Impacts of Africa RISING in Tanzania

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The Africa Research In Sustainable Intensification for the Next Generation (Africa RISING) program comprises three research-in-development projects supported by the United States Agency for International Development (USAID) as part of the U.S. Government's Feed the Future initiative.

Through action research and development partnerships, Africa RISING is creating opportunities for smallholder farm households to move out of hunger and poverty through sustainably intensified farming systems that improve food, nutrition, and income security, particularly for women and children, and conserve or enhance the natural resource base.

The three regional projects are led by the International Institute of Tropical Agriculture (in West Africa and East and Southern Africa) and the International Livestock Research Institute (in the Ethiopian Highlands). The International Food Policy Research Institute leads the program's monitoring, evaluation and impact assessment.

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Executive summary

Sustainable intensification (SI) of the smallholder sector in Africa south of the Sahara is among the approaches pursued to build resilient food systems that can supply nutritionally adequate food in the face of rapid population growth and climatic changes. This study assesses the impact of an SI program in Tanzania implemented in the poorest and most food insecure areas of the country since 2012. The program first validated and then scaled up a wide range of SI interventions focused on improved agronomic management and crop cultivars; improved livestock feed, housing conditions, and species; crop-livestock integration; integrated natural resource management; vegetable production and nutritional education; and small-scale mechanization. Impact is estimated on several SI indicators and domains using two rounds of quasi-experimental panel data (conducted in 2014 and 2022), propensity score matching, and difference-in-differences techniques. The study design allows us to estimate the impact of Africa RISING by comparing outcomes among program beneficiaries with two different counterfactual groups—one located inside program villages (within-village comparison) and another in non-program (control) villages (out-of-village comparison)—on several indicators across five SI domains environment, productivity, economic, human, and social. We also conduct a *placebo* test comparing non-beneficiaries in the two counterfactual groups. Results from panel data analyses show improvements in several indicators in the environmental and productivity domains. We also find positive impact of participation in Africa RISING on several indicators under all the considered domains: beneficiaries were less likely to experience soil erosion, used more inputs (fertilizers, pesticides, and seeds) per hectare, obtained higher legume yields, were more likely to produce meat and dairy, reported higher net livestock income, and experienced fewer months of food insecurity. Estimates based on *within-village*, *out-of-village*, *overall*, and *placebo* comparisons suggest important insights about the challenges in assessing the impact of agricultural programs in general and, specifically, participatory multi-intervention programs in the presence of sample (self-)selection and spillovers. Our study highlights useful empirical lessons learned for informing future program design and impact assessments.

1. Introduction

Despite improvements over the last several decades, Africa south of the Sahara (SSA) lags behind other developing regions on several fronts including productivity gains, poverty reduction, and food security. Average cereal yield stagnated at 1.6 tons/ha for SSA in 2020, roughly a third of the yield average of Southeast Asia (FAO 2022). SSA is also the only region where the number of chronically undernourished (stunted) children rose between 2000 and 2019 due to a slower rate of reduction in stunting prevalence and high population growth (UNICEF, WHO, and World Bank 2020). Demographic and Health Surveys data show that 32 percent of the children under five years old in the region are chronically undernourished (ICF 2022). The extreme poverty headcount rate, defined as the share of population living below the $1.90 (per capita/day) international poverty line, declined from 55 percent to 40 percent between 1990 and 2018 in SSA, while other developing regions such as South Asia experienced a higher rate of reduction—from 50 percent to 15 percent (Schoch and Lakner 2020). In addition, it is projected that the increase in temperature in SSA will be faster than the global average, posing a significant threat to agricultural production and food.

One approach pursued to enhance agricultural productivity, food security, and ecosystem services of the smallholder sector in SSA is sustainable intensification (SI). SI aims to improve resource-use efficiency, while increasing food supply from the same resources and enhancing beneficial environmental and social services (Garnett et al. 2013; Pretty et al. 2011; Smith et al. 2016). It provides a conceptual framework to achieve balanced outcomes across different dimensions of sustainability (Smith et al. 2016; Conway, Wilson, and Wilson 2013). SI encompasses a wide range of innovations including prudent use of chemical fertilizers, improved cultivars, integration of legumes and livestock into cereal-dominated farming systems, integrated soil and water conservation, crop rotation, agroforestry, and incorporation of manure and crop residues (D'Souza, Cyphers, and Phipps 1993; Lee 2005). It offers a departure from the historically narrow focus on enhancing the productivity of a few staple crops and overall profitability, with little consideration of the linkages with nutrition and health (Bouis and Welch 2010).

One of the largest SI programs globally is the *Africa Research In Sustainable Intensification* *for the Next Generation – Africa RISING.*[1] This program has been implemented in six African countries since 2012—Ethiopia, Malawi, Tanzania, Zambia, Mali, and Ghana. Its goal is "to provide pathways out of hunger and poverty for smallholder families through sustainably intensified farming systems that sufficiently improve food, nutrition, and income security, particularly for women and children, and conserve or enhance the natural resource base" (IITA, IFPRI, and ILRI 2012, 5). Phase I (2012–2016) focused on the validation of alternative demand-driven SI options with the potential to alleviate poverty and improve nutrition, equity, and ecosystem stability. Phase II (2016–2021) focused on the scaling of validated SI innovations in partnership with development partners (IFPRI, IITA, and ILRI 2016).

This impact evaluation study focuses on the interventions implemented in the districts of Babati, Kongwa, and Kiteto in Tanzania. Through a participatory and demand-driven approach, the program promoted several adaptive strategies including improved maize, groundnut, *bambara* nut, millet, sorghum, beans and pigeon pea; cereal-legume intercropping and crop rotation; livestock manure; improved fertilizers; physical erosion barriers (*fanya chini*) and shelterbelts to reduce soil erosion and foster land management; forage and stover quality improvement; poultry feeds with vegetable rations to improve livestock feed quantity and quality; and introduction of pre- and postharvest approaches to reduce food waste and improve food safety.

2. Materials and methods

2.1. Background

With an estimated population of 61 million, Tanzania is the fifth largest country in Africa. According to the World Bank, the poverty headcount ratio of $2.15 a day (2017 PPP) is about 45 percent. More than 70 percent of the population is engaged in agriculture, resides in the rural areas, and practices small-scale farming. Despite production being highly seasonal, consumption is relatively constant throughout the year in Eastern and Southern Africa (Gitonga et al. 2013). Maize storage is therefore important for food security because it smooths supply. Yet price differences are still in the range of 30 percent between trough and peak (Gilbert et al., 2017).

[1] More details about the program can be found at https://africa-rising.net/.

Although Tanzania transitioned from low-income to lower-middle-income status in 2020 (World Bank 2020), its economy remains highly vulnerable to climate impacts (Ires 2021). The average temperature is increasing, and precipitation is becoming more erratic across the country, leading to longer-than-average rainfall seasons with an early onset and late cessation of rains in the northern area, high frequency and severity of floods in the eastern area, and prolonged dry seasons in the southern area (Lema and Majule 2009; Paavola 2008; Kijazi and Reason 2009; Kahimba et al. 2015).

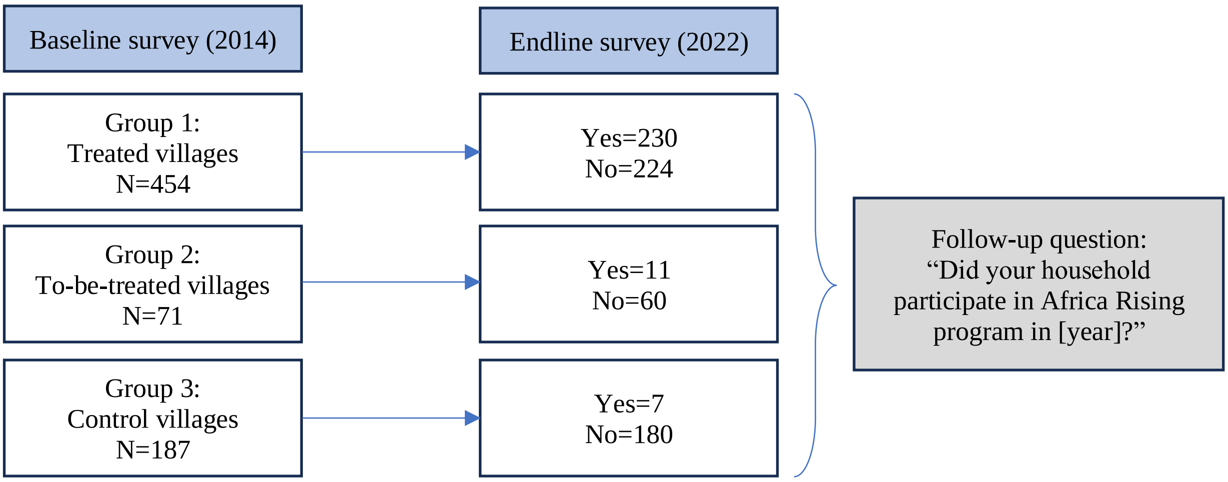
2.2 Data and study design

Panel data were collected as part of the monitoring, evaluation, and impact assessment of the Africa RISING program. Baseline data were collected in 2014, covering 25 communities drawn from the three project districts and three groups of households. The first group (group 1) consisted of 468 households that participated in the program at baseline, based on project monitoring data obtained from program implementers. The second group (group 2) included 57 households that were recruited into the program but did not participate in any program activities at baseline due to resource limitations. The third group (group 3) was a random sample of 187 households from control communities.

After stratifying wards based on geographic characteristics (rainfall and elevation), those with the highest population were sampled for both treatment and control villages. In the wards of Babati district, additional stratification was carried out based on cropping practices and population density. Project villages were chosen within project wards using the inverted alphabetical order of the village name, from Z to A. Control villages were chosen from a sample of villages in adjacent wards for which geographic distance was large enough to reduce the risk of potential contamination from beneficiary villages to control villages.

A follow-up survey was conducted in 2022. Comparable, highly consistent, and structured questionnaires were used to collect data on a wide range of topics including household demographics, agricultural production, food consumption, non-food expenditure, and anthropometric measurements among children under the age of five and women aged 15 to 49 years. The reference period for agricultural production data was the main cropping season while food consumption data were based on a 7-day recall. Figure 1 summarizes the study design: at endline, 98 households (12 percent) were lost due to attrition and 7 households in the control group were excluded due to potential contamination, resulting in a final sample of 705 households.

Figure 1. Study design



For an SI program such as Africa RISING with diverse interventions expected to improve agricultural production and economic outcomes, the identification of relevant indicators can be arbitrary. Indeed, the literature notes that SI is best defined as a multidimensional outcome of enhancing agricultural productivity while preserving social, economic, and environmental sustainability where each domain encompasses multiple elements (Haggar et al. 2021). Following previous research, we adopt a Sustainable Intensification Assessment Framework (SIAF) approach developed by Musumba et al. (2017).

While various indicators have previously been suggested to measure different aspects of SI (Smith et al. 2016; Xie et al. 2019), the SIAF is meant to provide guidance on indicators, metrics, and means to explore five domains of sustainability (agricultural production and productivity, economic, environment, human, and social). The framework is particularly appealing because of its flexibility for choosing indicators and its ability to examine potential trade-offs among domains and indicators. The SIAF has been used to assess patterns of SI in Ethiopia (Hammond et al. 2021), evaluate implications of groundnut production for SI in Ghana (Rahman et al. 2020), examine the implications of mechanization for equity and sustainability in Tanzania (Fischer et al. 2018), and evaluate farmers' preferences for different aspects of SI in Ghana (Kotu et al. 2022).

Given the diversity of program interventions and possible behavioral changes in the adoption of innovations that may be complementary to those promoted by the program, we consider several indicators of adoption under the *environment* domain including cereal-legume intercropping, use of improved seeds, crop residues and fertilizers and access to agricultural advisory services.

Under the agricultural *productivity* domain, we consider cereal and legume yields, the number of unique crops planted, and livestock diversity, engagement in livestock by-products, agricultural labor used, and labor profitability measured by total value of harvest per total number of person-days of labor used. Unit values computed by dividing total sales revenue by quantities sold are used to monetize harvest (for details, see Deaton 1988).

Under the *economic* domain, we examine net household income, per capita daily consumption expenditure, and poverty headcount ratio defined as the percentage of individuals with consumption expenditure below $1.9 per capita per day poverty line based on purchasing power parity (PPP) conversion. Total food consumption expenditure is the sum of self-reported expenditure on purchased food and imputed values of food consumed from own production or gifts. The latter two are monetized using unit values derived by dividing total expenditure on purchased foods with total quantity of purchased foods. To capture non-monetary dimensions of poverty, we construct asset-based poverty indices based on ownership of durable agricultural and non-agricultural assets using a principal-component factor method (Filmer and Pritchett 2001). Households that fall in the top tercile of asset-based indices are defined as non-poor. Unlike consumption-based poverty, which is prone to transient changes in expenditure, asset-based poverty captures long-term and persistent structural poverty (Carter and Barrett 2006; Brandolini, Magri, and Smeeding 2010). It has also been shown that the two do not always track well against each other (Foreit and Schreiner 2011).

Under the *human* domain, we consider two indicators based on food consumed at home over the last seven days. They are the household dietary diversity score (HDDS) based on 12 food groups (Kennedy, Ballard and Dop 2010) and food security status based on whether household dietary caloric intake is above the minimum dietary caloric requirement (MDER) (FAO 2008). We complement these indicators based on self-reported months of food shortages in the 12 months prior to the interview. While the first set of indicators captures the state of food security around the time of data collection, the latter captures food security over a longer period.

Under the *social* domain, for which we have relatively limited data, we examine the share of plots and livestock owned by women, either solely or jointly with men.

To complement household-level food security indicators, we use anthropometric data to construct individual-level nutritional indicators for children 0–59 months old and women 15–49 years old. We follow WHO child growth standards (WHO 2006) to construct child nutrition indicators of undernutrition: chronic undernutrition or stunting, severe undernutrition or wasting, and underweight. Stunting captures linear growth retardation and cumulative growth deficit due to a chronic state of deficiency resulting from undernutrition and illnesses. It is largely an irreversible outcome capturing past and predictive of individuals' future growth and potential to fulfill their development and economic potential (Leroy and Frongillo 2019). Wasting occurs when a child is too thin for their height and results from a recent and severe weight loss due to acute starvation and/or severe disease. Underweight is a manifestation and combination of both chronic and acute factors. For women, we use body mass index (BMI) as indicator for undernutrition (BMI<18.5).

To control for spatial and time-varying weather differences, we use the Normalized Difference Vegetation Index (NDVI) data from the Terra Moderate Resolution Imaging Spectroradiometer Vegetation Indices (MOD13Q1) Version 6 (Didan 2015).[2]

3. Identification strategy

One of the biggest challenges in evaluating participatory programs is sample (self-)selection. This is because these types of programs often employ targeting criteria based on expected effectiveness and returns by recruiting farmers who are (perceived to be) better endowed to adopt and disseminate technologies (Winters, Salazar, and Maffioli 2010; Phillips, Waddington, and White 2014). We consider three different groups:

1. Households in target villages that never participated in the program;

[2] The NDVI has a temporal resolution of 16 days, a spatial resolution of 250 meters, and covers the time period 2000 to 2021. It is a measure of greenness and vigor of vegetation with values ranging between 0 and 1 where NDVI<=0.1 represents bare rock, sand, or snow; 0.1<NDVI<=0.5 captures sparse vegetation; and NDVI>0.5 indicates dense, green vegetation. For both waves, we computed NDVI average value and coefficient for the completed cropping season prior to the data collection (October to May).

2. Households in target villages that were recruited into the program but never participated at baseline due to resource limitations; and

3. Households in non-target villages.

Table 1 shows the descriptive statistics of selected variables at baseline by group and mean-comparison tests across groups.

Table 1: Descriptive summary of selected variables at baseline by group

	(1) Beneficiary	(2) Non-beneficiary	(3) Control	(4) 1 vs 2	(5) 1 vs 3
Household demographic variables					
Household size	6.64	6	5.46	*	***
Age of the household head (years)	47.1	45.5	47.8		
Female-headed (%)	11.0	25.4	13.9	***	
Female adults in the household (#)	1.67	1.58	1.36		***
Household socioeconomic variables					
Education of the household head (years)	6.03	4.60	4.15	***	***
Mean education of adult members (years)	6.59	5.45	4.49	***	***
Plots operated (#)	2.26	2.36	1.91		***
Share of plots under female responsibility (partly or fully)	61.9	71.1	70.1		**
Share of livestock under female responsibility (partly or fully)	12.5	7.58	10.1	***	**
Tropical livestock units	3.56	1.61	3.24	***	
Real value of livestock owned (TZS)	115.2	67.2	74.0		
Real value of livestock sold (TZS)	179.2	140.4	189.3		
Durable non-agricultural assets (index)	0.082	0.17	-0.32		***
Durable agricultural assets (index)	0.20	-0.26	-0.29	***	***
Landscape level variables					
Mean monthly NDVI (historical for cropping months)	0.41	0.37	0.35	***	***
CV of NDVI (historical for cropping months)	8.52	8.79	9.05		***
Observations	454	71	187	525	641

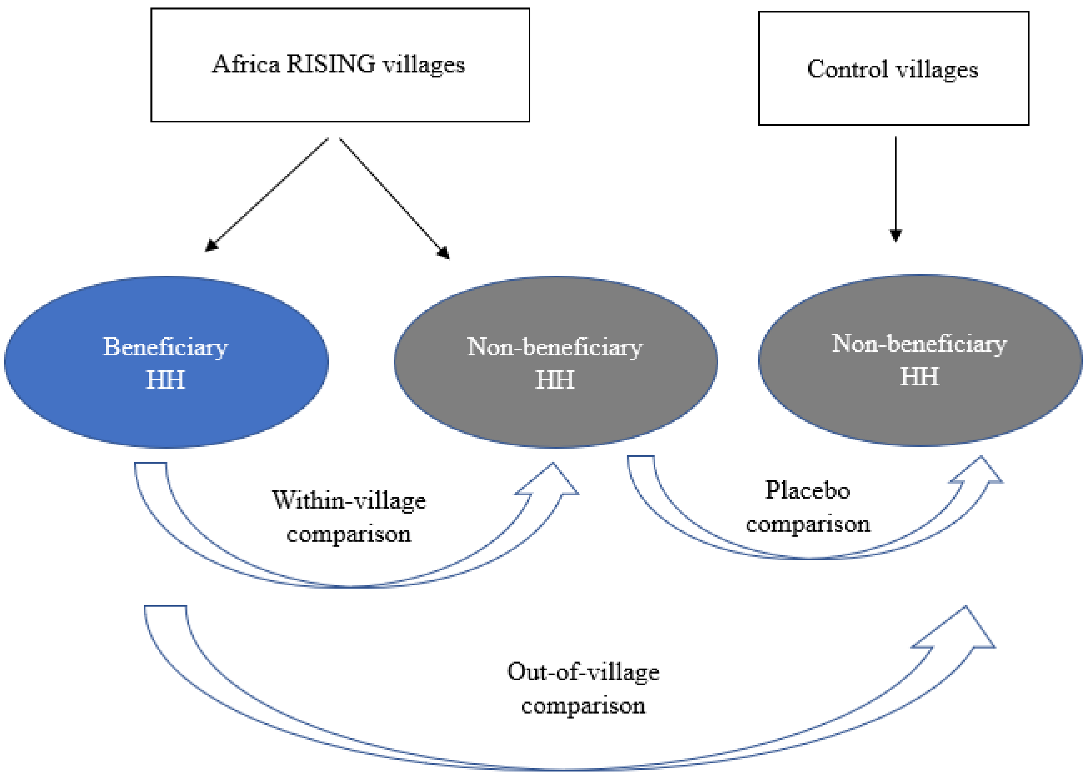
* p<0.1, ** p<0.05, *** p<0.01

Note: TZS stands for Tanzanian shilling.

On average, beneficiary households have 6.6 members, the head of the household has roughly 6 years of education, 11 percent are headed by a woman, 62 percent of plots are managed by a woman, and 13 percent of livestock were women's responsibility. Households in the control group are composed of 5.5 members on average, the head has on average 4 years of education, 14 percent of them headed by women, and 70 percent of plots and 10 percent of livestock were women's responsibility. Mean comparison tests show that households in treatment villages are larger and headed by a more educated individual than those in control villages. We find significant differences between the two groups in terms of durable agricultural and non-agricultural assets, with beneficiary households being wealthier than non-beneficiary households. Furthermore, whereas households in treatment villages were exposed to higher mean monthly NDVI than those in control villages, they also experienced lower variability in exposure.

Exploiting the unique study design discussed in Section 2.2, we conduct multiple pairwise comparisons to check the sensitivity of impact estimates and assumed impact pathways (Figure 2). These include comparisons between beneficiaries and non-beneficiaries in program target villages (*within-village* comparison), beneficiaries and non-beneficiaries in control villages (*out-of-village* comparison), beneficiaries and non-beneficiaries in program target and control villages (*overall* comparison), and non-beneficiaries in program villages and non-beneficiaries in control villages (*placebo* comparison).

Figure 2: Alternative pairwise comparisons



Note: HH stands for households.

By design, *within* village impact estimates are not prone to bias due to potential time-varying systematic village-level differences between program target and control villages that are correlated with the outcomes of interest. Nonetheless, these estimates may be prone to contamination bias if, for example, adoption behavior of households in program villages that have not directly participated in the program is affected by learning from beneficiaries who live in the same villages, that is, contamination via spillover effects. Spillovers are often expected in agricultural programs that promote adoption among direct beneficiaries for subsequent dissemination of innovations either as part of a scaling exercise or more informally (for example, through social networks).

While spillovers are desirable to magnify the impact of investments, they pose a challenge for impact evaluation by contaminating the counterfactual (Angelucci and Di Maro 2010; Winters et al. 2010). Spillovers can be especially important for a demand-driven and participatory program such as Africa RISING, as residents in program target villages can be exposed to SI innovations by attending field demonstration days. For example, in cases where non-beneficiaries in program villages benefit from significant spillovers but do not report being participants during follow-up, within-village impact estimates would be underestimated. On the other hand, out-of-village impact estimates can be biased in case of any systematic time varying, village-level differences correlated with the outcomes of interest. Finally, impact estimates based on the *placebo* comparison can be prone to both spillovers and omitted time- and location-varying confounding factors. Absent the latter effect, *placebo* comparison will capture potential spillover effect.

Given that participation in the program is voluntary and non-random, socio-demographic characteristics at baseline are not perfectly balanced between treatment and control group (as reported in Table 1). To address this unbalance between the two groups, our identification relies on a propensity score matching (PSM) and difference-in-differences (DiD) strategies, (see Wooldridge 2002 and Zeldow and Hatfield 2021 for general discussion).

PSM is used to estimate the causal impact of a program or policy when participation is non-random. This method allows the identification of a valid control group by matching each treated unit with a non-treated unit with similar characteristics. More specifically, PSM expresses the probability that a unit will enroll into a program based on observed characteristics—the propensity score-—which is then used to match treated and untreated units. This process balances differences in observable characteristics between the two groups and reduces bias, making it easier to compare outcomes between the two groups and draw more reliable conclusions about the impact of the treatment (Stuart et al. 2014).

In our analysis, we computed the propensity score based on the following characteristics at baseline: household size; age, gender, and educational level of the household head; household assets (agricultural and non-agricultural); size of the land the total number of person-days needed for agricultural production; and the historical monthly average and coefficient of variation of NDVI from 2000 to 2016 (Haile et al. 2016). More specifically, we estimated the following logistic regression:

$$\mathrm{P}(Y_h \neq 0 \mid X_{hj}) = \frac{exp(X_{hj}\beta_j)}{[1 + exp(X_{hj}\beta_j)]}$$

with Y_h being the dummy variable equal to 1 if the household is in the treatment group and X_{hj} being the covariates at the household and environmental level at baseline.

Figure 3. Distribution of propensity score before/after matching across the four comparisons

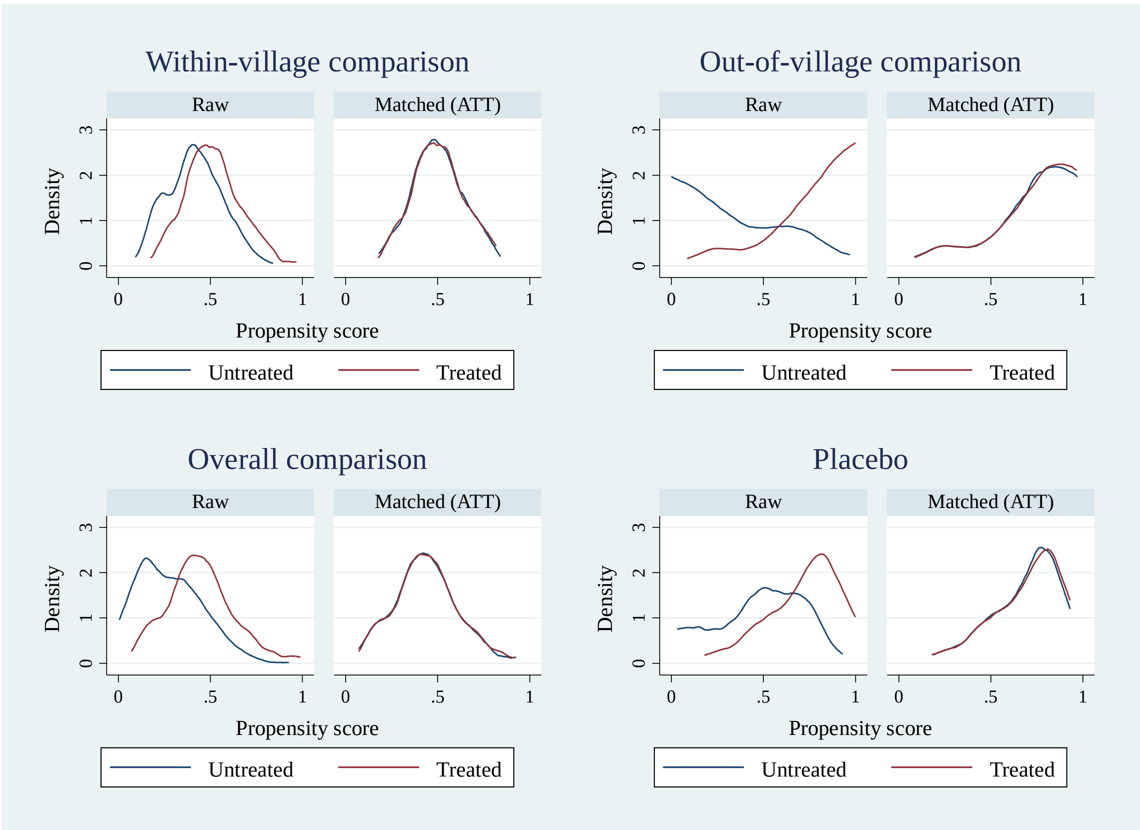


Figure 3 shows the distribution of the propensity score between treatment and control groups before and after the matching for all the pairwise comparisons conducted. After matching the distribution of the propensity score for the untreated group overlaps with that of the treated groups for all four comparisons, suggesting that the matching was successful in balancing the covariates between treatment and control groups.

Then, we include the estimated propensity score in the main DiD equation as a weight to obtain more balanced estimates (Stuart et al. 2014). The DiD strategy can be formalized as shown in Equation 2.

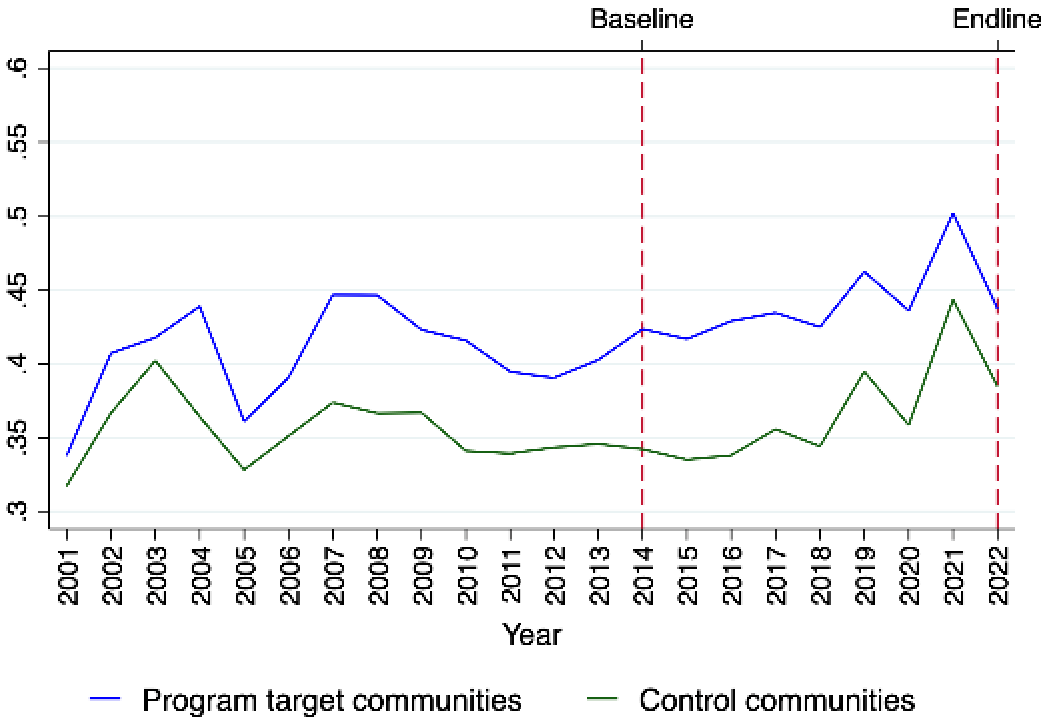
$$Y_{ht} = \alpha + \beta T_{ht} + \gamma P_{ht} + \delta(T_{ht} * P_{ht}) + \theta NDVI_{ht} + \varepsilon_{ht} \qquad 2$$

where *h* and *t* represent household and time, Y is an outcome indicator, T is an indicator that takes value one for program beneficiaries (treated group) and zero for non-beneficiaries (control group), P is an indicator that takes value one for follow-up and zero for baseline and captures aggregate factors affecting Y the same way between the two groups, $NDVI_{ht}$ expresses the NDVI average and coefficient or variation at baseline and follow-up included as control variables in the regression adjustment (RA) specification of the DiD, and ε is model error term assumed to be i.i.d.. An ordinary least squares (OLS) estimate of δ measures the average effect of treatment on the treated (ATT) on Y. Absent additional covariates, $\hat{\delta}$ is given by $(\bar{Y}_1^B - \bar{Y}_0^B) - (\bar{Y}_1^C - \bar{Y}_0^C)$, where superscript B and C represent the beneficiary and control groups, respectively; subscripts 1 and 0 represent post- and pre-treatment periods, respectively, and $\bar{Y}$ represents the sample average. For ease of interpretation, all dummy outcome indicators are multiplied by 100 so that $\hat{\delta}$ captures percentage changes in Y.

DiD relies on one key assumption: outcomes of the two groups would have evolved similarly in the absence of the treatment. This is known as the parallel trend assumption. This strategy produces unbiased estimates if the treatment is not systematically related to other confounding factors that affect Y. Unlike cross-section-based impact estimates, DiD estimates will be unbiased even when baseline covariates are unbalanced between the two groups as long as temporal trends in outcomes do not vary by treatment status (Zeldow and Hatfield 2021).

One approach to test the validity of the identifying assumption for DiD is to compare trends in outcome indicators over time. In our case, conducting such a test is not possible because only two data points are available for the outcome indicators and no time series data on the various other indicators are available. However, analysis of temporal trends in indicators such as NDVI can serve as an indirect test of the identifying assumption, given the reliance of the target population on rainfed agriculture. NDVI trends were generally comparable for treated and control villages over time, with cropping season NDVI being higher for target villages (Figure 4). These differences are most likely because both the treated and control villages are located in neighboring areas separated by a lake, with varying elevations and hence slightly different climates.

Figure 4. Average NDVI of the cropping season by community treatment status



To check for robustness, we conduct three additional analyses. First, we re-estimate a version of the model in Equation 1 controlling for NDVI (historical average as well as average and coefficient of variation for the cropping seasons for which agricultural production data were collected).[3] One strategy for dealing with bias in DiD estimates due to systematic time varying confounding factors such as NDVI is to control for their time varying effects on Y through RA. In a DiD with RA model, the OLS estimate of $\hat{\delta}$ no longer captures the double mean differences as shown for the simple DiD model but still measures the effect of program participation. Controlling for covariates will change $\hat{\delta}$ if one or more covariates are correlated with the

[3] We do not run a specification including socio-demographic characteristics, as we included these dimensions in the equation to estimate the propensity score.

interaction term between survey round and treatment status conditional on the main effects of survey round and treatment (Angrist and Krueger 1999).

Second, both the simple DiD and DiD with RA models are estimated using different counterfactuals as shown in Figure 2. By construction, $\hat{\delta}$ from the *overall* comparison will be an average of the impact estimate between the within-village and the out-of-village comparisons. Third, Equation 1 is estimated based on a *placebo* comparison where T equals one for non-beneficiaries in program villages and zero for non-beneficiaries in control villages. Given that both groups were randomly sampled and did not participate in the program, $\hat{\delta}$ should not be significant unless confounding factors are correlated with Y, there are spillovers, or both.

4. Results and discussion

In general, impacts were greater on the agriculture-related (productivity, environment) and economic domains than on the social and human domains. Consistently, Africa RISING was found to increase outcome indicators in all the five SI domains. Indeed, relative to program non-beneficiaries, Africa RISING beneficiaries were less likely to experience soil erosion, used more inputs (fertilizers, pesticides, and seeds) per hectare, obtained higher legume yields, were more likely to produce meat and dairy, reported higher net livestock income and higher share of livestock managed by women (solely or jointly), were less likely to be asset-poor, and experienced fewer months of food shortages.

Table 2 reports impact estimates on indicators under the environmental domain.[4] The *within* village estimation (columns 1 and 2) shows that the real value of fertilizers applied by treated households increased by 73 Tanzanian shilling (TZS) per hectare. The *out-of-village* comparison (columns 3 and 4) and the *overall* comparison (columns 5 and 6) both support these encouraging findings, with households in the out-of-village experiencing an increase of 119 TZS/ha and 100 TZS/ha, respectively. We also observe an increase in the value of pesticides used by 217 TZS/ha when considering the *out-of-village* comparison. The program

[4] In Tables 2 through 5, columns (1) and (2) report DiD impact estimates based on *within-village* comparison. Columns (3) and (4) report impact estimates based on *out-of-village* comparison. Columns (5) and (6) report impact estimates where all non-beneficiaries inside and outside program villages are used as control groups. Columns (7) and (8) report results from the *placebo* test. Results in columns (1), (3), (5) and (7) are from simple DiD, while those in columns (2), (4), (6), and (8) are from DiD with regression adjustment where we control for NDVI average and coefficient of variation between baseline and follow-up. Comments refer to parameters of the DiD with regression adjustment model.

also had a beneficial effect on the traditional value of actual seeds purchased (+311 TZS/ha) in the *out-of-village* comparison. Additionally, beneficiary households in all comparison groups were less likely to experience soil erosion by 11 to 20 percentage points.

Table 2. Impact on environmental domain

SI Practice	Within-village comparison (1)	(2)	Out-of-village comparison (3)	(4)	Overall comparison (5)	(6)	Placebo test (7)	(8)
HH used improved variety of maize (%)	-4.4	-5	-1.8	-4.3	-2.2	-3.6	-0.5	-4.1
HH used improved variety of sorghum (%)	-0.8	-0.8	-0.9	-0.9	-0.6	-0.6	-0.3	-0.3
HH used improved variety of pigeon pea (%)	4.6*	4.5*	2.5	2.1	4.2*	4*	-1.9	-2
HH used improved variety of groundnut (%)	-1.4	-1.4	0.7	0.8	-0.5	-0.5	0.7	0.8
HH used improved variety of pearl millet (%)	0	0	-0.3	-0.3	-0.1	-0.1	-0.7	-0.7
HH did not experience soil erosion	7.3**	7.8*	20.4***	20***	10.7***	11***	16.4**	17.5**
HH stored crops in sacks/bags (%)	5.1	5.1	0.4	1.6	3.1	3.1	-3	-3.3
HH used crop residue-based feed rations for animals (%)	-0.6	-0.4	10.4	9.9	2.2	2.1	6.9	5.8
Practices cereal-legume intercropping (%)	-5.5	-5.7	-7.3	-6.6	-5.6	-6.1	-0.7	-3.7
Intercropped cereals and pigeon pea at hh (%)	-6.7*	-7.1*	-7.7	-8.6	-7.6*	-8.4**	1.1	-0.6
Received agricultural advice (%)	5.4	6.2	1.6	2.9	4.3	5.1	-0.9	-0.9
Real value of fertilizers used ('000 TZS/ha)	80.7*	72.5*	138.6*	118.6*	110.2**	99.6**	58.6	54.6
Real value of pesticides used ('000 TZS/ha)	110.2	113.2	211***	216.9***	161.9	166.5	145.9*	142.3**
Real value of traditional seeds purchased ('000 TZS/ha)	165.9	163.3	306.8*	311.3*	235.5	232.7	205	185.6

Note: Columns 1 and 2 report DiD impact estimates based on within-village comparison. Columns 3 and 4 report impact estimates based on out-of-village comparison. Columns 5 and 6 report impact estimates where all non-beneficiaries inside and outside program villages are used as counterfactual. Columns 7 and 8 report results from the placebo test. Results in columns (1), (3), (5), and (7) are from simple DiD, while those in columns (2), (4), (6), and (8) are from DiD with regression adjustment where we control for NDVI average and coefficient of variation in the 12 months preceding the interview. 0.01 - ***; .05 - **; .1 - *

Table 3 reports the estimates under the production domain. Participation in Africa RISING increased yield by 0.3 tons/ha for beans, 0.43 tons/ha for pigeon peas, and 1.1 tons/ha for groundnuts in the *within-village* comparison (columns 1 and 2). Also, compared to non-beneficiary, beneficiary households experienced a decrease of 0.6 in the number of unique crops produced and were 13.1 percentage points more likely to produce dairy products. In the *out-of-village* comparison (columns 3 and 4), we find that beneficiary households are 15 and 10 percentage points more likely to produce dairy products and eggs, respectively. For this comparison, program participation also had a statistically significant impact on sorghum and groundnut yield, increasing by 2.5 ton/ha and 1.2 ton/ha, respectively. We also find that agricultural labor intensity grew by 27 person-days/ha. In the *overall* comparison (Table *3*columns 5 and 6), we document a positive impact of participation to Africa RISING on bean yield (+ 0.28 tons/ha), groundnut yield (+1.08 tons/ha), pigeon pea yield (+0.34 tons/ha), a decrease of 0.7 in the number of unique crops produced, an increase of 1.6 percentage points in the likelihood of producing meat, and an increase of 14 percentage points of producing dairy products.

Table 3. Impact on productivity domain

	Within-village comparison		Out-of-village comparison		Overall comparison		Placebo test	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Yield (ton/ha)								
Maize yield (ton/ha)	0.22	0.24	0.14	0.16	0.2	0.22	-0.12	-0.2
Bean yield (ton/ha)	0.27**	0.3**	0.36	0.41	0.25**	0.28**	0.2	0.22
Pigeon pea yield (ton/ha)	0.42**	0.43**	-0.06	-0.06	0.33*	0.34*	-0.36*	-0.38**
Sorghum yield (ton/ha)	1.43	1.25	1.92*	2.53***	1.87*	1.76	0.41	0.42
Groundnut yield (ton/ha)	1.16**	1.09**	1.22**	1.16**	1.15***	1.08***	-0.26	-0.18
Number of unique crops produced	-0.62**	-0.62**	-0.87**	-0.75*	-0.69***	-0.69***	-0.54	-0.57
Livestock diversity	0.15	0.17	-0.13	-0.13	0.09	0.1	-0.27*	-0.29*
HH produces meat (%)	1.48**	1.51*	1.08	1.13	1.51**	1.57*	-0.26	-0.22
HH produces dairy (%)	13.73***	13.11***	16.27***	15.03***	15.05***	14.26***	2.77	2.57
HH produces eggs (%)	-1.54	-1.53	10.68*	10.35*	1.89	1.7	11.67*	11.39**
HH produces honey (%)	-0.61	-0.48	-0.76	-0.46	-0.51	-0.34	-0.96	-0.66
Agricultural labor (person-days/ha)	9.02	7.86	26.98**	26.93***	16.21*	15.03	23.83*	22.35*
Labor profitability (TZS/person-day)	-0.83	-0.6	-2.99	-2.66	-1.52	-1.22	-3.72*	-3.75*

Note: Columns 1 and 2 report DiD impact estimates based on within-village comparison. Columns 3 and 4 report impact estimates based on out-of-village comparison. Columns 5 and 6 report impact estimates where all non-beneficiaries inside and outside program villages are used as counterfactual. Columns 7 and 8 report results from the placebo test. Results in columns (1), (3), (5), and (7) are from simple DiD, while those in columns (2), (4), (6), and (8) are from DiD with regression adjustment where we control for NDVI average and coefficient of variation in the 12 months preceding the interview. 0.01 - ***; .05 - **; .1 - *

Table 4 reports impact estimates for the economic domain. Program participation had generally positive effects on net livestock income, household earnings from meat sales, and household earnings from milk sales. However, we find virtually no impact on poverty indicators, except for the poverty headcount ratio based on the agricultural asset definition for which we observe an increase in the probability of being non-poor by 8.2 percentage points and 6 percentage points for the *out-of-village* and *overall* comparison, respectively. In the overall comparison, participation to Africa RISING increases net livestock income by $352 PPP, earnings from meat sales by $69 PPP, and earnings from milk sales by $623 PPP. These results are in line with the documented increase in production of dairy products.

Under the social and human domain (Table 5), the impact of Africa RISING reveals a complex picture across different comparisons. The *overall* comparison suggests a somewhat adverse effect of program participation on stunting prevalence (+16 percentage points). However, there is robust evidence that program participation enhanced food security, with an observable decrease in the months of food shortage in both the *out-of-village* (-1.7 months) and *overall* comparison (-0.8 months).

Table 4. Impact on economic domain

	Within-village comparison		Out-of-village comparison		Overall comparison		Placebo test	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Income/Earnings ($ PPP)								
Annual net household income	277.6	310.9	-600.7	-410.7	-4.6	53.5	-1102.7	-1019.2
Net crop income	-564	-518.2	-628.1	-513.5	-598.1	-540.3	-394.1	-318
Net livestock income ($ PPP)	448.5**	416.6**	282.6	275.5	383.4*	351.5**	-219	-228.9
HH earnings from meat sales ($ PPP)	66.6***	67.8***	66.9***	69.2***	66.8***	68.7***	-1	-0.9
HH earnings from milk sales ($ PPP)	642***	593.6***	698.1***	592.9***	685.3***	622.7***	87.9	78.5
HH earnings from egg sales ($ PPP)	-4.6	-4.1	4.9	4.9	-0.6	-0.4	8.1	7.6
Other income ($ PPP)	393**	412.5**	-255.2	-172.8	210.1	242.3	-489.5	-472.3
Poverty								
Per capita daily expenditure ($ PPP)	0.3	0.3	0.5*	0.5*	0.4*	0.4*	0	0
Non-poor (>$1.9 PPP) (%)	3.8	2.9	-11.8	-14.5*	-0.7	-2.2	-14.9*	-16.5**
Non-poor (agr. durable assets) (%)	4.6	5.8	5.7*	8.2**	4.5*	6*	0.2	0.4
Non-poor (non-agr. durable assets) (%)	0	-1.1	-2.2	-3.2	-0.2	-1.9	-3.2	-5.6
Diversified livelihood								
Households with diversified livelihoods (%)	8	7	2.9	0.3	6.7	5.2	-5.1	-6.8

Note: Columns 1 and 2 report DiD impact estimates based on within-village comparison. Columns 3 and 4 report impact estimates based on out-of-village comparison. Columns 5 and 6 report impact estimates where all non-beneficiaries inside and outside program villages are used as counterfactual. Columns 7 and 8 report results from the placebo test. Results in columns (1), (3), (5), and (7) are from simple DiD, while those in columns (2), (4), (6), and (8) are from DiD with regression adjustment where we control for NDVI average and coefficient of variation in the 12 months preceding the interview. 0.01 - ***; .05 - **; .1 - *

Table 5. Impact on human and social domains

	Within-village comparison		Out-of-village comparison		Overall comparison		Placebo test	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Human								
Household								
Household dietary diversity score (12 groups)	0.23	0.18	-0.24	-0.34	0.14	0.07	-0.63*	-0.7*
Incidence of food secure households (%)	-5.96	-5.92	3.14	3.39	-2.55	-2.56	5.94	6.33
Months of food shortage (last year)	-0.48	-0.51*	-1.61***	-1.68***	-0.77**	-0.79**	-1.21***	-1.14***
Child								
Height-for-age z-score (HAZ)	-0.32	-0.36*	0.19	0.09	-0.21	-0.25	0.48	0.46
Weight-for-height z-score (WHZ)	-0.25	-0.26	0.01	0.01	-0.2	-0.21	0.17	0.17
Weight-for-age z-score (WAZ)	-0.21*	-0.24*	-0.16	-0.19	-0.19*	-0.22*	0.17	0.17
Prevalence of wasting (%)	5.04	5.28	-1.25	-1.06	3.55	3.93	-5.79	-5.47
Prevalence of stunting (%)	19.39***	20.31***	-1.24	2.37	14.58***	15.89***	-19.74*	-18.89**
Prevalence of underweight (%)	6.52	6.78	6.44	6.85	6.93	7.09	-3.04	-3.16
Women								
Body Mass Index (BMI)	-0.33	-0.47	-0.72	-0.77	-0.59	-0.75	-0.38	-0.44
Prevalence of undernutrition (BMI<18.5)	5.32	6.04	4.13	4.77	5.29	6.24	-0.33	0.1
Panel B. Social								
Plots under female responsibility (%)	2.6	3.1	-2.5	0.1	-0.1	0.9	-3.9	-3.1
Livestock under female responsibility (%)	3.5	3.7	1.6	1.8	3*	3.3	-1.7	-2.1

Note: Columns 1 and 2 report DiD impact estimates based on within-village comparison. Columns 3 and 4 report impact estimates based on out-of-village comparison. Columns 5 and 6 report impact estimates where all non-beneficiaries inside and outside program villages are used as counterfactual. Columns 7 and 8 report results from the placebo test. Results in columns (1), (3), (5), and (7) are from simple DiD, while those in columns (2), (4), (6), and (8) are from DiD with regression adjustment where we control for NDVI average and coefficient of variation in the 12 months preceding the interview. 0.01 - ***; .05 - **; .1 - *

The radar graph (Figure 5) represents the DiD estimates from the *overall* comparison across a selection of relevant variables associated to the five domains of the SIAF framework, allowing us to compare the characteristics associated to beneficiaries and non-beneficiaries before (dashed green and red lines, respectively) and after (solid green and red lines, respectively) program participation, as well as to contrast the outcomes of interest between treatment and control groups based on standardized values of each variable.

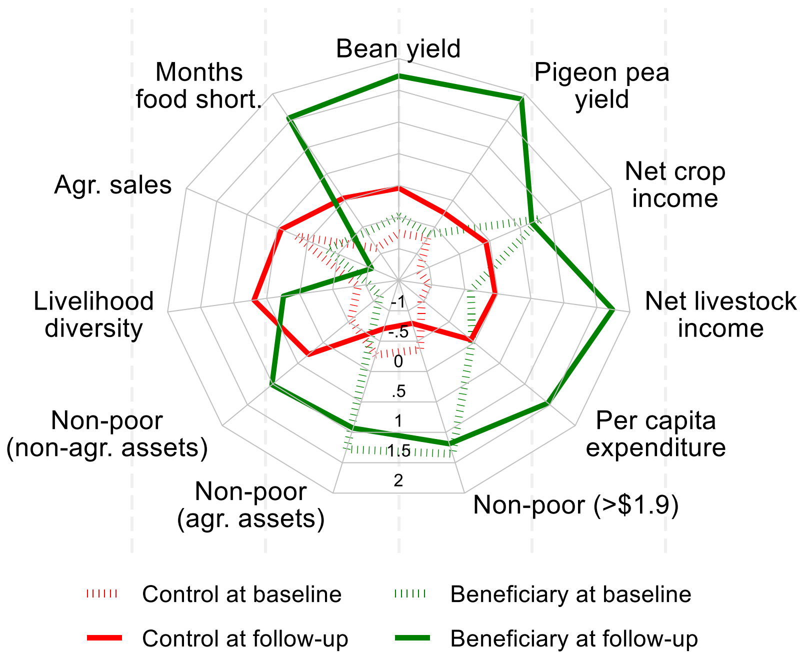
Bean yield, pigeon pea yield, net crop income, net livestock income, per capita expenditure, and the probability of being non-poor show the greatest variation between treated and control households, with outcomes among beneficiary households being significantly higher than among non-beneficiary households. Also, beneficiary households are significantly more likely to experience fewer months of food shortage. Households in the control group show higher estimates of impact on agricultural sales and livelihood diversity compared to treatment group households.

Beneficiary households show some significant differences in outcomes between baseline and follow-up, experiencing an increase in bean and pigeon pea yields, net livestock income, per capita expenditure, likelihood of being non-poor based on non-agricultural assets, and a decrease in months of food shortage. There are no substantial differences between baseline and follow-up in net crop income, likelihood of being non-poor based on consumption expenditure and agricultural assets, and in agricultural sales. Yet, a slight increase in livelihood diversity between baseline and follow-up suggests a possible broadening of income sources among the beneficiaries.

Even non-beneficiary households show significant differences in outcomes between baseline and follow-up, experiencing an increase in livelihood diversity, bean yield, pigeon pea yield, net crop income, net livestock income, and per capita expenditure. There are almost no differences instead in the likelihood of being non-poor based on the three indicators.

The graph illustrates pronounced differences among several variables for the Africa RISING beneficiaries. After the program, there is a greater distance between the two groups on agricultural yields, livestock income, and months of food shortage, confirming previous results and indicating the positive contribution of Africa RISING on these areas.

Figure 5. DiD estimates



Conclusion

Sustainable intensification (SI) of the smallholder sector has gained increased recognition as an effective strategy for improving food and nutrition security as well as ecosystem services in the face of projected population growth and climatic changes. SI focuses on improving resource-use efficiency while achieving higher production from the same resources and enhancing beneficial environmental and social services.

This study assessed the impact of an SI program in Tanzania implemented between 2014 and 2022. The main goal of the program was to provide smallholders pathways out of hunger and poverty. To that end, the program validated and promoted several SI innovations including cereal-legume intercropping, cereal-legume rotation, vegetable introductions, high quality protein maize, optimize fertilizer rate composts, inorganic fertilizer (*yara* or *minjingu*), improved postharvest technologies and soil conservation technologies. Given the diversity of interventions and expected effects on several dimensions of sustainability, we use the Sustainable Intensification Assessment Framework (SIAF) to guide the selection of indicators covering environmental, agricultural productivity, economic, human, and social domains. To account for systematic targeting of geographic areas, self-selection of participants, and contamination of the counterfactual group via spillovers we took advantage of the unique evaluation design using panel data collected in 2014 and 2022 and a propensity score matching (PSM) and differences-in-differences (DiD) strategies to estimate impacts based on alternative counterfactual groups. In addition, we conduct a *placebo* test to shed light on potential spillover effects to confirm the causality mechanism at play.

We document positive impact on soil erosion, value of fertilizers, groundnut, bean and pigeon-pea yields, meat and dairy production, net livestock income, and household earnings from meat and milk sales. However, we do not find improvements in access to agricultural information or women's and children's nutrition despite the program's particular focus on their nutritional status. Women's and children's undernutrition remains a persistent public health and development challenge in Tanzania, and integration of behavioral change communication into agricultural programs can help maximize nutritional gains of agriculture-focused programs.

Disentangling the contribution of different innovations to the overall impact of the program is necessary to inform targeted interventions. This objective would have required an adequate number of households to adopt the various SI innovations being offered as well as routine and frequent collection of monitoring data on the type and timing of innovations tested and applied. Given the diversity of program interventions rolled out over time, however, it was not possible to obtain accurate measures of impact of single, discrete interventions. Despite the limitations of our study design, which does not assess the impact of adoption of a specific (or package of) SI innovation(s) but rather estimates the overall impact of participation in Africa RISING program, we learned valuable lessons that could help improve future evaluations of SI programs.

Given the diversity of SI innovations promoted and the fact that a specific mix of SI innovations were tested as part of the agronomic trials conducted, our impact estimates based on program participation are likely prone to dilution bias, and thus provide a conservative, lower-bound estimate of the real effect. Moreover, the relatively small sample size did not allow us to examine potential heterogenous impacts by various dimensions of policy relevance, including intensity of program participation and location, the latter of which is particularly important given the diversity in agroecologies covered within the country.

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