	(0.81, 0.943)	0.823 (0.038)	(0.75, 0.881)

SOC spatial distribution in the cultivated field varied (Fig. 4b and Fig. 4c). The Mtubwi village cluster 1 had a higher SOC than the Mtubwi village cluster 2. At the low SOC village cluster, Mtubwi 2, several indicators had positive effects on SOC including clay content, fertilizer application, weed presence, and livestock. The tropical livestock unit was found to be positively related to the highest SOC cluster in central Malawi and the lowest SOC cluster in southern Malawi.

4. Discussion

4.1. Soil total and labile C

Overall, soil C status was low at the lakeshore site of Golomoti ($10.29 \text{ g C kg soil}^{-1}$) site and the Southern sites of Nyambi ($8.07 \text{ g C kg soil}^{-1}$), Nsanama ($6.31 \text{ g C kg soil}^{-1}$), and Mtubwi ($8.97 \text{ g C kg soil}^{-1}$).

In contrast, at the cool, mid-altitude site, Linthipe, soil C was $16.17 \text{ g C kg soil}^{-1}$, and we note that this site was fine-textured, with an average of 17.36 % clay. This site was at $0.67 - 3.23^\circ \text{C}$ cooler than other sites (Table 3). These findings are consistent with the widely reported role of fine-textured soil in SOC accrual through physical protection (Negasa et al., 2017; Shang and Tiessen, 1997). Cooler temperatures are also often associated with slow SOC turnover, as seen here (Fissore, et al., 2008).

The moderate soil C values we observed on Malawi farmers' fields generally are consistent with previous reports. A study with sites both north and south of our survey, reported values of 6 to $7 \text{ g C kg soil}^{-1}$ and 0.3 to $0.5 \text{ g N kg soil}^{-1}$ (Kihara et al., 2016). On the other hand, the mean value of SOC ($19.5 \text{ g C kg soil}^{-1}$) in Nsipe reported by Mponela et al., (2020) was higher than our findings for Nsipe, a mean value of $12.25 \text{ g C kg soil}^{-1}$. We note that the soil survey of Nsipe by Mponela and

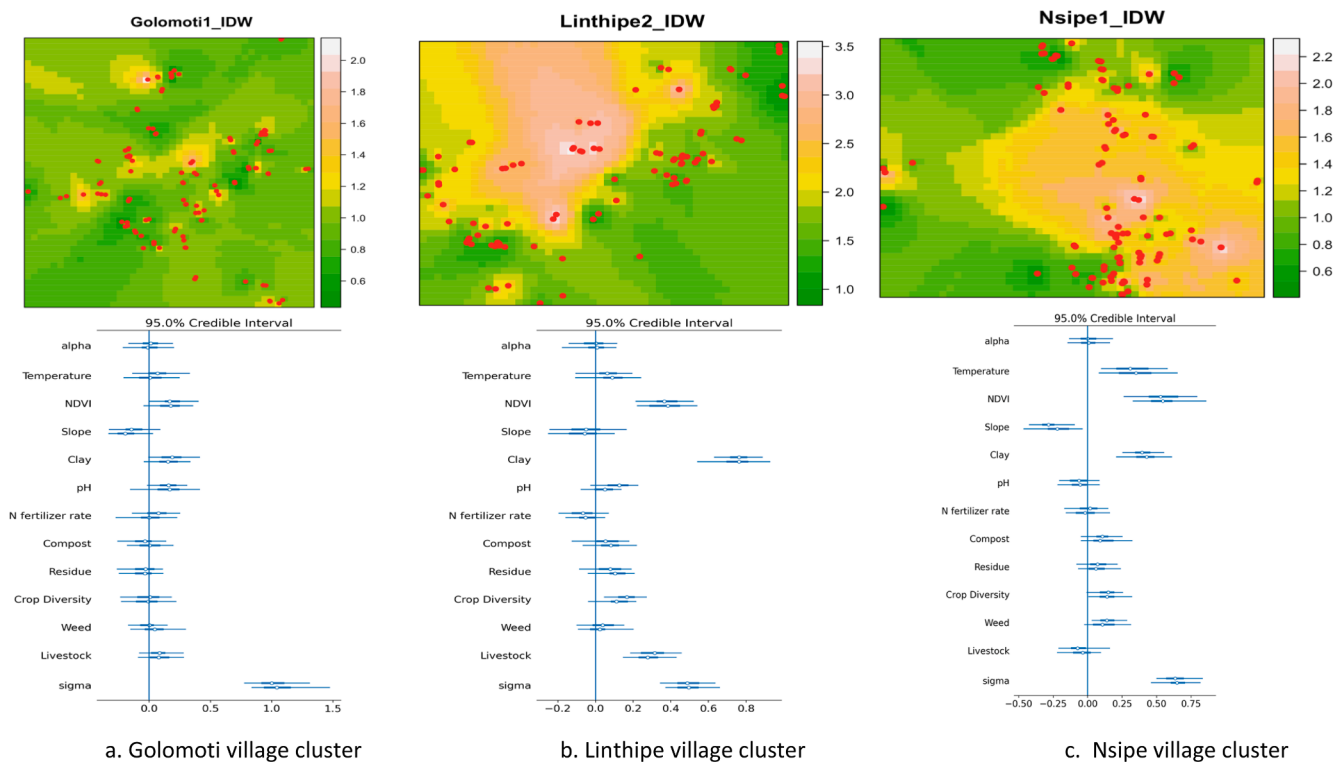


Fig. 3. Inverse Distance Weighting (IDW) interpolation map of SOC and posterior results of Bayesian regression model with 2 chains of 10,000 iterations explicit the 95% credible intervals associated with drivers of SOC at three village clusters, Golomoti ($n = 115$), Linthipe ($n = 96$), and Nsipe ($n = 112$) in Central Malawi.

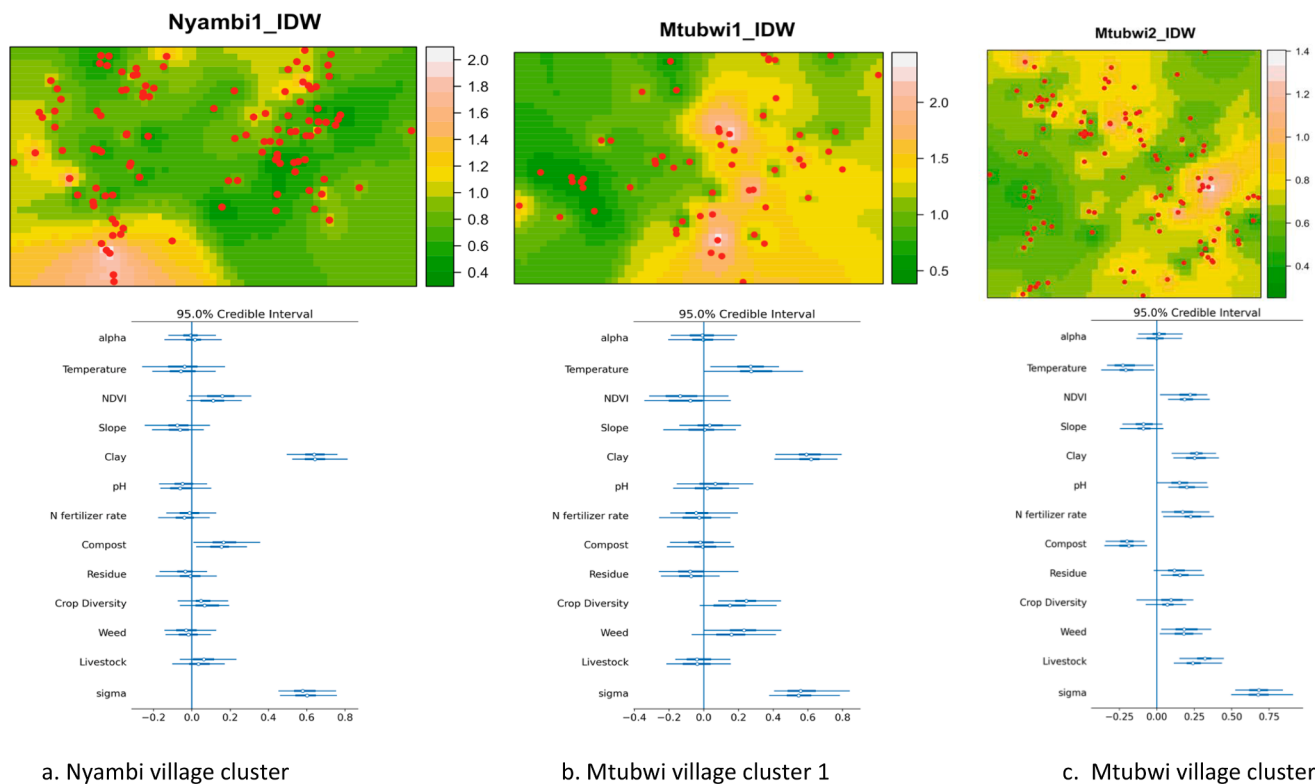


Fig. 4. Inverse Distance Weighting (IDW) interpolation map of SOC and posterior results of Bayesian regression model with 2 chains of 10,000 iterations explicit the 95% credible intervals associated with drivers of SOC at three village clusters, Nyambi 1 ($n = 115$), Mtubwi 1 ($n = 61$), and Mtubwi 2 ($n = 115$) in Southern Malawi.

colleagues (2020) included non-cultivated natural sites as well as cultivated sites, which is expected to lead to a higher mean value overall.

The extent to which soil C values have changed over time is not

possible to discern here. Perspective is, however, provided by a study by Snapp (1998) who reported a mean value of 17 g C kg^{-1} from hundreds of cultivated fields in Central Malawi, substantially higher than

observations reported here from the same region. Changes in soil C over two decades are reported in a longitudinal study in the Machinga district (which included three of our surveyed sites), consistent with a decline in SOC having occurred specifically for intensively cultivated fields (Mpeketula, 2016).

There is limited data on thresholds for soil C, which poses a challenge to the interpretation of the soil C status we observed. Literature summarized by Mponela et al. (2020) indicated critical limits of SOC for agricultural productivity that ranges from 5 to 20 g C kg soil⁻¹. Burke et al. (2020) evaluated the SOC threshold from cultivated fields from our site locations and found that 9.4 g C kg soil⁻¹ was the critical value in terms of a positive maize yield response to N fertilizer application. Based on these reports, the three EPA sites in Southern Malawi have poor SOC status generally, with a limited potential for high yield response to fertilizer amendments.

Active C indicators such as POXC and Cmin provide insights into soil C trends and function (Frost et al., 2019). Generally, a high correlation of these indicators was observed relative to SOC status. Cmin was found to be an exception at Linthipe and Nyambi, two sites with intensive production practices, as there was almost nil relationship to SOC at these sites. Cmin is sensitive to frequent disturbance, possibly more so than SOC (Jilling et al., 2020). The other exception was POXC levels in Southern Malawi at 291.5 mg C kg soil⁻¹ to 446.7 mg C kg soil⁻¹, which were levels similar to those observed in Central Malawi, and did not follow the low SOC observed in Southern Malawi (6.31 to 8.97 g C kg soil⁻¹). The high turnover rate of POXC in Southern Malawi could be due to the (modestly) higher temperature range observed at these sites. Active carbon fractions may be easily decomposed under high temperatures (Janzen et al., 1992), and lost through cultivation (Shang and Tiessen, 1997). We also note that sand fraction associated labile C is susceptible to oxidation and less stable compared to clay and silt (Shang and Tiessen, 1997), and we found high sand content in Southern sites. Such findings confirm that processes widely studied under controlled environmental conditions, such as temperature accelerated carbon loss from labile pools, can help explain POXC and Cmin distribution patterns found on cultivated fields. Model prediction of labile and stable C pools can be informed by this study, especially in setting parameters for soil types common on smallholder farms of Southern Africa.

4.2. Environmental factors

The surveyed smallholder farm sites with warmer temperatures were consistently associated with low soil organic C in this study (Fig. 1). Soil C loss is biologically mediated, thus a temperature rise is expected to be associated with rapid soil C loss due to high activity. Studies in the U.S. Central Plain Grassland found low SOC at sites with high annual temperatures (Burke et al., 1989). Indeed, the SOC to climate relationship is a vital component in most regional assessments of SOC (Burke et al., 1989; Calvo de Anta et al., 2020; Hontoria et al., 1999; Page et al., 2013). At the same time, variability in terms of climate is expected to be modest at a local scale. Not surprisingly, temperature was not always a significant driver of the SOC at individual sites. However, SOC was found to be positively related to temperature and NDVI at Nsipe, the coolest site; there could be high biomass accumulation within this area which had the highest NDVI mean value of 0.57 (Fig. 3, Table 1). The strong temperature the soil C pools are essential to predict the soil C change with future management and potential climate change.

The negative relationship of slope with SOC we observed has been found in other studies, due to processes associated with cultivated sloping lands, that of erosion and translocation of clay and silt particles (Negasa et al., 2017; Ottoy et al., 2017; Seibert et al., 2007). In a study conducted in Southern Ethiopia at smallholder farmers' managed land, SOC was found to be negatively influenced by the slope (Negasa et al., 2017). Though the majority of the fields were flat or moderately sloped, slope still showed a negative influence on SOC. This is consistent with erosional processes having a large effect on SOC loss, which may well be

underappreciated on fields that have almost no appreciable slope. Similarly, study across a range of land use classes in Southern Tanzania found erosion to be high on cultivated ground with less steep slopes (Wickama et al., 2014).

Consistent with the literature, we found a markedly positive relationship of clay content and high SOC (Burke et al., 1989; Meersmans et al., 2008; Tan et al., 2004). This was due to the large surface area and organo-mineral complexes associated with fine particle size (Chaplot et al., 2010; Six et al., 2002). This edaphic factor was a highly consistent positive driver of SOC, POXC and Cmin. It was an important positive factor at almost all sites at the local scale, as well as at the regional scale. Soil pH was positive at varying magnitudes for the total and labile C fractions. The positive relationship of soil pH and SOC in slightly acid soil was found earlier in forest soils in North America due to enhanced C stabilization through reduced mineral surface charges (Fissore et al., 2008).

The key role of soil texture shown in our study, as a determinant of total and labile soil C, is consistent with the need for management that targets organic amendments and continuous cover to coarse textured soils to maintain soil carbon. In addition, erosion control measures must be implemented on all sloped fields, including those of moderate degree, or with micro-topographical features.

4.3. Normalized Difference Vegetation Index

Vegetative cover, as reflected by NDVI values, is an important predictor of SOC (Kunkel et al., 2011; Page et al., 2013; Zhang et al., 2019). This is expected for natural areas where biomass inputs are a key determinant of SOC. However, cultivated soils are subjected to diverse management practices that influence decomposition as well as accrual processes, (e.g., soil disturbance, organic and inorganic amendments, and diversity of crops grown). Few studies of intensively cultivated lands have been conducted, and this is the first that we know of conducted at multiple scales for smallholder farms in the sub-humid tropics. The 10-year growing season average NDVI we used is a highly significant driver of both stable and labile C pools. This was observed at the regional scale and for SOC at three out of six sites at local scale. Golomoti village cluster is hot and dry with low SOC, and in this environment NDVI was not a significant positive driver for SOC. Modeling SOC in tropical cultivated fields requires consideration of vegetative cover, through remote sensing proxies such as NDVI. Further studies are needed to assess if NDVI is less useful at marginal sites, and local scales.

4.4. Farm management factors

This is one of the first reports of management practices as drivers of soil C pools at multiple scales across a cultivated smallholder landscape. Over 1000 farm plots are monitored in this project, where management practices were evaluated for effects on soil organic matter fractions at the regional and local scales. The documentation of the management practice across Central and Southern Malawi can serve as a guide for extension educators and policymakers regarding the preconditions for opportunities and challenges in promoting sustainable practices. Overall, we found consistent evidence for biomass in the form of crop diversity and weed presence that had positive effects on SOC. POXC, on the other hand, was not influenced by management practices except crop diversity. This may be related to the existence of high sand fractions in the soil, which has previously been shown to be associated with low or variable POXC values (Plaza-Bonilla et al., 2014; Wade et al., 2020). Crop diversity is a key component of sustainable agricultural intensification, and several studies have recently pointed to a unique role for intercrops in soil C accrual (Cong et al., 2015; Garland et al., 2017; Powlson et al., 2016).

Residue retention through incorporation had positive associations with SOC and Cmin in the regional level study. At the local level, residue retention was not associated with SOC, this may be due to the modest

size of the datasets at local levels which reduces the ability to detect drivers. Overall, the biological fraction C_{min} appears to be sensitive to crop management, including crop residue use, more so than POXC. A previous study of conservation agriculture trials conducted on-farm in Malawi over multiple years provides experimentation evidence that crop residue retention can enhance C_{min} (Ngwira et al., 2013). In our survey, farmer adoption of no-tillage was almost nil, so it was not possible to evaluate the effect of tillage, only the crop diversity aspect of conservation agriculture practices.

One of the challenges to promoting crop residue retention to build SOC is the high competition for this organic resource. It is often preferred to use crop stover as feed, rather than to retain to amend the soil (Tiftonell et al., 2015; Valbuena et al., 2015). In Central Malawi, however, livestock ownership is low, and a survey in 2013 indicated that residues are generally retained, with the incorporation of residues reported for three-quarters of plots either soon after crop harvest or within six months (Mungai et al., 2016).

Mixed cropping, which enhances residue biomass quantity and diversity of tissue types, is widely practiced in Malawi (Bezner Kerr et al., 2019; Wang et al., 2019). In our study, crop diversity (more than one crop per plot, grown as an intercrop) was found to be associated with enhanced SOC, and POXC. Maize intercrops are the dominant cropping pattern in Malawi (Silberg et al., 2017). This adds to growing evidence that biochemical diversity of residue tissues through crop diversity can positively influence soil organic matter fractions. Such processes may be influenced by the quantity of belowground root biomass, which appears to be high in an intercrop compared to a rotational system or a monoculture (Naab et al., 2017). Root inputs and high SOC accrual were also found in a six-year field experiment, associated specifically with intercrop diversity (Cong et al., 2015).

Weed presence is often considered as a negative factor in agriculture development, in terms of plant competition, and thus suppression of crop productivity. It has not, to our knowledge, been previously reported on in relationship to soil organic matter accrual at the regional scale, at least for cultivated fields in Malawi. Weeds are a source of biomass above and belowground in field plots, and thus would be expected to generally enhance soil organic carbon (Arai et al., 2014).

The management practices associated with high soil C status were all related to biomass, notably crop diversity, residue incorporation, and weed presence. Taken together with the key determinant of NDVI, this is indicative of the need to pay close attention to biodiversity and management of organic inputs as SOC regulating factors in agricultural landscapes. Consistent with these findings, a meta-analysis of smallholder farm studies recently highlighted the role of legume intercrops in providing enhanced organic inputs belowground, relative to sole cropping, leading to modest but significant SOC accrual (Powlson et al., 2016). Jayne et al., (2019) called for policies that support the management of organic in conjunction with inorganic inputs, for sustainable intensification to be achieved in Africa. Our findings corroborate the need for agricultural policies and mapping of soil carbon efforts, that pay close attention to mixed cropping patterns and weed distribution as mediators of soil carbon accrual in cultivated fields.

5. Conclusions

Through integrating the Bayesian statistical approach and on-farm study in Malawi cultivated fields, we found environmental and soil edaphic variables are determinants of labile and stable soil C pools. Overall, soil clay content and NDVI were key determinants, at both regional and local scales. Interestingly, the one exception was the hot, dry site of Golomoti, where SOC status was low, and there was no effect of NDVI. Local scale studies of marginal farm sites may not be able to rely on remote sensed NDVI, in contrast to countrywide and larger scale studies. Management variables had modest effects, but a consistent pattern was observed in that management associated with enhanced biomass quantity and diversity were positively associated with soil C

pools: namely, crop diversity, weed presence, and residue retention. Inorganic nutrient amendment (fertilizer) was associated with the operationally defined fraction of mineralizable C, but it did not show any positive influence on other C fractions that were evaluated in this study. Policy implications are that fertilizer access is not sufficient on its own for sustainable SOC management, that crop diversity should not be overlooked as a means to enhance soil C accrual. Weeds in resource-limited cropping systems in Sub-Saharan Africa may also provide SOC benefits, a research topic that may have been entirely overlooked. Overall, the benefits associated with enhancing the quality and quantity of organic resources on smallholder farms require urgent attention, to reverse soil degradation in support of sustainable intensification.

Declaration of Competing Interest

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

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.geoderma.2022.115746>.

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