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Soil organic matter underlies crop nutritional quality and productivity in smallholder agriculture

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ABSTRACT

Global crop yield gains have not be associated with increases in the many macro- and micro-nutrients needed for a balanced human diet. There is thus growing interest in improving agricultural practices to increase nutrient availability to people. Because nutrients in crops come from soil, soil management—such as building soil organic matter—could be a tool in managing agriculture to produce more nutritious food. To understand the relationship between soil organic matter and nutritional quality, we measured soil organic matter fractions, crop yield, and wheat nutrient composition on smallholder farms along a land-use and land-cover gradient in Ethiopia. We found that wheat yields and protein content were related to organic matter nitrogen, and zinc content was related to organic matter carbon. Increasing organic matter carbon by 1% was associated with an increase in zinc equivalent to the needs of 0.2 additional people per hectare; increasing organic matter nitrogen by 1% was associated with an increase in protein equivalent to the daily needs of 0.1 additional people per hectare. Soil organic matter—and its associated fractions—was greatest in soils closest to a state forest and in home gardens (as opposed to in wheat fields). Wheat fields closer to the forest had elevated soil organic matter fractions relative to wheat soils closest to the market town. Our results indicate that realistic gains in soil organic matter could make human-health-relevant increases in wheat nutrient content. Soil organic matter management can therefore be an additional tool for feeding the world well.

1. Introduction

Global yields of staple grains increased significantly starting in the early 1960s, even on a per capita basis as populations have grown (DeFries et al., 2015; Hazell and Wood, 2008). Production of the many nutrients required for a balanced human diet, however, has not kept pace with the growth in yield and calories, and even fallen for some nutrients (DeFries et al., 2015). In addition, there is growing evidence that increasing CO_2 concentrations could further suppress crop micronutrient content (Myers et al., 2014). Evidence from a more-than-century-old cropping trial suggests that this has already happened due to existing changes in atmospheric CO_2 concentrations (Fan et al., 2008). Ensuring food is nutritious, and not just calorically adequate, will therefore be important to future advances in agriculture.

The threat of decreasing crop nutrients—or decreasing crop nutrients per capita—raises concerns about hidden hunger, which is the high burden of vitamin and mineral deficiency around the world. To date, most nutrition interventions have focused on dietary supplementation, dietary diversification, and to a lesser degree biofortification of existing crops. Largely missing from this nutritional toolkit has been management of the environment conditions in which crops grow, such as soil properties, to optimize nutrient concentrations. Despite this absence, it is established that soils can contribute to nutrients in crops in sufficient levels to impact human wellbeing (Barrett and Bevis, 2015; Bevis, 2015). For instance, crops grown on soils with low levels of selenium have been shown to lead to selenium deficiencies in people consuming these crops (Chilimba et al., 2011; Hurst et al., 2013).

There is a need to combat hidden hunger by increasing the nutrient composition of crops and one avenue to do this is through integrated soil fertility management, which emphasizes building up the organic and inorganic nutrients needed by plants through land management and mineral fertilizer use (Bado and Bationo, 2018; De Valença et al., 2017). A key aspect of integrated soil fertility management is soil organic matter (SOM). Going back to the earliest work in agroecology, there have been claims that building SOM is associated with more

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nutritious food (Howard, 2010). Soil organic matter provides macronutrients for protein building in plants, as well as cation exchange capacity for the exchange of micronutrients. Despite a long history of this supposition, there is strikingly little quantification of the link between SOM and crop nutrient content. There are some specific examples, mostly for horticultural crops, such as higher levels of flavonoids in tomatoes under organic production (Mitchell et al., 2007).

The main goal of this study was to assess if SOM was associated with nutrient composition of wheat in a smallholder farming setting in Ethiopia. We focused on SOM because it is known to impact nutrient availability through elevated cation-exchange capacity, and also because it is a manageable soil property (unlike texture, which is also related to cation-exchange capacity). We measured SOM fractions—-mineral-associated and particulate—on the expectation that particulate organic matter would be more associated with nitrogen (N) release and mineral-assosciated organic matter would be more associated with cation-exchange capacity (Wander, 2004).

Our first objective was to determine the drivers in wheat yields and nutrient content across a landscape characterized by a gradient of distance to a state forest. We hypothesized two competing patterns in wheat yields. First, we expected that yields would be greatest for households closer to the market town (and thus having greater access to mineral fertilizers and other inputs) where farmers had also transformed their surrounding landscape the most for crop production (e.g., low tree cover; Baudron et al., 2017). Secondly, we expected that wheat yields would be greatest for farms with the greatest level of native SOM, suggesting agroecological—rather than conventionally intensive—approaches would be optimal for production. For wheat nutrients, we expected that nutrient content could be impacted by mineral fertilizers or native organic matter, when statistically controlling for soil type.

Our second objective was to determine the drivers in soil properties that we hypothesized could be important predictors of wheat yield and nutrient status. We posed two competing hypotheses for drivers in SOM—particulate and mineral organic matter as well as microbial biomass. First, we expected that SOM would decrease with distance from a state forest on the expectation that households closer to vegetation patches would have greater inputs of organic matter to their soil—mainly from manure from grazing cattle (see Baudron et al., 2017). Second, we hypothesized that patterns in SOM would be dominated by immediate land use—whether a soil sample was taken from a wheat field or home garden—regardless of distance to forest or grazing land. Because home gardens have high levels of organic inputs from household waste and household livestock, we expected this would wash out any distance-decay spatial pattern in SOM.

2. Material and methods

2.1. Site description

Nationally, Ethiopia is at severe risk of hidden hunger (Muthayya et al., 2013). Our study site was located in the *woreda* (district) of Arsi Negele, located in the Oromia region of Ethiopia (Baudron et al., 2017; Duriaux Chavarría et al., 2018). We studied six villages in an area of about 100 km^2 in three *kebele* (sub-district). Each village was selected to lie along a distance gradient from the state forest of Munesa (Baudron et al., 2017). Households were grouped into three geographical clusters: near-to-forest, middle, and near-to-main-market. The furthest villages from the state forest lie about 11 km from the forest area. The near-to-forest, middle, and near-to-main-market villages lie about 16, 11.5 and 6.5 km from the main market in Arsi Negele town (Fig. 1).

The study area lies between 2050 and 2214 m above sea level. Its climate is characterized by a mean annual rainfall of 1075 mm and a mean annual temperature of 15 °C. There are three main seasons: a short rainy season from March to May; a long rainy season from July to September; and a dry season from October to February. The natural vegetation is classified as dry Afromontane forest. Prior to land reform that took place in the mid-1970s, the landscape was largely forested and people were mainly pastoralists. Resident tenants only cultivated small fields. Today, the area outside of the state forest has been largely deforested for mixed crop-livestock agriculture. The main crops are wheat (*Triticum* sp. L.), maize (*Zea mays* L.), potato (*Solanum tuberosum* L.), and enset (*Ensete ventricosum* (Welw.) Cheesman). Soils are loam and clayey loam (Fig. S1). Most farmers keep livestock in the form of cattle, sheep, goats, horses, donkeys and chickens. Residents of villages neighboring the forest use the forest for grazing and collection of fuelwood. Middle villages are about 3 km from the forest and do not use it for grazing and fuelwood. They do, however, have access to a large communal grazing area for livestock grazing and fuelwood collection. Villages furthest from the forest—and closest to the market town—do not have access to any common land for livestock grazing and fuelwood collection. More site information can be found in Baudron et al (2017) and Duriaux Chavarría et al. (2018).

2.2. Field sampling and household surveys

Household surveys were conducted with 266 households—representing all of the households in each zone—between December 2014 and February 2015. Questions were asked regarding household composition, assets, income sources, crop and livestock production, forest use, market access and trading (Duriaux Chavarría et al., 2018). Based on survey results and a farm typology delineated through self-categorization exercises (Duriaux Chavarría et al., 2018), a stratified sample of nine farms per zone was selected for in-depth sampling and analysis.

Crop measurements—yield and nutrient content—were only collected for wheat fields while soils were collected from wheat fields, home gardens, and the municipal forest. Wheat yields were estimated by dividing the quantity of grain harvested from the field – as recalled by the head of the farm during the interview – and dividing it by the area of the field – as measured by a handheld GPS. Most farmers harvested their wheat field with a combine harvester (custom hire services) and thus had accurate records of their harvest. Because of the large diversity of crops in homegardens (enset, vegetables, coffee, maize, etc.), it was not possible to acquire data on the productivity of these other crops. Wheat samples were collected in November 2016, immediately after harvest. We collected about 500 g of wheat, which was sub-sampled from each farm's harvest after it was brought back to the household.

Soil samples were collected in December 2016 with a 2-cm probe. For each sample, we collected fifteen subsamples to 15 cm depth and aggregated and homogenized the subsamples to a single sample.

2.3. Crop analyses

Crude protein, iron and zinc contents of wheat grain were analyzed at Bless Agri Food Laboratory Services P.L.C. in Addis Ababa, Ethiopia (a ISO 17025-2005 accredited laboratory). Crude protein content was determined using Kjeldahl method (AOAC979.09) and iron and zinc contents were determined using atomic absoption spectrophotometry after microwave digestion (AOAC999.10).

2.4. Soil analyses

We analyzed soil for texture (% sand, silt, and clay), pH, microbial biomass, and carbon (C) and N of two SOM fractions: the particulate (> 53 μm) fraction and the mineral-associated (< 53 μm) fraction. Texture and pH analysis were done at the University of Connecticut soil testing facility. Microbial biomass was estimated using a modified substrate-induced respiration assay (Bradford et al., 2008a; Fierer et al., 2003). Briefly, we added 4 mL of autolyzed yeast to 4 *g* of dry-weight equivalent soil in 50-mL centrifuge tubes. We shook tubes on a bench-top shaker table for one hour, after which tubes were capped and

Fig. 1. Map of sampling locations in the Arsi Negele study zone. Points further west are closer to the forest, which is shaded in grey, and points further east are closer to the main market town. Points are colored by land use / land cover type. The polygons around sampling points indicate community clusters corresponding with the variables in the statistical model.

flushed with CO_2-free air at 1 L per minute for 2 min. We incubated the samples at 20 °C for 4 h and analyzed CO_2 concentration in 5 mL of headspace air on an infra-red gas analyzer. Final values are reported as μg C g dry soil^{-1} h^{-1}. This method has been shown to be highly correlated with other methods to estimate microbial biomass, namely chloroform fumigation extraction (Anderson and Domsch, 1978).

Soil organic matter fractions were measured using a size-based, wet-sieving fractionation procedure (Bradford et al., 2008b), as applied to African agricultural soil in Wood et al (2016). Briefly, we added 10 g of soil and 30 mL of sodium hexametaphosphate solution to 100-mL square, plastic Nalgene bottles. Sodium hexametaphosphate acts as a dispersal agent and breaks apart soil aggregates. We capped and shook the bottles for at least 18 h on a benchtop shaker table. We then washed the bottle contents through a 53-μm sieve, using 1 L of water to wash the contents through the sieve. We took a 150-mL sub-sample of what passed through the sieve and dried it to constant mass at 70 °C. Similarly, we retained the entire > 53-μm fraction and also dried it to constant mass at 70 °C. The dried < 53-μm fraction was ground to homogeneity by hand with a mortar and pestle; the dried > 53-μm fraction was ground in a Spex mill for 1 min. We took a 25-mg sub-sample of the homogenized sample and analyzed it for C and N on an elemental analyzer (Costech) at the Yale Analytical and Stable Isotope Center. Final values are reported as mg C or N g dry soil^{-1}. We refer to the two fractions as particulate organic matter (POM) (> 53 μm) and mineral-associated organic matter (MAOM) (< 53 μm).

2.5. Statistical analyses

We used generalized linear regression to determine the response of both crop and soil properties to a set of covariates. Generalized linear models are linear regression models that do not necessarily adhere to the assumption of normal distributions. We determined the appropriate distribution of response variables based on visual inspection and knowledge of the underlying processes generating the data. Predictor variables were chosen based on hypothesized impact on the response variable, rather than through threshold-based model selection, following Hobbs and Hilborn (2006). For models of crop yield and nutrient concentrations, we included N fertilization rates and pH because of their well established relationship to crop yields. We also tested models of nutrient concentrations with yield as a predictor, because of the expectation that greater yields could dilute nutrients (Janssen et al., 1990), but we found no evidence for this so did not include yields in the final nutrient models because of endogeneity with other covariates. Because our hypotheses related to conventional vs ecological intensification, we also included proximity to main market town (proxy for conventional intensificiation) and SOM (ecological intensification). For wheat yield and protein models we included POM N and MAOM N as the organic matter variables because we expected that yield and protein would be most strongly impacted by mineralization of N from organic matter. For micronutrient models, we used MAOM C because we expected that micronutrient concentration would be most strongly related to cation exchange capacity, which is driven by soil C, of which MAOM C is the largest fraction for our soils. For models of SOM, we included land use (home garden vs wheat field vs forest), land cover (proximity to forest), and an aggregate texture variable—defined as (percent silt + percent clay) / percent sand. We selected texture as a general soil type control for our SOM models because it partially determines the colloidal environment of soils that bind organic matter and

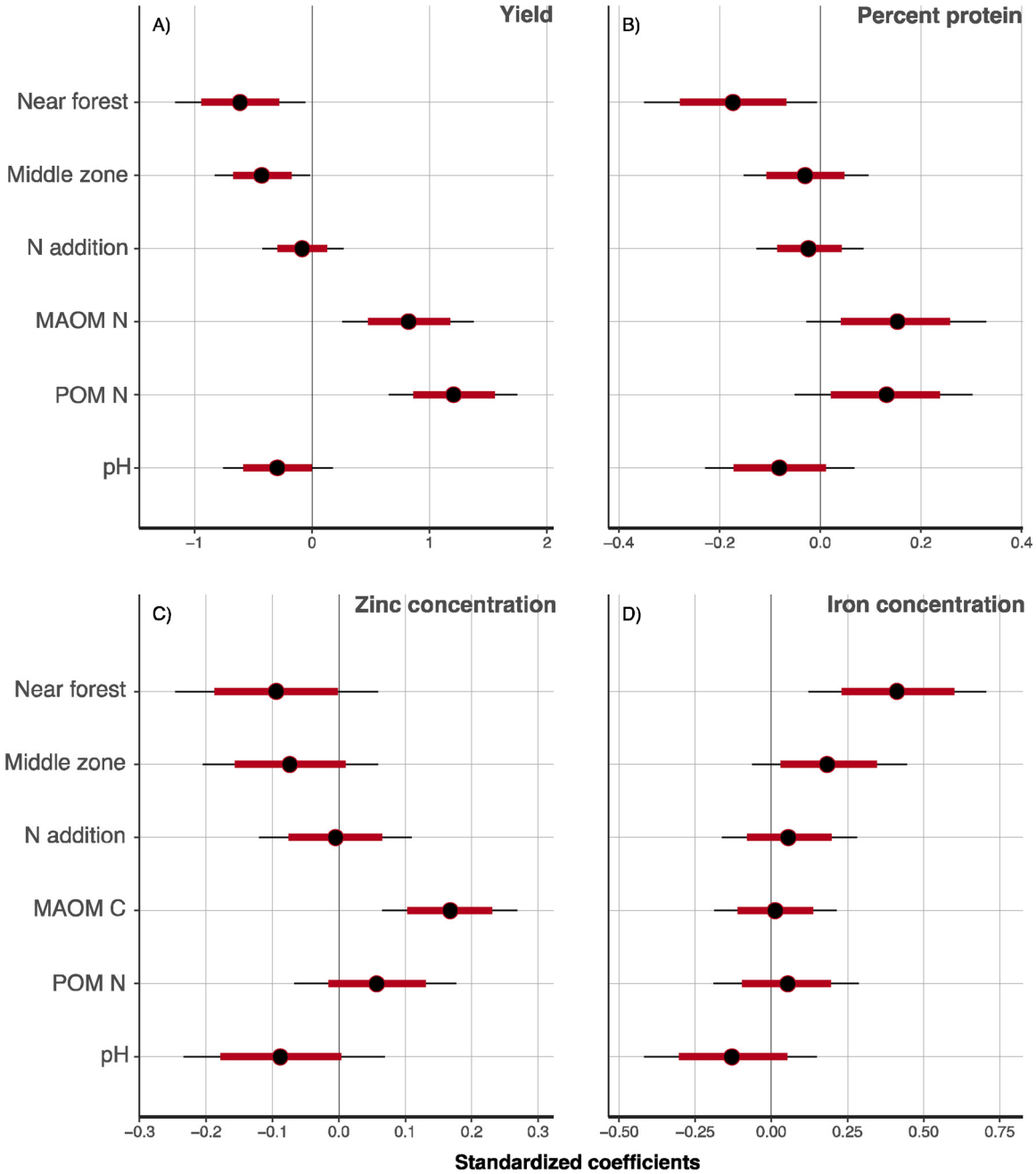

Fig. 2. Wheat model standardized coefficient plots showing the relative effect size of variables within a model, for yield (A), protein (B), zinc (C), and iron (D). Black vertical line is 0. Red bars indicate 80% of full distribution, black bars indicate 95%, and points are coefficient median values. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

determines residence time (Lehmann and Kleber, 2015). Because crop nutrient samples were taken exclusively from wheat fields, we ran separate organic matter models for wheat field soils to assess the impact of land use on SOM for the fields from which we collected crop samples.

In our statistical models, we standardized predictor variables by subtracting the mean and dividing by two standard deviations (Gelman, 2008). This allows direct comparison of the magnitude of the effect of each predictor variable. A variable with a standardized mean coefficient of 0.2 would therefore have twice as strong of an influence on the response variable as a predictor with a mean coefficient of 0.1. Model coefficients were estimated using the No-U-turn sampler algorithm of Hamiltonian Monte Carlo simulation, as implemented through the Stan software (Bettancourt, 2018). We used Stan to implement our linear models because Hamiltonian Monte Carlo is a probabilistic estimation procedure that can capture, and include, multiple sources of error, making it more conservative for prediction. Because we use our models to predict impact of increasing soil organic matter on human nutrient needs, we elected to use this more conservative approach. Briefly, this approach to estimation generates distributions of parameters, rather than point estimates common in frequentist approaches. We report the mean and standard deviation of the mean for each parameter. We also report Bayesian credible intervals for each parameter distribution. For the credible intervals, we report estimates at 5% and 95%. To evaluate model goodness-of-fit, we used posterior predictive checks (Gelman et al., 2014; Gelman and Shalizi, 2012). Specifically, we compare the distribution of our observed response variables with the distribution of values predicted by the model. High overlap between predicted and observed data indicates strong explanatory power of the model. We

Table 1
Crop data from wheat fields. Standard deviation is in parentheses.

	Protein %	Iron mg kg^{-}	Zinc mg kg^{-1}	Yield kg ha^{-1}	Area ha	N application kg ha^{-1}
Near market (n = 8)	9.06 (0.69)	25.69 (2.16)	27.73 (2.63)	2767.67 (997.88)	1.33 (0.83)	28.07 (16.75)
Middle (n = 9)	9.35 (0.98)	30.96 (4.87)	25.86 (3.35)	2295.06 (1670.32)	1.34 (0.8)	17.79 (11.68)
Near forest (n = 8)	8.75 (0.89)	36.63 (8.82)	27.19 (3.43)	2145.24 (269.61)	1.13 (0.78)	23.49 (8.99)

present these predictive checks in Supplementary figures (Figs. S2, S3).

We used the *rstan* package to interface with Stan through R. Our Stan and R code are available at: http://www.github.com/swood-ecology/arsi_gradient. Our data have been archived with the Knowledge Network for Biocomplexity (Wood, 2018).

2.6. Nutritional adequacy calculations

We sought to determine the number of people who could be nourished by an increase in crop nutrient contents associated with SOM. To do this, we used regression model coefficients for particulate and mineral-associated organic matter, which represent the increase in nutrient concentration (measured in mg g^{-1}) associated with a 1 mg g^{-1} increase in each fraction. We converted units for SOM so that values are associated with a 1% increase. To do this we divided the coefficient by 10. We then estimated the raw amount of nutrient gain by multiplying the concentration gain (plus the original concentration) for each farm by the reported yield for that farm. This is also a conservative assumption because we demonstrate that OM also is associated with higher yield, which would lead to more aggregate nutrients. By multiplying yield and nutrient concentration we derived total nutrients produced over the year, which we divided by the number of days in the year, and divided by an Ethiopia-specific estimate of daily nutritional requirements for each nutrient (Wood et al., 2018). This allowed us to determine the number of additional people per hectare whose nutritional requirements could potentially be met as a result of a 1% increase in SOM. A 1% increase is the approximate difference between the wheat field in our data set with the lowest SOM level and the wheat field with the highest SOM level. Because crop iron concentration was not significantly impacted by organic matter (see Results), we only did this estimation for zinc and protein.

3. Results

3.1. Are yields and nutrient concentration more driven by conventional intensification or soil organic matter?

3.1.1. Crop yields

We hypothesized that crop yields would be greatest either on farms with proximity to the main market town (Hyp. 1a), or on farms with greater levels of SOM (Hyp. 1b). In support of hypothesis 1a, we found that farms closest to the main market had higher yields, all other variables held constant, than farms closer to the municipal forest (Fig. 2a). We also found that this distance-to-market effect was smaller than the effect of increased SOM, where farms with more organic matter N—in both particulate and mineral forms—had higher crop yields (Fig. 2a). A marginal increase in POM N was associated on average with about 1900 kg per ha increase in wheat yield and a marginal increase in MAOM N was associated on average with a 4400 kg per ha increase in yield (Table 3). Also in support of 1b, we did not find evidence that N application was related to crop yield, holding all other variables constant (Fig. 2a; Table 3).

3.1.2. Crop nutrient concentrations

We hypothesized that crop nutrient concentrations would follow a similar pattern to crop yields and either be more strongly associated with fertilization and proximity to market, or more strongly associated with SOM. We found that wheat percent protein and zinc concentration were greater near the main market town (Fig. 2b, c), however iron concentration was greater further from the market town (Fig. 2d). Organic matter N (both particulate and mineral-associated) was positively related with wheat grain percent protein, though the credible interval for this relationship overlapped with zero at 95% (but not 80%). For protein, proximity to forest was the strongest (negative) driver (Fig. 2b). For zinc, the strongest driver was mineral-associated organic matter C, which is the only variable without a credible interval overlapping with zero (Fig. 2c). This effect was nearly twice as large as the distance to market effect for zinc (Fig. 2c). An increase in one g MAOM

Table 2
Soils data. Standard deviation is in parentheses. SIR is substrate-induced respiration, an indicator of microbial biomass; POM is particulate organic matter; MAOM is mineral-associate organic matter.

		SIR ug C h^{-1} g soil^{-1}	POM C mg g^{-1}	MAOM C mg g^{-1}	POM C:N	MAOM C:N	Sand %	Silt %	Clay %	pH
Home gardens	Near market (n = 2)	42.65 (3.04)	14.44 (NA)	29.12 (NA)	13.62 (NA)	11.69 (NA)	37.20 (0.85)	45.10 (1.27)	17.70 (2.12)	6.75 (0.07)
	Middle (n = 8)	42.65 (9.86)	11.63 (6.06)	25.52 (5.12)	13.30 (3.2)	14.97 (6.53)	47.75 (7.47)	35.03 (7.99)	17.23 (10.07)	6.73 (0.37)
	Near forest (n = 8)	37.68 (2.84)	14.17 (6.17)	30.37 (5.54)	12.99 (4.34)	11.15 (2.30)	47.25 (8.65)	34.13 (11.50)	18.63 (8.46)	6.91 (0.31)
Wheat fields	Near market (n = 8)	34.55 (5.13)	3.68 (0.93)	20.17 (4.12)	15.76 (8.98)	24.19 (17.1)	40.67 (5.52)	37.69 (8.32)	21.64 (8.26)	6.02 (0.27)
	Middle (n = 9)	29.75 (4.18)	3.42 (0.69)	19.23 (3.63)	19.69 (7.39)	19.90 (19.17)	42.80 (3.41)	29.78 (5.75)	27.42 (4.29)	5.59 (0.49)
	Near forest (n = 8)	34.68 (5.61)	5.11 (1.23)	24.04 (3.75)	15.92 (1.72)	10.74 (0.50)	39.78 (5.78)	37.48 (4.75)	22.75 (6.42)	6.24 (0.31)
Forest	n = 3	67.74 (26.84)	29.34 (12.23)	36.44 (0.59)	10.78 (2.25)	12.02 (4.41)	53.80 (12.49)	27.60 (5.10)	18.60 (17.50)	6.60 (0.10)

Table 3
Non-standardized regression results of crop models. For each parameter, we give the mean and standard deviation on the mean of the parameter distribution, as well as the values at 5% and 95% of the distribution.

Coefficient	Mean	Std. err.	5%	95%	Mean	Std. err.	5%	95%	Mean	Std. err.	5%	95%	Mean	Std. err.	5%	95%
	Crop yield (kg)				Protein (%)				Zinc concentration (mg kg^{-1})				Iron concentration (mg kg^{-1})			
N application (kg ha^{-1})	−6.13	0.32	−32.91	21.24	0.00	0.00	−0.01	0.00	0.00	0.00	−0.02	0.02	0.03	0.00	−0.06	0.12
MAOM C (mg g dry soil^{-1})									0.14	0.00	0.07	0.20	0.02	0.00	−0.29	0.31
POM N (mg g dry soil^{-1})	4112.03	21.65	2520.71	5731.25	0.26	0.01	−0.08	0.62	0.63	0.01	−0.13	1.35	0.54	0.05	−3.20	4.23
pH ([H$^+$])	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	−0.59	0.01	−1.38	0.26	0.00	0.00	0.00	0.00
Near to forest (1/0)	−1675.06	18.81	−3192.52	−197.96	−0.33	0.00	−0.65	−0.01	−0.34	0.01	−1.26	0.56	6.47	0.06	2.06	11.07
Middle zone (1/0)	−835.48	9.62	−1624.03	−63.79	−0.01	0.00	−0.17	0.14	−0.44	0.01	−0.84	0.18	2.87	0.03	0.32	5.39
MAOM N (mg g dry soil^{-1})	1711.89	13.78	707.42	2734.61	0.20	0.00	−0.02	0.43								

C per kg of soil was associated with a 0.15 mg kg^{-1} increase in wheat grain zinc concentration (Table 3). Soil organic matter C and N were not significant drivers of crop iron concentration (Fig. 2d). Wheat manganese concentration was not highly variable among farms (Table 1) and all specifications of statistical models had low explanatory power. We, therefore, did not include it in the manuscript.

We estimated that a 1% increase in SOM N would be associated with an increase in crop protein content equal to the daily needs of 0.1 people ha^{-1} (Fig. 3). A 1% increase in SOM C would be associated with an increase in crop zinc content equal to the daily needs of 0.2 people ha^{-1} (Fig. 3). Increasing SOM by the average difference between homegardens and wheat fields (1.65%) was associated with an increase in ability to meet nutrient needs of 0.2 people ha^{-1} for protein and 0.5 people ha^{-1} for zinc. These estimates are associated with multiple sources of error, including error around the coefficient from our statistical model and error associated with the variation in response among farms.

3.2. *Does soil organic matter differ with distance to forest or with land cover?*

We hypothesized that SOM concentrations would either follow a distance-to-forest gradient (Hyp. 2a), with soils closest to forest having highest organic matter, or be principally driven by local land cover (Hyp. 2b), i.e. whether a soil came from a wheat field, forest, or home garden.

3.2.1. *Particulate organic matter carbon*

For particulate organic matter C (POM C), we found that local land cover was the strongest predictor, with the greatest POM C being in forest soils, and then with near forest slightly higher than closest-to-market and no difference between middle and closest-to-market (Fig. 4a). Home garden soils also had higher POM C than wheat fields (Fig. 4a). Controlling for other variables, home gardens had 17 mg g^{-1} soil more POM C than wheat fields; forest soils had 61 mg g^{-1} soil more POM C than the furthest fields from the forest (Table 4). Wheat fields closest to the forest had the greatest POM C, with 0.81 mg g^{-1} more POM C than wheat fields closest to the main market town (Table 4;

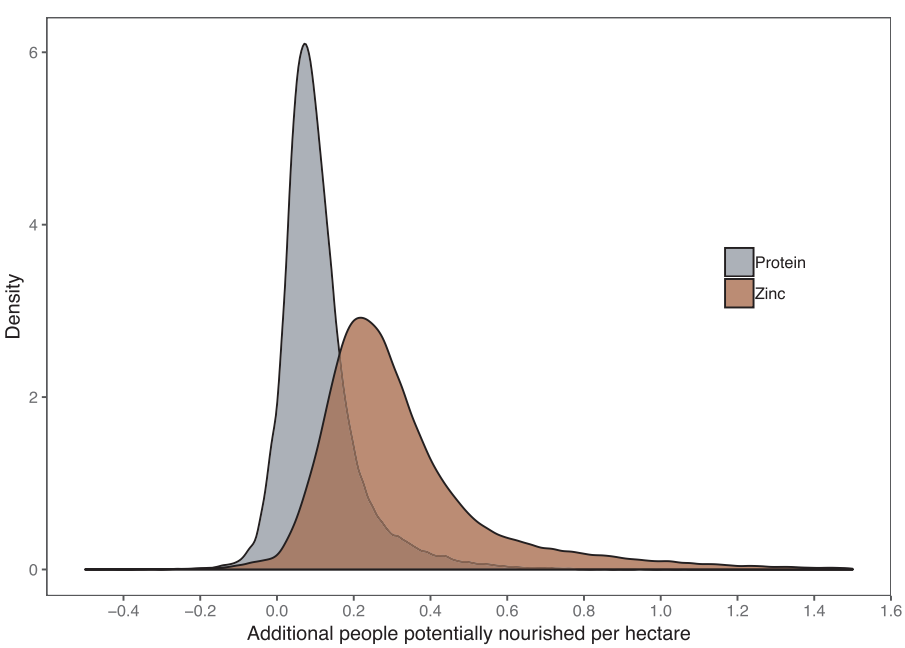

Fig. 3. Density plot of potential number of additional people per hectare whose nutrient needs could be met by increasing particulate and mineral-associated soil carbon by 1%. This is calculated by multiplying regression model coefficients for soil carbon effects on nutrient concentration by yield and dividing by the daily dietary needs in Ethiopia.

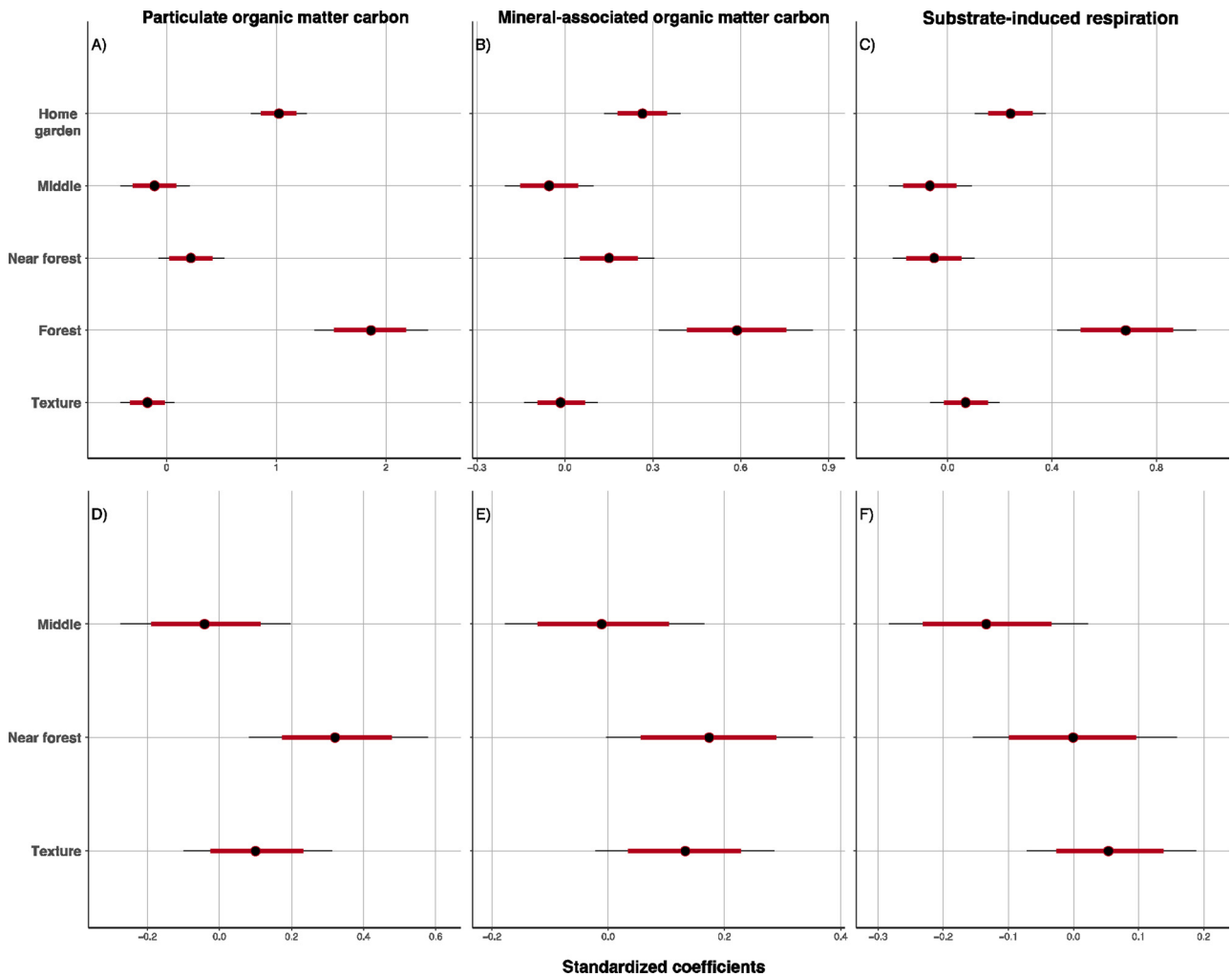

Fig. 4. Soil organic matter model standardized coefficient plots showing the relative effect size of variables within a model, for particulate organic matter carbon (A, D), mineral-associated organic matter carbon (B, E), and substrate-induced respiration (C, F). All sampling points are presented in plots A, B, and C; wheat fields only are presented in D, E, and F. Black vertical line is 0. Red bars indicate 80% of full distribution, black bars indicate 95%, and points are coefficient median values. For the local land use, wheat field coefficients is the reference category. For the proxy of distance to forest, the closest-to-market community is the reference category. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Fig. 4d). Middle and closest-to-market areas did not differ in POM C. Texture was slightly positively related to POM C.

3.2.2. Mineral-associated organic matter carbon

Patterns in MAOM C were qualitatively similar to POM in that local land cover was the strongest predictor of MAOM C concentrations, with the highest MAOM C in the forest—more than twice as strong as any other variable (Fig. 4b). The magnitude of change in MAOM C, however, was lower than for POM C (Table 4). Controlling for other variables, forest soils had 15 mg g^{-1} more MAOM C than wheat fields closest to the market town (Table 4). Home gardens closest to the market town had 4 mg g^{-1} more MAOM C than their associated wheat

Table 4
Non-standardized regression results of soil organic matter pool models, for all samples and for only wheat fields. For each parameter, we give the mean and standard error on the mean of the parameter distribution, as well as the values at 5% and 95% of the distribution. The reference level for home garden and wheat field binary variables is the state forest.

Coefficient	Mean	Std. err.	5%	95%	Mean	Std. err.	5%	95%	Mean	Std. err.	5%	95%
	Mineral associated organic matter C				Particulate organic matter C				Substrate-induced respiration			
All samples												
Home garden (1/0)	3.53	0.01	2.15	4.98	17.12	0.03	13.56	20.77	5.89	0.03	3.20	8.62
Middle zone (1/0)	−0.70	0.02	−2.48	1.08	−1.93	0.05	−6.31	2.40	−1.60	0.04	−4.89	1.78
Near to forest (1/0)	2.04	0.02	0.20	3.84	3.72	0.05	−0.69	7.99	−1.25	0.04	−4.76	2.14
Forest (1/0)	15.30	0.06	9.63	21.00	60.67	0.16	45.76	74.59	32.85	0.12	21.91	43.77
Texture	−0.21	0.02	−2.01	1.60	−4.08	0.05	−8.78	0.56	2.25	0.04	−1.30	5.75
Wheat only												
Middle zone (1/0)	−0.09	0.01	−1.30	1.20	−0.10	0.00	−0.57	0.38	−1.47	0.02	−2.86	−0.06
Near to forest (1/0)	1.56	0.01	0.24	2.91	0.81	0.00	0.32	1.34	0.00	0.02	−1.40	1.43
Texture	1.78	0.02	0.06	3.49	0.39	0.01	−0.25	1.03	0.93	0.02	−0.89	2.81

fields (Table 4), though the credible interval of this effect overlaps with zero at 95% (Fig. 4b). Wheat fields near the forest had 1.6 mg more C per gram of soil than wheat fields nearest to the market town (Table 4; Fig. 4e). Texture was also positively related with MAOM C for wheat fields (Table 4).

3.2.3. Microbial biomass

Substrate-induced respiration (SIR), a proxy for microbial biomass, showed qualitatively similar responses to land cover than POM and MAOM C (Table 4). Local land use was the strongest driver (Fig. 4c) and forest soils had 33 $\mu g\, h^{-1}\, g^{-1}$ soil more microbial biomass than soils in other land uses. Home gardens, on average, had 6 $\mu g\, h^{-1}\, g^{-1}$ soil more than wheat fields (Table 4). For wheat fields in the middle zone, substrate-induced respiration is lower than wheat field soils nearest to market (Fig. 4f). Neither proximity to forest nor texture were related to substrate-induced respiration for wheat soils.

4. Discussion

4.1. Yields and nutrient concentration are related to soil organic matter

We hypothesized that crop yields and nutrient contents would either be explained by proximity to the main market (a proxy for conventional intensification), or by SOM status (a proxy for ecological intensification). Our data support the second hypothesis, that SOM drives crop yields and nutrient contents. Both wheat yield and protein content were positively related to organic matter N (both in particulate and mineral-associated forms). Particulate OM is a faster-cycling OM pool (on the order of weeks to years) and is thought to provide nutrients to plants as it mineralizes (Wander, 2004). Therefore, one would expect that the N status of POM would be important for plant production. The slow mineralization of nutrients is also important to cropping systems through time and slower-cycling organic matter, like MAOM N, has been integrated into agroecological planning to optimize nutrient release through time (Palm et al., 2001). Our findings, however, conflict with findings from maize-based systems showing that MAOM C can be negatively associated with maize yields (Cates and Ruark, 2017; Wood et al., 2016). Thus, there is a need to better understand the mechanisms underpinning the relationship between organic matter fractions and to crop yields for specific crops and on specific soil types.

Wheat zinc concentration was mostly related to MAOM C. We believe this effect was due to the fact that C is associated with cation-exchange capacity and zinc in soil is often found in cation form (Zn^{2+}). We used C—rather than N—as the variable of interest for zinc because we expected that higher cation-exchange capacity would be the mechanism by which plants had greater access to micronutrients. Because cation exchange capacity is associated with organic C, and the bulk of our soils organic matter is in mineral-associated forms (Table 2), we expected that MAOM should be a relevant indicator of cation-exchange capacity and thus crop micro-nutrient composition. Our finding that MAOM C is associated with greater zinc crop concentrations is especially significant because Ethiopia is at medium risk for lower crop zinc concentrations due to elevated CO^2 (Myers et al., 2015). Thus, integrated soil fertility management could counteract these potential future crop nutrient losses.

Iron is also found in cation form (Fe^{2+}) and was not positively related to MAOM C. We believe this might be due to fairly strong controls on plant iron uptake other than simply soil iron content, such as varietal type, microbial activity in the rhizosphere, and concentrations of other essential nutrients (Audebert and Sahrawat, 2008; Benckiser et al., 1984). Other work has shown that SOM can be important for zinc availability to plants, but not for iron and some other nutrients (Bindraban et al., 2015).

We expected that N application rate would be significantly associated with wheat yield, given the known importance of fertilizers for crop yield, and crude protein. Although the mean of the coefficient on N application was directionally consistent with this expectation (e.g. slightly positive), it was variable and overlapped with zero. This non-effect of mineral fertilizer application could be explained by the fact that N application remains low (below 30 kg N /ha, Table 1) and probably on par with baseline mineralization of SOM. In similar agroecologies, there have been yield responses of smallholder wheat to N up to about 100 kg/ha (Baudron, unpublished data). Lack of yield response to mineral fertilizer, all other variables held constant, could potentially be due to limitation of other elements (Janssen and Guiking, 1990).

We estimated that a 1% increase in SOM would be associated with an increase in the protein needs of 0.1 people ha^{-1} and the zinc needs of 0.2 people ha^{-1}. An increase in SOM by 1.65% would be associated with an increase in 0.2 and 0.5 people ha^{-1} potentially nourished, for protein and zinc. This estimate is an approximation linked to several assumptions. First, we assumed that all farms could increase SOM by 1%. We believe this is a realistic assumption because a difference of 1% is approximately the difference we observe between the highest-SOM wheat field and the lowest-SOM wheat field in our data set. Generally, cultivated soils tend to have low organic matter and a 1% gain is relatively small relative to the amount of soil C that has been lost through cultivation (Minasny et al., 2017; Sanderman et al., 2017). We also assumed a 1.65% gain because that was the average difference between wheat fields and homegardens. However, the maximum potential gain would be higher. Second, we based our estimate on reported yields—not yield gains that would be associated with increased organic matter. This is an overly conservative assumption and the effect of increasing SOM on nutrient production could be greater if we allowed for yield increases as well. Third, the gains in nutrient content relative to biofortification targets is low. We estimate gains in zinc, for instance, of about 1–2 $mg\, kg^{-1}$ from SOM management, whereas biofortification efforts, like HarvestPlus, aim to increase zinc content in wheat by 12 $mg\, kg^{-1}$ (Bouis and Saltzman, 2017). Despite these assumptions, we still demonstrate that a plausible SOM increase could increase crop nutrient concentrations enough to be relevant to dietary needs. Our work adds to a body of literature showing that variation in soil nutrient status can impact human health and crop nutrient contents (Barrett and Bevis, 2015; Bevis, 2015; Hurst et al., 2013). Our work is of interest because SOM is a manageable soil property, unlike many of minerals associated with soil parent material.

4.2. Local land use is the strongest driver of all types of organic matter; farming system is secondary

Given the importance of SOM to crop yield and nutrient content we sought to understand the drivers of SOM concentrations among households and local land cover types. Because of evidence that different SOM fractions can impact different agronomic and environmental outcomes, we analyzed slow and medium cycling OM pools as well as a proxy for microbial biomass. We hypothesized that organic matter would either be most strongly impacted by distance to the state forest—because of regular inputs, mainly through the movement of livestock (Baudron et al., 2017)—or by local land use type, specifically wheat field vs. home garden vs. forest. We found that forest soils had the most SOM, regardless of the type of OM. For wheat fields, proximity to forest was the strongest driver of SOM, with soils closest to the forest having the greatest levels of SOM C. Home gardens had higher OM than wheat fields for all types of SOM and SIR (proxy for microbial biomass).

5. Conclusions

We found that crop yields and crop nutrient content were more closely related to SOM content than to mineral fertilizer application and proximity to market. This supports the notion that building up SOM is an important strategy for maintaining fertility of smallholder agriculture, especially in cases where access to mineral inputs is limited. We

also found that SOM—of multiple forms—is impacted strongly by local land use type. This suggests that farmer management can have a strong impact on SOM fractions, which we would expect to increase crop yields and nutrient content based on our findings. We estimated that an increase in SOM equal to the observed difference between homegardens and wheat fields would be associated with a gain in the number of people whose nutrient needs could be met per hectare of 0.2 (protein) and 0.5 (zinc). Our results indicate that realistic gains in soil organic matter can make human-health-relevant increases in crop nutrient content. Integrative soil organic matter management can therefore be a tool for feeding the world well.

Author contributions

SW and FB conceived the analysis; FB collected field data and provided crop data; SW analyzed soil samples, analyzed data, and wrote the first draft of the manuscript; SW and FB revised the manuscript.

expressed in this publication are those of the authors and do not necessarily reflect the views of the funders.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.agee.2018.07.025.

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