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Distributional impacts of soil erosion on agricultural productivity and welfare in Malawi

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ABSTRACT

We investigate the economic distributional effects of soil loss in Malawi, where erosion deprives rural households of the natural capital necessary to boost agricultural production and lifts food security. We employ a two-year dataset combining unique topsoil loss data with socio-economic, agro-ecological and climatic information both at household and plot level. We consider heterogenous impacts of soil loss in productivity, total consumption and caloric intake by estimating an unconditional quantile regression model. The role of different agricultural practices in mitigating the negative impacts of soil loss is also considered to assess cost-effective policy options and compensation mechanisms and to provide aggregated effects. We show that large heterogeneous impacts currently exist across the most exposed population groups and such impacts could translate in a production loss equivalent to 1 to 3% of Malawi's GDP under different increasing soil erosion scenarios.

1. Introduction

Agricultural modernization has been at the top of the political agenda of sub-Saharan African (SSA) countries since the 1990s. In a region of the world with more than 20% of the rural population afflicted by stagnating undernourishment (WDI, 2019), structural productivity shifters are necessary to increase both livelihood in the short run and to foster development in the midterm (Senbet and Simbanegavi, 2017). Growth in agricultural production has been framed as a mechanism of intersectoral transmission where higher yields should promote shifts of labor productivity in both secondary and tertiary sectors. To this end, a strand of literature (de Vries et al., 2015, among others) has attempted to identify the drivers of a stagnating yield of 1,300 kg/ha in the SSA *vis-à-vis* 4,171 and 3,130 respectively in Latin America and Caribbean, and South Asia (Food and Agriculture Organization of the United Nations, 2017).

Inertia in the convergence of SSA agricultural productivity is likely driven by structural latent factors, among which a low nutrients availability in the topsoil endowment plays a critical role (McArthur and McCord, 2017). This characteristic is further exacerbated by the soil erosion phenomenon (Drechsel et al., 2001; Delgado-Baquerizo et al., 2013). Soil erosion is the absolute loss of topsoil and nutrients carried away from the land by water or wind and transported to other surfaces. It is a natural process especially in steep areas, but poor management practices can increase the potential of soils to be eroded (Hediger, 2003; Panagos et al., 2015). Soil loss can disrupt the natural soil balance leading to a decrease in productivity potential (Pimentel et al., 1995; Sanchez, 2002). As a consequence, exposed farmers face reductions in yield and, indirectly, income loss, a decline in crop and livestock farming activities and a drop in the value of agricultural land, which leads to vulnerability, food insecurity and migration (Blaikie, 2016). The impact of soil loss is expected to worsen in the coming decades because of high population growth, rapid deforestation and intensive agriculture combined with the effects of climate variation (Borrelli et al., 2017).

SSA represents a major source of concern in relation to the expected climatic trends considering the regional dependence on subsistence agriculture in rainfed lands (Mendelsohn and Dinar, 2009). Poorly capital endowed farmers are likely unable to manage and adapt to irregular climate and upward erosion trends, particularly if the land constitutes their principal asset (Noble et al., 2014). This causes a process that Barrett and Bevis (2015) define a self-reinforcing poverty mechanism, in which households (HHs) *ex-post* smooth their meagre expenditure and food consumption in response to shocks for which they do not have an *ex-ante* insurance. In this scenario, a mix of policy instruments is necessary since the soil erosion heterogeneously affects

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communities and individuals (Kurian and Dietz, 2013).

Rural development programs need to identify how costs of soil erosion are distributed among farmers. Thanks to this assessment, cost-effective approaches could be based on tailored interventions that mix standard agricultural policies with emerging programs such as conservation and climate-smart agriculture (Banwart, 2011; Lipper et al., 2014).

Recent studies have defined a framework for the economics of land degradation (Labrière et al., 2015; Nkonya et al., 2016a, b; Pierce and Lal, 2017) and quantified the total costs of soil erosion with different methods (for a complete review, see Telles et al., 2011). In particular, research on the on-site costs[1] has focused on the additional expenditure for erosion control technologies or fertilizers required to minimize the loss of soil nutrients and productivity reduction (Pimentel et al., 1995; Lal, 2001), but it has also concentrated on the assessment of macroeconomic impacts combining empirical biophysical models (Borrelli et al., 2017) with global computable general equilibrium models (Pimentel et al., 1995; Panagos et al., 2018; Sartori et al., 2019).

Nevertheless, we know much less on how the on-site costs of soil loss are distributed across a local population of rural HHs and how policymakers could rely on this information to minimize impacts of erosion. In this paper we fill this gap by studying the socio-economic impacts of topsoil loss and its distributional effects on agricultural productivity and two important welfare outcomes: per capita real consumption and per capita caloric intake. We analyze the case of Malawi, where topsoil loss represents a major threat to the overall economic development since the value-added of the agricultural sector accounts for approximately 26% of GDP and the rural population is more than 80% (WDI, 2019). Moreover, according to recent studies (Stevens and Madani, 2016; Msowoya et al., 2016; Food and Agriculture Organization of the United Nations, 2017; Warnatzsch and Reay, 2019; Katengeza et al., 2019), climate change in Malawi is expected to reduce the yield of major subsistence crops from 5 to 14% by 2050, with potential reinforcing feedback effects caused by projected severe soil erosion rates; all together these factors make the country a recognized global hot spot of land degradation (Borrelli et al., 2017).

In analyzing the impacts of soil loss, we employ a two-year novel dataset with on-field validated data on topsoil loss rates, geographically aligned with socio-economic and climate data both at HH and plot level. We empirically estimate both a crop production function and two welfare functions to evaluate the negative effects of soil loss on these outcomes. To catch heterogenous impacts across different HHs, we employ an unconditional quantile regression model, which presents the strong advantage that quantiles are not defined by a vector of control variables required to consistently estimate the functions. We find large heterogeneous impacts of top soil loss, with larger and significant effects across the most exposed and vulnerable population groups. These results are confirmed by robustness checks carried out with alternative estimators.

Moreover, we evaluate the effectiveness of soil loss on-site mitigation interventions provided by strategic livelihood assets and adoption of agricultural practices, and assess the cost-effectiveness of the main Malawian agricultural development programme in face of hypothetical topsoil loss scenarios. These additional results provide policy suggestions useful to minimize the economic impacts of topsoil loss at national aggregate level, to reorient the existing strategies, and to compensate more vulnerable HHs with a support to adopt erosion control practices.

[1] Reduction in productivity is an on-site private costs caused by soil erosion. Nevertheless, large impacts, in terms of total economic value loss arise from off-site social costs as well (Colombo et al., 2005; Kirui, 2016). These can consist of desertification, rural depopulation, siltation of waterways or reductions in biodiversity and should be internalized by policy makers when planning benefit/cost analysis of intervention to reduce the soil erosion (Nearing et al., 2017).

2. Background

2.1. Topsoil loss and rural development in Malawi

Soil erosion is a complex process driven by soil properties, ground slope, land cover, agricultural practices and climate (Montgomery, 2007). These drivers, such as droughts and floods, variations in intensity and length of rainy seasons, fires, unsuitable land uses and land management practices, affect directly the land ecosystems (Nkonya et al., 2016a, b). Land tenure, poverty, population density, weak regulatory environment in the agricultural and environmental sectors represent, instead, underlying causes of soil erosion since they affect investment decisions on land management (Rosa-Schleich et al., 2019; Tarfasa et al., 2018; Boserup, 2017).

While the increase of soil erosion constitutes the main cause of land degradation in the world (Borrelli et al., 2017), the dynamics of climate, land use and underlying drivers makes soil erosion a largely impelling problem in SSA, generating negative impacts on already stagnating agricultural production. A recent assessment of the soil erosion uses a universal soil loss model (Fenta et al., 2020) to estimate soil loss rates in 11 SSA countries, which range from 1.7 to 58.3 t $ha^{-1}yr^{-1}$.

As a case study, Malawi is among the most relevant since it is subject to severe rates of erosion, where erosion rates are considered severe if higher than 10 t $ha^{-1}yr^{-1}$ (Holden and Lunduka, 2012; Borrelli et al., 2017). Vargas and Omuto (2016) performed a local assessment that revealed an average soil loss rate of 29 t $ha^{-1}year^{-1}$ at national level and 15 t $ha^{-1}year^{-1}$ at farmland level. These figures are coherent with global soil loss modelling which identifies Malawi within the world's 12 most exposed countries (Borrelli et al., 2017). Recently, the *Soil Loss Atlas of Malawi* (2019) updated official national data of soil loss, obtained by means of the Soil Loss Estimation Model for Southern Africa (SLEMSA), a model belonging to the Universal Soil Loss Equation (USLE) family models (Lal, 2001), and subsequent validation using field measurements (Thakur and Nema, 2018). With over three-quarters of the agricultural land exposed to severe topsoil loss, erosion represents the major threat to food security and agricultural growth. In addition, local projections of the effects of climate change raise concerns on future exacerbation of the erosion rates (Warnatzsch and Reay, 2019).

An increase of topsoil loss rates downward shifts the land productivity potential since it reduces the nutrients in the soil, enlarging the risk of locking-in farmers in a poverty trap (Carter and Barrett, 2006). This mechanism is expected to severely hit HHs with a lower chance to *ex-post* adjust their consumption level after an agricultural stress, since their endowment of valuable marketable assets is limited. Recent statistics in Malawi confirm that 50.7% of the population is poor and 24.5% is ultra-poor, while the caloric intake of 50% of the population is below the minimum level of 2100 calories per day (World Bank, 2017). These figures worsen in the rural population, confirming the link between the performance of the agricultural sector and the welfare of farmers with limited chance of off-farm income diversification (Darko et al., 2018).

Most of the Malawian rural development strategies have been dedicated to promote growth of the agricultural productivity. The universal Farm Input Subsidy Program (FISP) is a prominent example of such strategy since 2005. This program massively subsidized the NPK fertilizers and modern maize seed varieties, which is the main crop cultivated by subsistence farmers (Kassie et al, 2015). Nonetheless, when the topsoil loss rate is severe, these policies could be cost-ineffective since the remaining subsoil layer has a weaker responsiveness to external inputs (Bender and van der Heijden, 2015). Since at national level less of 1% of the rural population received assistance on sustainable erosion control practices (Dougill et al., 2017), a debate has emerged about the best strategy to minimize the costs of interventions while increasing productivity and individual rural welfare (Arndt et al., 2015).

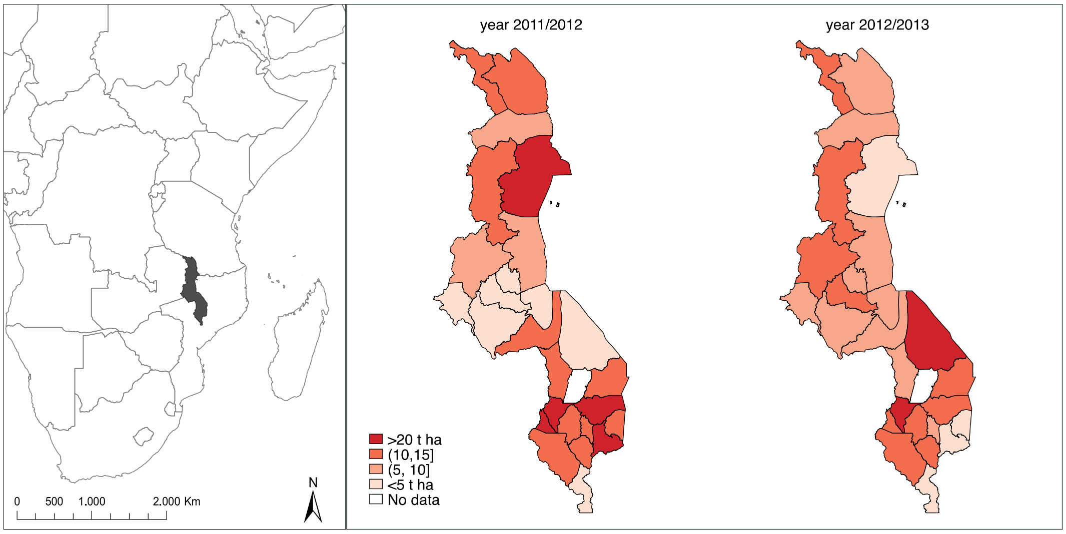

Fig. 1. Left - Malawi; right - topsoil loss (t ha^{-1}yr^{-1}), by district.

2.2. Conceptual framework

We investigate the distribution of socio-economic impacts of topsoil loss drawing from the sustainable rural livelihood framework (SRL), which provides a theoretical framework to analyze the choices made by a farmer that manages her welfare in a context of market failures and agricultural stresses (Ellis, 2000). The SRL has been widely adopted in the context of SSA since markets and institutions are weak and climatic or agroecological factors can limit the livelihood options available to HHs (Asfaw et al., 2018a, b; Call et al., 2019; Donkor, 2019). We adapt this framework to the context of Malawi, which suffers severe topsoil loss rates and climatic shocks, and where the opportunities to spread the agricultural risks with off-farm activities are limited by failures in wage labor market (Walther, 2018; Asfaw et al., 2019).

We consider a rural HH, i, who represents a decision-making unit whose welfare level is a function of available options to tackle adverse events, such as soil loss. These options depend on a set of assets, K_i, to which the HH i has access. In particular, K_i includes $\{K_i^N; K_i^P; K_i^H; K_i^F; K_i^S\}$ that symbolizes natural, physical, human, financial and social capital, respectively. K_i interacts with the institutional and organizational local context to define the livelihood strategies suitable to HHs (Scoones, 1998). At a local or administrative level, this context is homogenous to farmers (Michalopoulos and Papaioannou, 2014), but the cost of coping with soil loss is heterogeneous since heterogenous is the mix of tangible and intangible assets that compose K_i (Suri, 2011).

Severe topsoil loss rates cause a reduction in HHs' land productivity, which in turn affects the national agricultural sector. At the same time, the welfare of poorly endowed HHs risks to be disproportionally impacted on, increasing rural vulnerability and inequality. In order to be cost-effective, rural development programs need to identify how costs of soil erosion are distributed among farmers and which components of K help to distress the productivity shock. Then the Government should tailor a set of mixed interventions that target best responsive farmers and compensate the welfare reduction of losers (Sheahan and Barrett, 2017; Asfaw et al., 2017).

3. Material and methods

3.1. Data

We employ three sources of data to analyze the distributional impacts of soil loss on farmers' productivity and welfare. First, the recent *Soil Loss Atlas of Malawi* (Omuto and Vargas, 2019), implemented by FAO, UN Environment Programme, UN Development Programme and the Malawian Ministry of Agriculture, Irrigation and Water Development (MAIWD), constitutes a novel and unique data source collecting information on topsoil loss expressed as tons per hectare per year. The *Atlas* addresses the urgent need for updated national statistics and information on soil loss rates, which were not reviewed since 1992. The approach used in the assessment is based on the application of the Soil Loss Estimation System for Southern Africa (SLEMSA) model (Lal, 2001; Liu et al., 2013; Breetzke et al., 2013; Thakur and Nema, 2018). SLEMSA is a soil loss models based on mathematical/empirical relationships between lost soil and soil loss contributing factors (Nearing et al., 2017). It consists in a crop ratio model, a soil loss from bare soil model and a topography model (Elwell, 1978; Elwell and Stocking, 1982). The outputs of these sub-models are combined to obtain the soil loss rate. Each of these sub-models is further developed from modifications or combinations of the following input factors: climate, soil texture, crop cover fraction, and topographic slope-length (see Abdullah et al., 2017 for a review). The application of the SLEMSA model in Malawi was accomplished by defining a protocol for sourcing the input data, exploitation of GIS software and hardware with secondary data on soil conditions, vegetation covers, agroecological zones, rainfall, wind patterns, and soil slopes. In a second step, the outcomes have been on-field validated on 104 sites and then calibrated on the input factors related to the GIS coordinates available for the socio-economic survey that we use in this study. For full details on the SLEMSA model and on field validation in Malawi see Omuto and Vargas (2018). Fig. 1 illustrates both the placement of Malawi on the left panel and the level of topsoil loss at the district level for the years 2011/2012 and 2012/2013 on the right panel.

Our second data source consists in climate information collected from the Africa Rainfall Climatology 2 database (ARC2)[2]. These data enable us to calculate the standardized precipitation evapotranspiration index (SPEI), which is increasingly employed in economic studies to address the impact of climatic variability on welfare and agricultural production (Asfaw et al., 2017, 2018a, b; Di Falco et al., 2018, among others). This index presents specific advantages over other indicators. It is based on the probability of recording a given amount of evapotranspiration, which is the amount of water lost from a cropped surface. The probability is standardized, with a value of zero indicating the median amount (half of the historical amounts are below the median, and half are above the median), thus the index is negative for drought,

[2] For further details, see Novella and Thiaw (2013).

and positive for wet conditions. The characteristic of being standardized provides a straightforward interpretation and allows for a fully indexed comparison through time and space (Vicente-Serrano, 2010). Moreover, SPEI is able to capture both short-term and long-term anomalies depending on the time scale over which is calculated. We compute SPEI at a six month time scale, which captures the rainfall deviations during the rainy season spanning from November to April in Malawi[3].

The horizontal gray lines in Fig. 2 indicate, respectively, a threshold level higher than 1.5 and lower than −1.5, which are considered levels of SPEI over which severe rainfall excess or drought shocks, respectively, are faced by the population. The black line shows the SPEI dynamics averaged over all the EAs in the sample during the period 1988–2014. The blue (red) circles represent the maximum (minimum) SPEI values registered over the period 1988–2014 in specific EAs; these represent local "hot spots" whit SPEI values much larger than the in-sample mean (black line), meaning that Malawi experienced repeated and severe climate shocks at a local level.

The third source of data is the World Bank LSMS-ISA socio-economic survey. It supports multiple rounds of a panel survey and provides detailed information on individual agricultural activities at HH and plot level, HHs' socio-economic characteristics and community (EA) infrastructures. The survey has been conducted in Malawi during 2011 and 2013. The overall sample is representative at the national, regional, district and urban/rural levels. In total, 3247 HHs were visited twice in 2011 (in the post-planting and post-harvest periods with respect to the rainy agricultural seasons) and were tracked and re-interviewed in 2013.

The final sample of our analysis is obtained by firstly matching the LSMA-ISA survey with the soil loss assessment data through GIS coordinates; we then align this dataset with the ARC climate data at the EA, HH and plot level to allow for a complete and representative pooled dataset with economic, social, agronomic and climatic information.

Table 1 shows the descriptive statistics of all the relevant variables included in the econometric model.

Maize yield represents our agricultural outcome to measure productivity since maize represents the most cultivated crop across the country, while for welfare we estimate impacts on the real per capita consumption in Malawian Kwacha (MWK) and per capita caloric intake per day.

Fig. 3 shows the probability density function of topsoil loss by deciles of maize yield. Fig. 4 reports the violin plots with density, median interquantile ranges and extreme values of the two welfare indicators according to three categories of topsoil loss, ranked by severity.

In both graphs we observe a large heterogeneity of the outcome distribution in relation to the investigated erosion phenomena, signaling that soil loss might indeed disproportionately affect least-productive and poorest HHs. We also observe that the values of welfare outcomes corresponding to low topsoil loss are higher than other categories.

Covariates in Table 1 are selected according to the relevant literature related to the SRL framework. As discussed in Section 2, HH's options to adjust their production and welfare level in response to agricultural stresses depend on an endowment of assets K_i, along with agricultural inputs and institutional/contextual variables (Carter and Barrett, 2006). In our setting, the natural capital is represented by the size of cultivated area and agroecological zone (AEZ) (Nguyen et al., 2017). To control for the physical endowment of the HH we use the rural wealth index (Hargreaves et al., 2007). The human capital is represented by the HH members, education level, age and gender of the HH head, and men days of labor employed on a plot (Asfaw and Maggio, 2018). The financial capital is represented by the index of access to infrastructure as a proxy for credit and market access (Beck et al., 2009), the percentage of income depending on the agricultural activities as an indicator of financial vulnerability (Dercon, 2002) and a parliament representative hailing from the EA as a proxy for the capacity to obtain agricultural subsidies, extension services or post-stress coping measures (Snapp and Fisher, 2015). Finally, we use the distance from the main urban center expressed in kilometers and the endowment of ICT technologies (TVs, mobiles, radios, computers) to capture the social capital and networking capacity. There is strong empirical evidence suggesting that spatial proximity favors market and information access, thereby facilitating a labor diversification process that increases the capacity of HHs to response to agricultural income shocks (Shiferaw et al., 2015). District fixed effects are also included to account for systematic differences in the institutional context (Scoones, 1998).

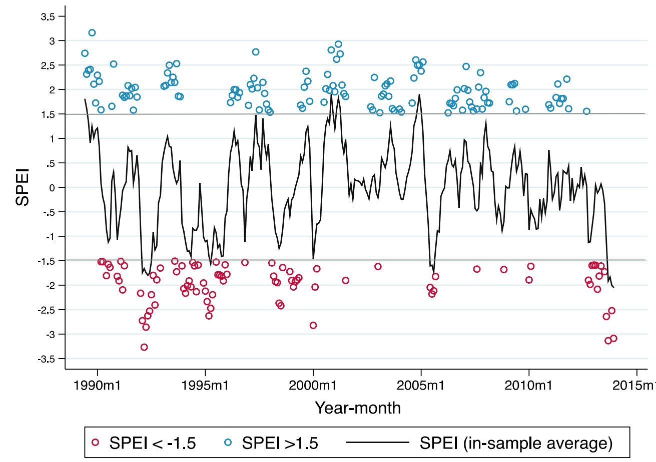

Fig. 2. Monthly mean SPEI values and SPEI shocks, during the period 1990–2013.

Among the covariates presented in Table 1, we include a set of agricultural inputs, including those incentivized by the Malawian government with the FISP program through the distribution of coupons. These consist of NPK fertilizers and pesticides, and the adoption of modern seeds varieties of maize. Moreover, we also include controls for practices favoring a subsistence risk-adverse type of agriculture, such as the legume intercropping or the crop diversification calculated with the Shannon index[4] at plot level (Gollin et al., 2002; Chavas and Di Falco, 2012; Coromaldi et al., 2015) and for other agricultural practices that can sustain productivity (Teklewold et al., 2013). To this end, Table 2 reports the proportion in the implementation of a set of erosion control practices and the plot fallow during the past five survey years $t_{-1}, \cdots, t_{-5}$, along with the mean and standard deviation of topsoil loss. A significance test for the equality of means of topsoil loss by categories of the two practices is also reported.

[3] To calculate SPEI values we employ the SPEI R package by Beguería and Vicente-Serrano (https://cran.r-project.org/web/packages/SPEI/SPEI.pdf). SPEI values represent, essentially, a water balance calculated at different times and geographical areas. The required inputs for computing the SPEI are monthly differences between precipitation and potential evapotranspiration (PET) on a set of geographical coordinates. PET is the amount of evaporation and transpiration that would occur if a sufficient water source were available.

[4] The Shannon diversity index is calculated as: $H_j = -\sum_{c=1}^{C} p_c \ln p_c$, where p_c is the proportion of area cultivated with crop c on the total cultivated area of the farmer j. The index calculates the uncertainty to predict the species identity of an individual that is randomly observed from a community. The higher is the value of the Shannon index, the higher the uncertainty and consequently the evenness in the dataset is lower. The use of Shannon index is diffused in literature (Di Falco and Perrings, 2005; Coromaldi et al., 2015; Pallante et al. 2016; Di Falco et al., 2014; Asfaw et al., 2018a, b). For a review of the diversity indicators, with their pro and cons, see Duelli and Obrist (2003).

Table 1
Descriptive statistics (EA, HH and plot level).

Variable	Description	Mean	Std. Dev.
Dependent variables			
maize_yield	Maize productivity (kg/ha)	1912.44	1208.73
rexpaggpc	Real per capita expenditure in Malawian Kwacha (MWK/pc)	50727.46	47727.52
calories	Caloric intake per capita per day (cal/pc/pd)	1968.17	1040.64
Shocks			
topsoil_loss	Top soil loss (tons per ha) at plot level	15.24	8.25
s_r_spei	Rainfall shock experienced (%) in the EA	0.38	0.49
s_d_spei	Drought shock experienced (%) in the EA	0.46	0.50
Agricultural inputs			
fert1	Chitowe (kg/ha) applied on plot	128.49	203.90
fert2	Urea (kg/ha) applied on plot	102.91	181.45
fert3	Compound (kg/ha) applied on plot	13.03	57.13
fert4	Other fertilizers (kg/ha) applied on plot	6.86	56.95
organic_fert	Organic fertilizer (kg/ha) applied on plot	106.92	383.36
pesticides	Pesticides (kg/ha) applied on plot	0.079	2.91
seeds	Seeds amount (kg/ha) applied on plot	39.13	40.79
D_crop_groundnut	HH cultivates groundnut on maize plot (%)	0.27	0.44
D_crop_legume	HH cultivates legumes on maize plot (%)	0.10	0.31
D_crop_other	HH cultivates other crops on maize plot (%)	0.42	0.49
MV	Modern Variety Seed (%) applied on plot	0.52	0.50
S	Shannon index of crop diversity	1.67	0.90
Natural Capital			
plot_area	Area of cultivated plot (ha)	0.43	0.40
aez1	Tropic -Warm/Semiarid (%)	0.41	0.49
aez2	Tropic-Warm/Subhumid (%)	0.36	0.48
aez3	Tropic-Cool/Semiarid (%)	0.10	0.31
aez4	Tropic-Cool/Subhumid (%)	0.12	0.33
Physical capital			
wealth	HH rural wealth index	0.23	1.34
Human Capital			
agehead	Age of HH head (years)	43.92	16.20
femhead	Female headed HH (%)	0.24	0.43
educave	Ave. no. of school years of HH members aged 15–60	5.21	2.69
hhsize	Number of HH members (count)	5.03	2.32
labor	Men days of labor on plot (men days/ha)	248.32	186.54
Financial Capital			
infraindex	EA index of access to infrastructure	−0.02	0.88
spfarm2	HH is specialized in agriculture (greater than75% of income)	0.42	0.49
parliament	In the EA resides a parliament member (%)	0.11	0.31
Social capital			
disturban	Distance of HH from the main urban center (Km)	113.72	107.31
tech_endow	HH is owner of communication technologies (%)	0.60	0.49
year_2013	Year of survey = 2013 (%)	0.22	0.41
N	Number of households (HH)	7255	
N	Number of plots	9244	

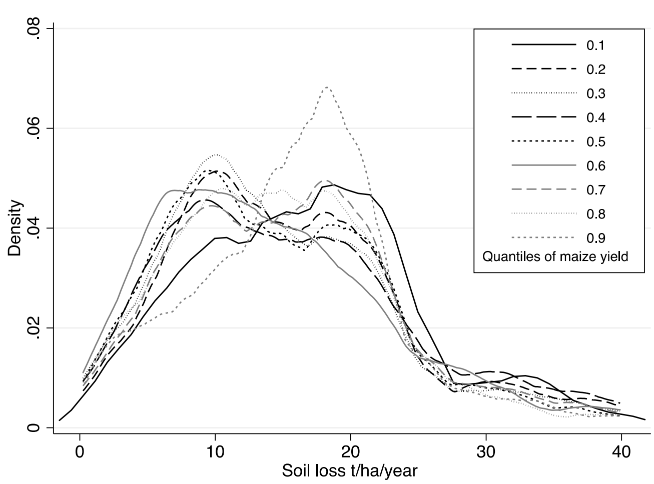

Fig. 3. Probability density function of topsoil loss, by deciles of maize yield.

3.2. Empirical strategy

Our objective is to estimate the different expected impact across HHs of the topsoil loss on maize productivity Y (kg/ha) and welfare per capita indicators W, namely the real consumption expenditure (MWK/pc) and per day caloric intake (cal/pc/pd). To this aim, we estimate a Cobb-Douglas productivity function at plot level (1) and two welfare functions at HH level (2), as follows:

$$Y_p = \alpha + \beta Loss_p + \gamma K_{p/i} + \xi AI_p + \vartheta AP_p + \varphi(loss_p * AP_p) + \delta SPEI_{EA} + t + \varepsilon_p \tag{1}$$

$$W_i = \alpha + \beta Loss_i + \gamma K_i + \rho C_i + \delta SPEI_{EA} + t + \varepsilon_i \tag{2}$$

where p indicates the plot, and i the HH. $Loss$ is the soil loss converted in kg/hectare, K is a vector of endowments which includes natural, physical, human, financial and social capital both at HH or plot level, AI is a vector of agricultural inputs, while AP is a vector of erosion control agricultural practices interacted with $Loss$ to evaluate their topsoil loss mitigation capacity, C is a vector of additional relevant controls to

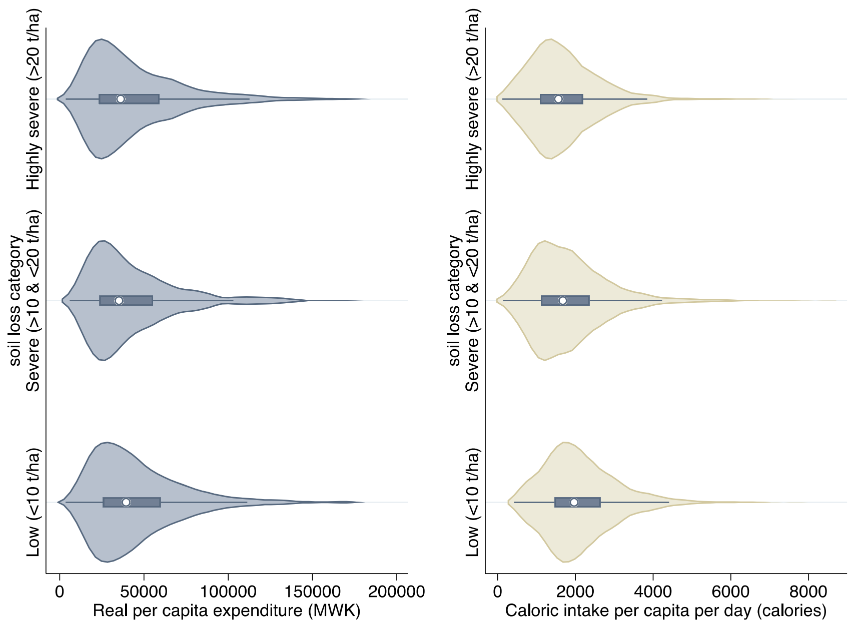

Fig. 4. Violin plots of expenditure per capita (MWK) and caloric intake per capita (calories per capita per day), by soil loss category.

Table 2
Descriptive statistics of erosion control and fallow practices.

Variable (plot level)	Description	Proportion (%)	topsoil loss ($t\ ha^{-1}$/year)	
			mean	Std. dev.
Erosion control				
• no measures		60.95	15.19**	8.40
• terraces		3.64	14.07***	7.96
• bunds		27.45	15.70***	7.83
• vetiver grass		6.18	14.34***	9.39
• tree belts		1.28	14.08**	6.71
D_Fallow				
• no	No fallow applied during the past 5 years	86.79	15.38*	8.33
• yes	Application of fallow during the past 5 years	13.21	15.15*	7.98

Notes: t test on the equality of means of topsoil loss: * significant at 10%; ** significant at 5%; *** significant at 1%.

explain the two welfare outcomes, *SPEI* is a vector of binary indicators for rainfall and drought shocks at EA level assuming value 1 for SPEI ≥ 1.5 or SPEI ≤ -1.5, respectively; t is a dummy representing the survey year, ε is a random error term and α, β, γ, ξ, ϑ, φ, ρ and δ are unknown parameters to be estimated. We also include agroecological zone (AEZ) dummies in equation (1) and district dummies in equation (2).

Since we are interested in the distributional impacts of the topsoil loss on the welfare measures Y and W, simple OLS estimates are not able to catch such impacts since it estimates conditional mean of the outcome variables while its distribution could vary in many ways that are imperfectly revealed by looking at the simple mean. Therefore, we estimate equations (1) and (2) by means of a class of quantile regressions. As documented in Figs. 3 and 4, our empirical strategy is motivated by the observation of a high degree of heterogeneity in the distribution of maize productivity and welfare indicators, conditional to the topsoil loss; the conditional quantile regression (CQR) is a powerful estimator to discover the effects over the entire distribution (Koenker and Bassett, 1978).

This approach has been the cornerstone in estimating the distributional effects in social sciences. Nevertheless, the CQR has been recently questioned by the fact that quantiles are defined conditional on the control variables. As a consequence, including a vector of controls, such as the vector K, determines a different redefinition of quantiles with respect to the exogenous treatment of the topsoil loss level. Considering this shortcoming, the unconditional quantile regression (UCR) model, developed by Firpo et al. (2009), presents the strong advantage that quantiles are pre-regression defined, so that the model is not guided by the vector of right hand-side variables (Borgen, 2016). While both CQR and UQR can capture the topsoil loss differential effect on a spectrum of maize productivity and welfare distribution, the main distinction is that the CQR estimates $\frac{\partial Y(q^{th}|Loss, K, AP, SPEI)}{\partial Loss}$, while the UQR estimates $\frac{\partial Y(q^{th})}{\partial Loss}$, where q^{th} represents the value of the outcome variables at the th quantile. In simpler words, the CQR reports a "within-group" marginal effect conditional on the mean values of all the regressors included in the empirical specification, while the UQR allows to estimate the impact of the topsoil loss on the th quantile of the unconditional distribution of the welfare outcome. This feature is highly appealing in our setting since adding or changing control variables does not alter the interpretation of the topsoil loss effects. To estimate the UQR, we use the re-centered influence function (RIF) proposed by Firpo et al. (2009). The RIF can be defined as follows:

$$\mathrm{RIF}(Y; q^{th}, F_Y) = q^{th} + \frac{th - \mathbb{I}\{Y \leq q^{th}\}}{f_Y(q^{th})} \tag{3}$$

where $\mathbb{I}\{Y \leq q^{th}\}$ is an indicator function equal to one when the value of outcomes at the individual level is below the quantile q^{th} and zero otherwise, f_Y represents the unconditional probability density function (PDF) of Y evaluated at q^{th}, and F_Y is the cumulative distribution function (CDF). The RIF regression model is the conditional expectation $\mathrm{E}[\mathrm{RIF}(Y; q^{th}, F_Y)|X] = X\beta^{th}$, where X is a vector of covariates which includes *Loss* and other controls presented in equation (1) and (2)[5].

Finally, from equation (1), we simulate the aggregated national effect in terms of total tons (T) of maize production loss associated to an increase in the topsoil loss as follows:

$$\Delta T = \frac{\sum_{p=1}^{N}\left[(\beta^{th}\bullet dLoss_p)\bullet\frac{ha_p}{\omega_p}\right]}{national\ maize\ production} for\ th = 1, .., 9. \tag{4}$$

where $dLoss_p$ is a hypothetical percentage increase of the topsoil loss for each plot p, while ha are the cultivated hectares, weighted using sample plot weights on the total national maize area ω_p. Dividing by the total national maize production, we obtain the percentage of total loss generated by alternative scenarios of topsoil loss increase. Moreover, by multiplying the numerator in (4) by the average national maize unit price of P, and dividing by the national GDP, we obtain a measure of the monetary value of maize production loss expressed in terms of GDP[6], which in formula corresponds to:

$$\Delta GDP = \frac{\sum_{p=1}^{N}\left[(\beta^{th}\bullet dLoss_p)\bullet\frac{ha_p}{\omega_p}\right]\bullet P}{GDP} for\ th = 1, .., 9. \tag{5}$$

In addition, a policymaker may be interested in the aggregate mitigation effects provided by specific erosion control measures. In our framework, this can be estimated by substituting β^{th} with φ^{th} in (4) and (5) from the *RIF* estimation of Equation (1) and comparing the overall loss with the baseline case where the erosion control measures are absent.

4. Results

4.1. Impact on productivity

Table 3 presents the results from the UQR estimates of the impact of topsoil loss on maize productivity (full results are shown in Appendix A, Table A1).

The function is specified as a log–log functional form for all continuous covariates and contains estimates from the first to the ninth decile. As suggested by Firpo et al. (2009), robust standard errors are bootstrapped with 500 replications[7].

The impact of soil loss appears heterogeneous and significant along the distribution of the productivity variable, with monotonically negative effects ranging from the highest level of −0.26 on the first decile and the lowest one on the sixth decile. Conversely, higher deciles of productivity are not significantly influenced by soil erosion.

Results from the UQR are compared with results obtained from OLS and CQR models; Fig. 5 shows the impacts of soil loss, by decile, and associated 95% confidence intervals[8].

The CQR model provides significant negative impacts of soil loss on all deciles, compared with the coefficients estimated by means of UQR. Moreover, the magnitude in the first three deciles is lower than the one obtained from the UQR model. Nonetheless, some caveats exist when comparing CQR and UQR since the UQR provides the distributional effects at the outcome population level, showing how, *ceteris paribus*, Y and W change at any quantile of their distribution for a 1% increase of the topsoil loss (Peeters et al., 2017).

The other covariates included in the analysis show the expected signs (see Table A1 in the Appendix A). Six patterns of our results deserve a comment. To begin with, the human capital endowment influences both negatively and positively the productivity through, respectively, the gender of the HH head and the education level. Second, all the agricultural inputs are associated with an increase in productivity. Third, a larger natural capital, represented by the plot size, is associated with a lower productivity as a consequence of reduced efficiency in production for large land endowments; this effect is more pronounced in the lower deciles of the distribution. Fourth, a mixed intercropping, represented by the coefficients of the Shannon diversity and those of groundnut and legumes cultivation, favor the maize productivity, with larger impacts along the higher deciles of the distribution. Fifth, among the erosion control practices, the plantation of vetiver grass emerges as the most effective in boosting maize productivity. Finally, weather shocks are significantly associated with productivity changes. Specifically, we observe that an excess of rainfall boosts the productivity in the first and second deciles, while a drought shock is associated with a persistent negative productivity performance along the whole distribution, with least-productive farmers relatively more affected.

Figs. 6 and 7 report marginal effects with 95% CIs from a set of UCR estimates obtained by interacting the soil loss with AEZ and erosion control practices, respectively. Fig. 6 shows that the highest negative effect of topsoil loss concentrates in tropic-cool semiarid areas, followed by the tropic-warm semiarid, while for sub-humid areas we do not observe any significant impact on the higher deciles. Fig. 7 shows the mitigation effect determined by the implementation of erosion control practices for a 1% increase of the topsoil loss. While among the investigated practices the terraces are never significant in explaining changes in maize productivity, the other practices are significantly associated with a reduction in the loss of maize yield compared to the baseline case in which these measures are absent.

Taken together, our results suggest that the most effective measure for topsoil loss mitigation is the vetiver grass system. Moreover, we also observe that the tree belts practice is less efficient than other measures in the lower deciles and not significant in the higher deciles.

4.2. Impact on consumption and caloric intake

Turning to the welfare effects, Table 4 reports the coefficients of the topsoil loss on real per capita consumption (model a) and caloric intake (model b). Both models are specified on a log–log functional form.

We observe that the magnitude of the impact of topsoil loss on the welfare indicators is highly reduced compared with the effect on maize productivity. Moreover, while across the distribution of the per capita consumption the negative impacts are limited up to the median class, in the case of per capita caloric intake the topsoil loss is significant across all the distribution deciles. The effect of other covariates is reported in Appendix A (Tables A2 and A3) and confirms as HHs that do not diversify the income sources show lower levels of consumption and caloric intake, while larger endowment of physical and financial capital is particularly effective in increasing welfare.

4.3. Aggregate effects

Following the methodology described in Section 4.2, we offer an assessment of the impacts of topsoil loss at national level to provide a cost-effectiveness analysis of the main existing rural development programme in face of potential erosion trends.

Table 5 reports the costs of three scenario hypotheses of topsoil loss increase, assuming an incremental growth of, respectively, 10, 20 and

[5] The UQR is practically estimated by means of a two-step procedure, where in the first step a non-parametric kernel density of f_Y is obtained. In the second stage, an OLS of the RIF regression model is implemented in order to obtain unconditional quantile partial effects β^{th}. Given the two step procedure, robust standard errors are obtained through bootstrapping (Baltagi and Ghosh, 2017) and the UQR estimator is $\sqrt{n}$ consistent, asymptotically normal and efficient (Frölich and Melly, 2013).

[6] Both measures calculated in (4) and (5) are aggregate measures of the quantile effects expressed in terms of reliable macroeconomic indicators but should not be interpreted as national real macroeconomic adjustments to external shocks.

[7] A limitation of UQR is that there is no statistically valid method to cluster standard errors. Nevertheless, in Section 4.4 we provide a robustness check of our results that relies on a fixed effect estimator with bootstrapped clustered robust standard errors at HH-plot level.

[8] The full set of estimates are available as supplementary material in Table S2.

Table 3
Unconditional quantile regression (UQR): impact of soil loss on maize productivity.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90
Topsoil loss	−0.262***	−0.235***	−0.173***	−0.106***	−0.099***	−0.069**	−0.032	−0.028	−0.032
	(0.065)	(0.041)	(0.035)	(0.028)	(0.028)	(0.027)	(0.022)	(0.027)	(0.032)
N	9244								

Notes: robust standard errors in parentheses are obtained through bootstrapping with 500 replications. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; agroecological zone dummies and interactions between agroecological zone and topsoil loss are included.

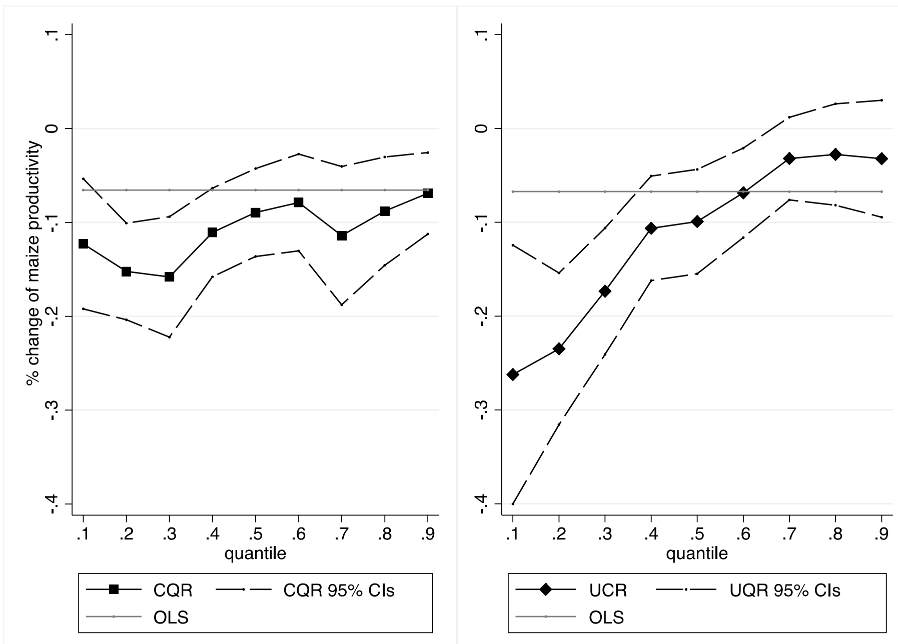

Fig. 5. Estimated quantile effect of topsoil loss on maize productivity; left - Ordinary Least Squares (OLS) vs Conditional Quantile Regression (CQR); right - OLS vs Unconditional Quantile Regression (UQR), with 95% confidence intervals (CIs).

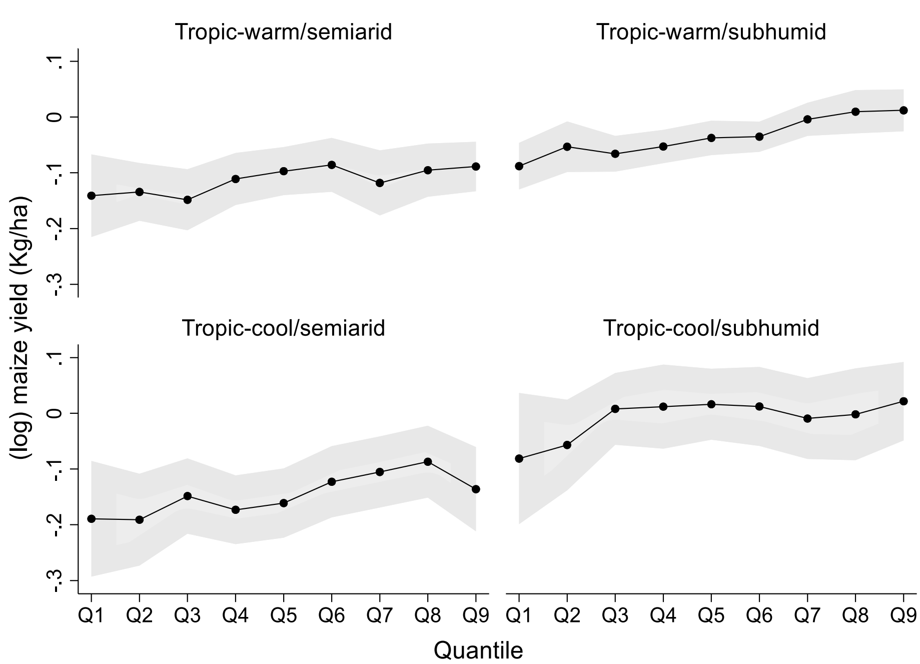

Fig. 6. Marginal effects of topsoil loss increase, by AEZ.

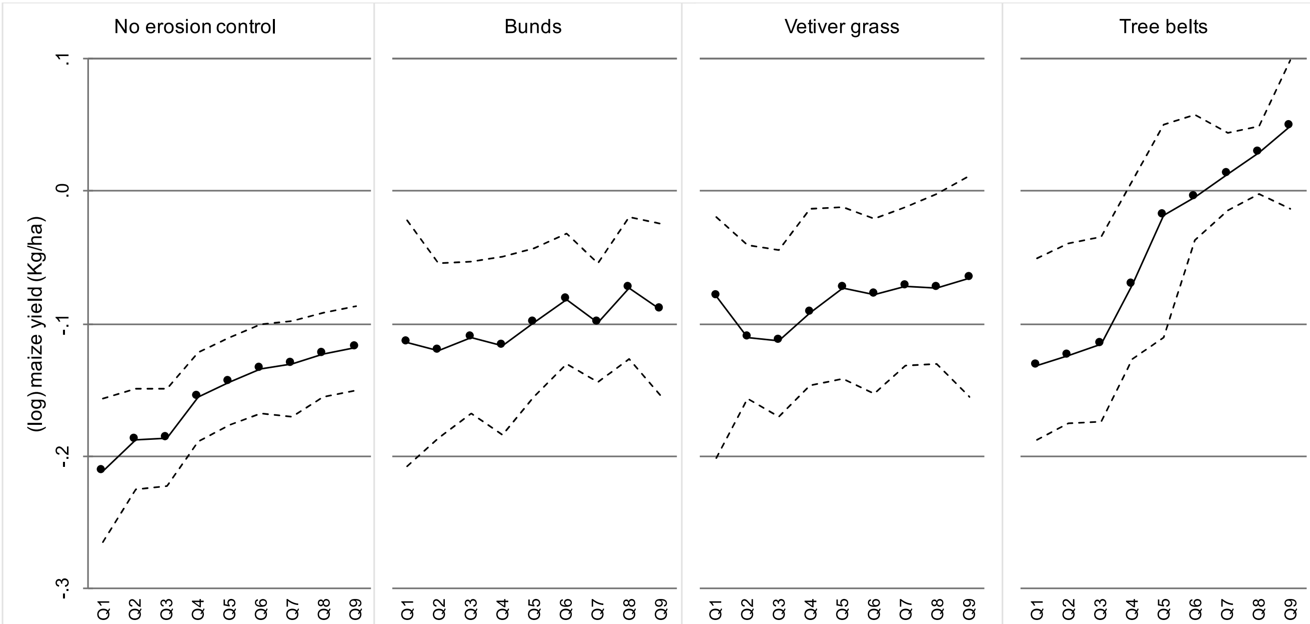

Fig. 7. Marginal effects of topsoil loss increase, by erosion control practices.

Table 4
UCR - welfare indicators.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90
a) rexpaggpc									
Topsoil loss	−0.065***	−0.081***	−0.087***	−0.068***	−0.044***	−0.015	−0.017	0.028	0.027
	(0.016)	(0.015)	(0.014)	(0.015)	(0.015)	(0.016)	(0.017)	(0.019)	(0.025)
b) calories									
Topsoil_loss	−0.063***	−0.089***	−0.060***	−0.061***	−0.039***	−0.042***	−0.038***	−0.025*	−0.027*
	(0.022)	(0.014)	(0.012)	(0.012)	(0.012)	(0.012)	(0.011)	(0.013)	(0.016)
N	7255								

Notes: robust standard errors are in parentheses obtained through bootstrapping with 500 replications. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; agroecological zone dummies and district dummies are included; interactions between AEZ and topsoil loss are included.

Table 5
Aggregate effects of topsoil loss increase scenarios in terms of total maize production and GDP value.

	No Antierosion		Bunds		Vetiver grass		Tree belts	
Topsoil loss increase	ΔT	ΔGDP	ΔT	ΔGDP	ΔT	ΔGDP	ΔT	ΔGDP
+10%	−6.87%	−1.01%	−4.42%	−0.65%	−3.83%	−0.56%	−5.88%	−0.87%
+20%	−13.74%	−2.03%	−8.84%	−1.30%	−7.66%	−1.13%	−11.77%	−1.17%
+30%	−20.62%	−3.04%	−13.26%	−1.95%	−11.49%	−1.70%	−17.65%	−2.62%

Notes: macroeconomic data used in the analysis, Source FAOSTAT - total maize area harvested (ave. 2011–2013) = 1,676,067.5 ha; Maize producer price 2011 (LCU/ton) = 30,319 MWK; Maize producer price 2013 (LCU/ton) = 106,648 MWK; GDP 2011 (millions LCU) = 1,252,750 MWK; GDP 2013 (millions LCU) = 1,901,100 MWK.

30%. The total loss in maize production is expressed in tons, ΔT, while the loss in maize production is expressed in terms of GDP value, denoted by ΔGDP. We estimate these impacts both for a baseline case without erosion control practices, and when adopting one of the practices that result significant in explaining the erosion mitigation.

In terms of maize production, our estimates suggest that for topsoil loss increases between 10% and 30%, the reduction would range from 6.87 to 20.62% compared with the baseline case. However, these reductions could be less severe with the application of vetiver grass, followed by erosion bunds and tree belts. In addition, we observe a loss in maize production corresponding to 1% to 3% of the GDP value compared with the baseline case, which could be reduced up to 0.56% and 1.7% by adopting vetiver grass measures, respectively in the two worsening scenarios.

4.4. Robustness check

Given the cross-sectional nature of our baseline econometric setup, it could be argued that the level of topsoil loss may be correlated with time-invariant unobservable characteristics of the HH or plot which would lie in the error term. To address this concern, we present an additional set of estimates of the impact of topsoil loss based on an alternative estimator, namely the unconditional fixed effect quantile regression (FE-UCR) (Graham et al., 2018). The FE-UCR estimator

Table 6
FE-UQR.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90
(a) maize_yield									
Topsoil loss	−0.213***	−0.193***	−0.094**	−0.085**	−0.055	−0.024	−0.031	−0.047	−0.033
	(0.080)	(0.066)	(0.047)	(0.044)	(0.043)	(0.041)	(0.041)	(0.052)	(0.052)
N	3054								
(b) rexpaggpc									
topsoil_loss	−0.131***	−0.122***	−0.097***	−0.075**	−0.048	−0.004	−0.022	−0.020	−0.042
	(0.057)	(0.046)	(0.042)	(0.040)	(0.041)	(0.041)	(0.040)	(0.044)	(0.051)
N	2816								
(c) calories									
topsoil_loss	−0.102**	−0.086***	−0.080***	−0.064*	−0.045*	−0.036*	−0.006	−0.021	−0.025
	(0.051)	(0.033)	(0.031)	(0.035)	(0.025)	(0.021)	(0.027)	(0.030)	(0.037)
N:	2816								

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; Model (a): robust standard errors clustered at HH-plot level in parentheses are obtained through bootstrapping with 500 replications; strongly balanced group = (hhid, plot_id). controls (agehead femhead educave hhsize plot_area labour fert1 fert2 fert3 fert4 organic_fert pesticides seeds MV D_crop_groundnut D_crop_other D_crop_legumes S s_r_spei s_d_spei topsoil_loss 4 Iplot_meas_2 _Iplot_meas_3 _Iplot_meas_4 _Iplot_meas_5 _ID_fallow_1); Model (b): robust standard errors clustered at HH level are in parentheses, obtained through bootstrapping with 500 replications; controls (agehead femhead educave hhsize plot_area spfarm2 wealth infraindex parliament D_crop_groundnut D_crop_other D_crop_legumes s_r_spei s_d_spei topsoil_loss); Model (c): robust standard errors clustered at HH level are in parentheses, obtained through bootstrapping with 500 replications; controls (agehead femhead educave hhsize plot_area spfarm2 wealth infraindex parliament labour fert1 fert2 fert3 fert4 organic_fert pesticides seeds MV D_crop_groundnut D_crop_other D_crop_legumes s_r_spei s_d_spei topsoil_loss)

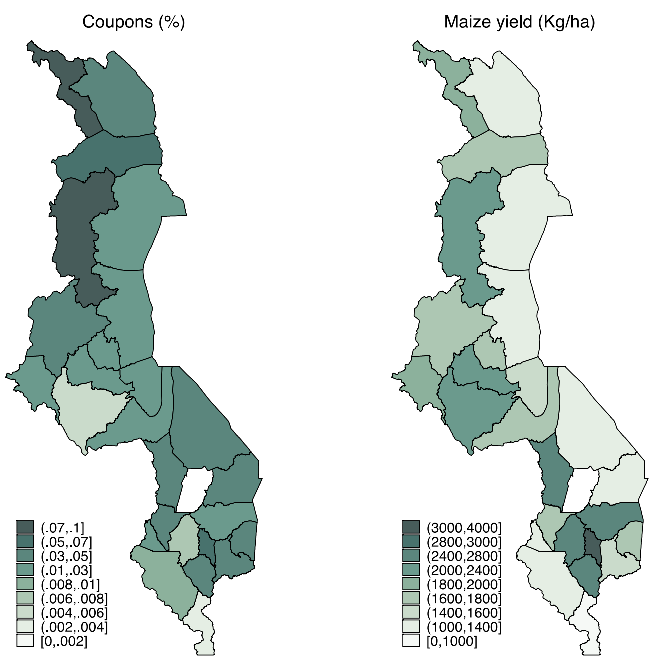

Fig. 8. Proportion of coupons FISP distribution (%) and yield (Kg/ha), by district (average 2011–2013).

accounts for both the heterogeneous effect along the distribution of the outcome and the unobserved heterogeneity (Borgen, 2016). This feature is particularly relevant if the soil loss is correlated with plot or HH's unobservable characteristics such as skills or structural soil nutrients availability. In order to obtain FE-UCR estimates, we build a two-year balanced panel subsample, which consists in 1527 plots and 1408 HHs. Table B1 in Appendix B provides a comparison of the two samples at plot level based on the outcomes means and covariates. From the comparison between column 1 (pooled) and column 2 (panel) it emerges that the baseline sample does not substantially differ from the total LSMA population and it is plausibly not affected by selection.

Table 6 reports FE-UCR estimates of the impact of soil loss on maize productivity (model a) and on the two welfare outcomes (model b and c)[9]. Results are consistent with our main findings obtained in Sections 4.1 and 4.2.

These estimates confirm, with a slight difference in magnitude on the first decile, the negative impact of soil loss on productivity, with heterogeneous and decreasing effects that depict a sharper pattern since less than 50% of the sample distribution is influenced by soil loss. Similarly, effects on the welfare outcomes show a similar pattern, with coefficients larger in magnitude[10].

As second robustness check, we offer an estimation based on a generalized quantile regression estimator (GQR), which relies on an instrumental variable (IV) approach to estimate counterfactual quantiles of the maize productivity distribution for different values of the soil loss (Chernozhukov and Hansen, 2005; Powell, 2016). In this setting, we test whether the soil loss is correlated with specific ability to cope with soil erosion and other unobservable characteristics which would make topsoil loss as-good-as random across farmers, giving rise to endogeneity. Results from the GQR estimator (Table S5 in the supplementary material) confirm the same pattern as observed in both UQR and FE-UQR estimates.

5. Discussion

Our results show that topsoil loss has sizable impacts on maize productivity of the most vulnerable HHs, while not having influence on higher deciles of the distribution. This evidence is robust to different estimators and model specifications.

This heterogeneity should be considered by policymakers when planning interventions aimed at enhancing rural development. In this

[9] The full set of estimates are available as supplementary material in Table S1, S3 and S4.

[10] We use a dummy variable of the inherited plot property as an instrumental variable for the suspected endogenous variable. The rationale for this instrument lies in the fact that, if an HH inherits the land (71% of plots in our sample), this status is binding in defining the initial endowment (the stock), and does not directly affect the annual current productivity. The literature indeed demonstrates that the annual productivity mostly depends on the degree of tenure security (Lovo, 2016). This mechanism has been extensively explained in reviews studies (Place, 2009; Fenske, 2011) and confirmed also within the Malawian historical context (Place & Otsuka, 2001; Lovo, 2016; Deinenger et al., 2019).

respect, our study confirms the importance of the farmers' endowment in allowing rural livelihood options in order to face agricultural shocks (Call et al., 2019). In fact, more productive HHs are likely to be endowed with a richer set of assets, in particular physical, human and financial assets, which can help them contrast the productivity impacts of topsoil loss and contemporaneously enhance their livelihood potential (Davis et al., 2017).

In addition, when comparing marginal effects of topsoil loss *vis-à-vis* those of fertilizers, we find a larger magnitude of topsoil loss coefficients. Since more productive farmers are not affected by an increase in erosion, it could be verified that mid-productive HHs are those for which the access to fertilizers has a relatively larger impact in offsetting the negative effects of topsoil loss. Put differently, while fertilizers increase the productivity, policymakers should orient the subsidies distribution towards mid productive HHs in order to obtain a cost-effective mitigation impact. We show that this reduction is within a range of 1–3% of Malawi's GDP value. Hence, since mid-productive HHs minimize the gap between the negative effects of soil loss and the beneficial effects on the productivity, providing most vulnerable HHs with the largest share of coupons to obtain subsidized fertilizers, as in the Malawian FISP (Asfaw et al., 2017), could result in a sub-optimal policy targeting with limited productivity mitigation in aggregate terms. To explain this point, Fig. 8 compares at district level the proportion on national distribution of received FISP coupons with deciles of maize yield. Some southern districts, that received a relatively large share of subsidies (dark green in Fig. 8), match with highest deciles of productivity (clear green Fig. 8).

Moreover, some north-eastern districts with low levels of productivity received a relatively larger share of coupons. This suggests that, at constant budget, still exists room for redistributing subsidies to help mitigate the impact of topsoil loss in a cost-effective manner.

On the other hand, less productive farmers would be net losers from revising the targeting criteria of fertilizers coupons and should be compensated for the reduction of productivity and welfare. This compensation could come from a support to the adoption of erosion control practices, which show a relatively larger topsoil mitigation potential for HHs in the lowest productivity deciles; vetiver grass and control bunds, in particular, offer the largest mitigation effects for this population group.

Nevertheless, these practices are expensive to poorer HHs and might be supported by public intervention. To this end, our results suggest that the opportunity cost of public budget allocation would be reduced from incentivizing the adoption of effective erosion control practices by losers HHs and, thus, such a support would not increase the public expenditure on rural assistance.

Our results also suggest that topsoil loss deteriorates the HH welfare, but these effects are mild or even disappear for wealthier HHs, which are likely to better *ex-ante* adapt or *ex-post* cope with increasing erosion phenomena. Finally, an important distressing mechanism is provided by income diversification, which can reduce the proportion of on-farm income and, as a consequence, the risk of productivity reduction induced by topsoil loss. Therefore, increasing wage labour opportunities should be a priority for the policy makers, considering that a large fraction of Malawian HHs relies on consumption of self-produced food and, as a consequence, agricultural stresses could produce large fluctuations on the rural welfare (Wuepper et al., 2018; Frelat et al., 2016).

6. Conclusions

In this paper we investigate the distributional economic effects of soil loss in Malawi by carrying out a micro-econometric analysis using socio-economic, climatic and topsoil loss data both at plot and HH level for the periods 2011/2012 and 2012/2013. Malawi offers a favorable setting for our analysis, being a country with a severe soil erosion and increasing exposure to climate shocks that contribute to worsening the erosion phenomena.

The empirical analysis employs a set of unconditional quantile regression models to catch the distributional impacts on maize productivity and welfare outcomes, namely per capita consumption and caloric intake. Overall, we show that the topsoil loss severely impacts the productivity and welfare of most vulnerable HHs, undermining the capacity to escape from a poverty status. Incentivizing *ex-ante* adaptation strategies seems to be an effective strategy to increase their welfare as well as their *ex-post* coping ability. Policy makers should thus sustain the adoption of these practices for poorer HHs in order to increase their livelihood options in face of increasing natural events, such as erosion phenomena. At the same time, increasing wage labor opportunities would enhance the income diversification, mitigating the risks of welfare fluctuations.

Our analysis on the aggregated effects indicates that the impact of topsoil loss in the Malawian economy is sizable, corresponding to a reduction of national maize production ranging from 6.8 to 20%; the monetary value of this loss ranges from 1% to 3% of GDP for a topsoil loss increase of 10% and 30%, respectively. Moreover, both effects on agricultural productivity and welfare outcomes are not equally distributed, disproportionately affecting least-productive HHs and contributing to worsen their condition.

We suggest that subsidizing fertilizers to least productive HHs facilitates the replenishment of nutrients lost with the topsoil, but it does not provide cost-effective targeting criteria. Conversely, erosion control practices appear more effective in helping vulnerable farmers. Scope for sustaining information services on sustainable agricultural practices and suitable erosion control measures exist for the national and local administrators. Overall, these results depict a situation where priorities of interventions to tackle soil erosion and ranking of beneficiaries should be based on both the maximization of net returns from subsidy policies and placed-based criteria (e.g. agroecological zone), where incentive to erosion control practices could better contribute to compensate less productive HHs after reviewing targeting rules for the subsidies.

Alternatively, these farmers could also be rewarded by the adoption of crop diversification and legumes intercropping which favor the substitution of chemical fertilizers. Such planning would enhance the overall country mitigation capacity in facing topsoil loss since adopting erosion control practices can determine gains up to a half production and GDP value loss, compared to the baseline case.

Although our analysis focuses on Malawi, the empirical approach and the results obtained could be useful in other contexts with comparable levels of topsoil loss erosion and context. In this respect, we provide novel findings and policy indications under the plausible hypothesis of a topsoil loss increase scenario. Indeed, defining the range of topsoil loss financial and social effects should be a priority in order to control the rate of national soil deprivation and the expected returns from related mitigation actions. To this end, further research would benefit from collecting additional data to expand regional and temporal coverage, which is limited in our study. Finally, it should be highlighted that our analysis focuses on the on-site distributional effects of topsoil, while the aggregate effects provided must be intended as static. Reinforcing feedback loops as a reaction to increasing erosion phenomena should be further addressed along with the sizable off-set costs of soil erosion.

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

Table A1
Unconditional quantile regression (UQR): impact of soil loss on maize productivity.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90
agehead	0.002	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
femhead	−0.190***	−0.148***	−0.107***	−0.101***	−0.065**	−0.055**	−0.047**	−0.059**	−0.042
	(0.068)	(0.042)	(0.029)	(0.026)	(0.026)	(0.025)	(0.022)	(0.029)	(0.033)
educave	0.048***	0.039***	0.034***	0.033***	0.033***	0.025***	0.026***	0.026***	0.027***
	(0.010)	(0.007)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)
hhsize	0.009	0.016**	0.011**	0.008	0.012**	0.009**	0.009**	0.004	−0.000
	(0.011)	(0.007)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.006)	(0.006)
disturban	−0.020	−0.014	−0.003	−0.015**	−0.025***	−0.026***	−0.042***	−0.048***	−0.064***
	(0.016)	(0.012)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.010)
plot_area	−0.728***	−0.559***	−0.465***	−0.432***	−0.418***	−0.345***	−0.330***	−0.342***	−0.338***
	(0.068)	(0.043)	(0.026)	(0.022)	(0.022)	(0.022)	(0.021)	(0.026)	(0.029)
labour	0.205***	0.129***	0.088***	0.091***	0.096***	0.073***	0.068***	0.067***	0.060***
	(0.039)	(0.023)	(0.016)	(0.014)	(0.014)	(0.014)	(0.013)	(0.015)	(0.018)
fert1	0.157***	0.135***	0.115***	0.102***	0.095***	0.078***	0.072***	0.077***	0.059***
	(0.016)	(0.012)	(0.008)	(0.007)	(0.007)	(0.006)	(0.006)	(0.007)	(0.007)
fert2	0.159***	0.139***	0.101***	0.089***	0.096***	0.082***	0.079***	0.083***	0.061***
	(0.019)	(0.011)	(0.008)	(0.007)	(0.007)	(0.006)	(0.006)	(0.007)	(0.007)
fert3	0.051*	0.053**	0.055***	0.058***	0.065***	0.068***	0.062***	0.078***	0.059***
	(0.029)	(0.021)	(0.015)	(0.013)	(0.014)	(0.013)	(0.015)	(0.018)	(0.019)
fert4	0.099***	0.119***	0.100***	0.086***	0.081***	0.056***	0.054***	0.041**	0.035
	(0.037)	(0.026)	(0.019)	(0.018)	(0.019)	(0.018)	(0.017)	(0.019)	(0.023)
organic_fert	0.038***	0.031***	0.026***	0.025***	0.022***	0.023***	0.020***	0.028***	0.008
	(0.012)	(0.008)	(0.006)	(0.005)	(0.006)	(0.005)	(0.005)	(0.007)	(0.008)
pesticides	−0.254	−0.191	−0.036	0.008	0.029	−0.028	−0.059	−0.020	0.139
	(0.227)	(0.178)	(0.122)	(0.119)	(0.117)	(0.134)	(0.105)	(0.130)	(0.144)
seeds	0.237***	0.220***	0.158***	0.132***	0.124***	0.119***	0.113***	0.147***	0.133***
	(0.040)	(0.027)	(0.020)	(0.017)	(0.017)	(0.015)	(0.015)	(0.017)	(0.020)
MV	0.100*	0.057*	0.056**	0.065***	0.044**	0.039*	0.021	0.069***	0.037
	(0.051)	(0.034)	(0.025)	(0.021)	(0.022)	(0.021)	(0.021)	(0.024)	(0.028)
D_crop_groundnut	0.105	0.144**	0.147***	0.148***	0.192***	0.127***	0.133***	0.110*	0.069
	(0.101)	(0.067)	(0.047)	(0.051)	(0.049)	(0.048)	(0.048)	(0.061)	(0.076)
D_crop_other	0.310***	0.231***	0.169***	0.173***	0.237***	0.189***	0.125***	0.227***	0.176***
	(0.090)	(0.056)	(0.041)	(0.045)	(0.044)	(0.038)	(0.040)	(0.051)	(0.063)
D_crop_legume	0.258***	0.287***	0.241***	0.245***	0.367***	0.389***	0.333***	0.471***	0.571***
	(0.077)	(0.057)	(0.042)	(0.041)	(0.045)	(0.044)	(0.049)	(0.061)	(0.080)
s_r_spei	0.144**	0.079*	0.057	0.029	0.023	0.020	−0.009	−0.002	−0.037
	(0.067)	(0.045)	(0.035)	(0.029)	(0.030)	(0.027)	(0.026)	(0.032)	(0.036)
s_d_spei	−0.480***	−0.350***	−0.226***	−0.165***	−0.169***	−0.154***	−0.106***	−0.126***	−0.064*
	(0.070)	(0.047)	(0.038)	(0.030)	(0.030)	(0.026)	(0.025)	(0.032)	(0.035)
topsoil_loss	−0.262***	−0.235***	−0.173***	−0.106***	−0.099***	−0.069**	−0.032	−0.028	−0.032
	(0.065)	(0.041)	(0.035)	(0.028)	(0.028)	(0.027)	(0.022)	(0.027)	(0.032)
year_2013	0.526***	0.290***	0.245***	0.187***	0.206***	0.190***	0.137***	0.146***	0.079*
	(0.098)	(0.066)	(0.051)	(0.041)	(0.043)	(0.036)	(0.035)	(0.042)	(0.047)
eros_contr: terraces	0.091**	0.144*	0.098*	0.089*	0.049	0.027	0.015	0.004	0.133**
	(0.045)	(0.085)	(0.058)	(0.052)	(0.058)	(0.055)	(0.055)	(0.072)	(0.064)
eros_contr: bunds	−0.067	−0.016	0.012	−0.018	0.002	0.038*	0.003	−0.038	−0.034
	(0.054)	(0.039)	(0.027)	(0.022)	(0.026)	(0.023)	(0.023)	(0.027)	(0.030)
eros_contr: vetiver grass	0.148*	0.167**	0.092*	0.090*	0.087*	0.096*	0.106**	0.142**	−0.020
	(0.090)	(0.074)	(0.054)	(0.051)	(0.048)	(0.050)	(0.048)	(0.064)	(0.056)
eros_contr: tree belts	0.015	0.190	−0.099	0.014	0.023	0.032	0.022	0.073	0.061
	(0.335)	(0.222)	(0.183)	(0.157)	(0.169)	(0.145)	(0.145)	(0.199)	(0.187)
D_fallow: yes	−0.078	−0.041	−0.092**	−0.062*	−0.047	−0.043	−0.027	−0.025	−0.057
	(0.079)	(0.058)	(0.040)	(0.036)	(0.036)	(0.033)	(0.031)	(0.038)	(0.042)
S	0.176***	0.185***	0.174***	0.206***	0.190***	0.170***	0.237***	0.247***	0.264***
	(0.050)	(0.031)	(0.022)	(0.025)	(0.026)	(0.022)	(0.024)	(0.032)	(0.036)
_cons	5.070***	5.937***	6.252***	5.981***	6.147***	6.463***	6.340***	6.459***	7.025***
	(0.613)	(0.390)	(0.320)	(0.265)	(0.272)	(0.263)	(0.222)	(0.258)	(0.311)
N	9244								

Notes: robust standard errors in parentheses obtained through bootstrapping with 500 replications. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; agroecological zone dummies and interactions between agroecological zone and topsoil loss are included.

Table A2
UCR – effect of topsoil loss on HH real per capita consumption expenditure (ln MWK).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90
agehead	0.001	0.001	0.001	0.001	0.000	0.001	0.000	0.000	−0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
femhead	−0.136***	−0.152***	−0.149***	−0.120***	−0.099***	−0.098***	−0.063***	−0.002	0.075**
	(0.030)	(0.026)	(0.024)	(0.021)	(0.022)	(0.024)	(0.024)	(0.025)	(0.035)
educave	0.018***	0.015***	0.017***	0.018***	0.016***	0.016***	0.018***	0.025***	0.024***
	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.005)
hhsize	−0.116***	−0.125***	−0.136***	−0.142***	−0.149***	−0.149***	−0.148***	−0.152***	−0.166***
	(0.007)	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.008)	(0.010)
disturban	−0.010	−0.008	−0.026**	−0.019	−0.016	−0.024*	−0.034**	−0.039**	−0.034
	(0.016)	(0.013)	(0.013)	(0.013)	(0.013)	(0.014)	(0.013)	(0.016)	(0.023)
spfarm2	−0.109***	−0.101***	−0.112***	−0.099***	−0.064***	−0.024	−0.007	−0.021	0.024
	(0.027)	(0.022)	(0.021)	(0.019)	(0.020)	(0.021)	(0.021)	(0.023)	(0.030)
wealth	0.111***	0.130***	0.151***	0.159***	0.182***	0.202***	0.219***	0.277***	0.375***
	(0.010)	(0.009)	(0.010)	(0.010)	(0.011)	(0.011)	(0.012)	(0.016)	(0.026)
infraindex	0.071***	0.081***	0.089***	0.113***	0.130***	0.129***	0.126***	0.110***	0.104***
	(0.012)	(0.012)	(0.011)	(0.012)	(0.013)	(0.014)	(0.015)	(0.017)	(0.025)
parliament	0.078**	0.093***	0.060**	0.070**	0.004	0.036	0.027	0.022	0.045
	(0.035)	(0.032)	(0.030)	(0.030)	(0.032)	(0.032)	(0.034)	(0.040)	(0.051)
plot_area	−0.011***	−0.008**	−0.006*	−0.005	−0.003	−0.005	−0.005	0.003	0.002
	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
D_crop_maize	0.221**	0.161**	0.147**	0.141**	0.137**	0.051	−0.005	−0.076	−0.145
	(0.094)	(0.066)	(0.062)	(0.057)	(0.060)	(0.057)	(0.059)	(0.065)	(0.089)
D_crop_groundnut	0.056**	0.042*	0.065***	0.068***	0.077***	0.081***	0.078***	0.062**	0.027
	(0.027)	(0.023)	(0.024)	(0.022)	(0.025)	(0.024)	(0.024)	(0.029)	(0.038)
D_crop_legumes	0.012	0.044	0.053	0.042	0.054*	0.020	−0.009	−0.001	0.072
	(0.040)	(0.034)	(0.032)	(0.032)	(0.033)	(0.029)	(0.034)	(0.042)	(0.056)
D_crop_other	0.037	0.038*	0.024	0.029	0.032	0.004	−0.013	−0.025	−0.045
	(0.026)	(0.023)	(0.022)	(0.021)	(0.023)	(0.023)	(0.023)	(0.026)	(0.036)
s_r_spei	0.058	0.046	0.064**	0.051	0.030	0.018	−0.009	−0.052	−0.013
	(0.036)	(0.033)	(0.031)	(0.032)	(0.029)	(0.032)	(0.033)	(0.038)	(0.054)
s_d_spei	−0.077*	−0.061*	−0.055*	−0.019	−0.048	−0.066**	−0.059*	0.054	0.022
	(0.045)	(0.037)	(0.033)	(0.033)	(0.030)	(0.030)	(0.030)	(0.033)	(0.043)
topsoil_loss	−0.065***	−0.081***	−0.087***	−0.068***	−0.044***	−0.015	−0.017	0.028	0.027
	(0.016)	(0.015)	(0.014)	(0.015)	(0.015)	(0.016)	(0.017)	(0.019)	(0.025)
year_2013	0.555***	0.717***	0.864***	0.995***	1.157***	1.291***	1.421***	1.610***	1.632***
	(0.043)	(0.038)	(0.038)	(0.039)	(0.040)	(0.045)	(0.056)	(0.074)	(0.090)
cons	10.085***	10.658***	11.010***	10.953***	10.982***	11.015***	11.398***	11.343***	11.746***
	(0.224)	(0.187)	(0.191)	(0.178)	(0.189)	(0.192)	(0.200)	(0.224)	(0.308)
N	7255								

Notes: robust standard errors in parentheses obtained through bootstrapping with 500 replications. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; district dummies are included to account for administrative fixed effects.

Table A3
UCR – effect of topsoil loss on per capita caloric intake (ln calories).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90
agehead	0.002*	0.001**	0.001	0.001	0.001	0.001**	0.001***	0.001**	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
femhead	−0.051	−0.058**	−0.036*	−0.049**	−0.032*	−0.010	−0.001	0.016	0.014
	(0.038)	(0.024)	(0.019)	(0.019)	(0.017)	(0.016)	(0.019)	(0.020)	(0.025)
educave	0.009*	0.007**	0.007**	0.008***	0.008***	0.009***	0.008***	0.004	0.005
	(0.005)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)
hhsize	−0.036***	−0.049***	−0.060***	−0.072***	−0.077***	−0.079***	−0.083***	−0.083***	−0.082***
	(0.007)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
disturban	−0.019	−0.001	−0.001	−0.009	−0.004	−0.003	−0.003	0.005	0.017
	(0.023)	(0.013)	(0.011)	(0.010)	(0.010)	(0.009)	(0.010)	(0.011)	(0.012)
spfarm2	−0.038	−0.042**	−0.043***	−0.058***	−0.052***	−0.027*	−0.054***	−0.051***	−0.016
	(0.032)	(0.021)	(0.016)	(0.016)	(0.016)	(0.014)	(0.015)	(0.016)	(0.020)
wealth	0.072***	0.051***	0.049***	0.053***	0.047***	0.048***	0.048***	0.050***	0.046***
	(0.012)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.011)
infraindex	0.048***	0.031***	0.024**	0.020**	0.019**	0.011	0.015	0.012	0.024
	(0.017)	(0.011)	(0.010)	(0.009)	(0.010)	(0.009)	(0.011)	(0.012)	(0.015)
parliament	0.043	0.028	0.011	0.027	0.030	0.038	0.019	0.022	−0.032
	(0.046)	(0.030)	(0.027)	(0.025)	(0.024)	(0.025)	(0.026)	(0.027)	(0.032)
plot_area	−0.003	0.003	0.005	0.006*	0.005*	0.002	0.002	0.004	0.002
	(0.005)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
D_crop_maize	0.145	0.018	0.014	0.033	0.019	−0.011	−0.005	−0.020	−0.033
	(0.126)	(0.068)	(0.056)	(0.050)	(0.049)	(0.045)	(0.044)	(0.048)	(0.064)
D_crop_groundnut	0.032	0.008	0.024	0.038*	0.008	0.006	0.021	0.026	0.032
	(0.040)	(0.023)	(0.019)	(0.020)	(0.018)	(0.018)	(0.019)	(0.020)	(0.027)
D_crop_legumes	0.002	0.023	−0.001	−0.007	0.002	0.008	0.026	0.011	0.018
	(0.056)	(0.035)	(0.027)	(0.028)	(0.025)	(0.024)	(0.028)	(0.027)	(0.035)
D_crop_other	−0.044	−0.015	−0.024	−0.020	0.003	−0.018	−0.009	−0.014	0.007
	(0.037)	(0.023)	(0.020)	(0.019)	(0.017)	(0.017)	(0.017)	(0.021)	(0.024)
s_r_spei	−0.065	−0.052	−0.017	−0.004	0.012	−0.006	−0.005	0.013	0.003
	(0.052)	(0.033)	(0.028)	(0.024)	(0.025)	(0.023)	(0.025)	(0.026)	(0.032)
s_d_spei	−0.079*	−0.059*	−0.024	−0.025	−0.025	−0.022	−0.024	−0.005	−0.009
	(0.045)	(0.032)	(0.016)	(0.014)	(0.005)	(0.017)	(0.022)	(0.025)	(0.029)
labour	0.001	0.000	−0.001	−0.002	−0.001	0.000	−0.002	−0.003	−0.002
	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
fert1	0.000	0.002	0.003	0.004**	0.002	0.002	0.002	0.002	0.003
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
fert2	0.005	0.007***	0.005***	0.005***	0.005***	0.004**	0.003*	0.004**	0.002
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
fert3	0.014***	0.001	0.004	0.002	0.005	0.006*	0.004	0.006*	0.009*
	(0.005)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)
fert4	−0.003	−0.003	0.003	0.004	0.006*	0.005	0.004	0.002	0.002
	(0.008)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
organic_fert	−0.001	0.001	0.002	0.003**	0.003**	0.003**	0.002	0.003**	0.005**
	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
pesticides	−0.025	−0.042	−0.012	−0.004	−0.001	−0.001	−0.012	−0.014	−0.019
	(0.049)	(0.028)	(0.022)	(0.020)	(0.020)	(0.019)	(0.017)	(0.020)	(0.024)
seeds	0.011	0.008*	0.008*	0.009**	0.009**	0.006	0.010**	0.011**	0.007
	(0.008)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
topsoil_loss	−0.063***	−0.089***	−0.060***	−0.061***	−0.039***	−0.042***	−0.038***	−0.025*	−0.027*
	(0.022)	(0.014)	(0.012)	(0.012)	(0.012)	(0.012)	(0.011)	(0.013)	(0.016)
year_2013	−0.062	0.059	0.054*	0.102***	0.118***	0.118***	0.172***	0.170***	0.209***
	(0.063)	(0.038)	(0.031)	(0.030)	(0.029)	(0.027)	(0.029)	(0.031)	(0.041)
cons	6.999***	7.700***	7.746***	7.928***	7.827***	7.972***	8.060***	8.028***	8.239***
	(0.300)	(0.182)	(0.152)	(0.143)	(0.146)	(0.140)	(0.144)	(0.162)	(0.191)
N	7255								

Notes: robust standard errors in parentheses obtained through bootstrapping with 500 replications. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; district dummies are included to account for administrative fixed effects. AEZ dummies are included to account for agroecological fixed effects.

Appendix B

Table B1
Comparison of samples at plot level.

	Pooled		Panel	
variables	Mean	Std. dev.	Mean	Std. dev.
maize_yield	1912.44	1208.73	1895.79	1869.62
topsoil_loss	15.25	8.26	15.47	8.24
s_r_spei	0.38	0.49	0.38	0.49
s_d_spei	0.46	0.50	0.51	0.49
plot_area	0.43	0.40	0.44	0.33
fert1	128.50	203.91	124.88	192.16
fert2	102.91	181.45	76.00	145.71
fert3	13.00	57.14	31.04	83.41
fert4	6.86	56.95	9.98	78.05
organic_fert	106.93	383.36	122.98	398.90
pesticides	0.08	2.91	0.07	2.67
seeds	39.10	40.79	38.21	43.69
D_crop_groundnut	0.27	0.44	0.03	0.36
D_crop_legume	0.10	0.31	0.10	0.35
D_crop_other	0.42	0.49	0.36	0.37
MV	0.52	0.50	0.49	0.50
S	1.67	0.91	1.65	0.90
agehead	43.92	16.20	45.11	16.33
femhead	0.24	0.43	0.24	0.43
educave	5.21	2.69	5.30	2.59
hhsize	5.03	2.32	5.35	2.43
labor	248.33	186.54	230.87	271.57
eros_contr:terraces	0.03	0.18	0.03	0.21
eros_contr:bunds	0.27	0.43	0.30	0.45
eros_contr:vetiver grass	0.06	0.21	0.06	0.24
eros_contr:tree belts	0.01	0.05	0.01	0.07
Fallow	0.13	0.33	0.17	0.35
N	9244		3054	

Appendix C. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolecon.2020.106764.

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