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Climate smart agricultural practices and gender differentiated nutrition outcome: An empirical evidence from Ethiopia

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ABSTRACT

Since the beginning of the decade, climate resilient green economy strategies have been proposed in many African countries. One of the pillars of the strategies is the adoption and diffusion of various climate smart agricultural practices for improving crop and livestock production and farmer income while reducing greenhouse gas emissions. The effects of these innovations on household nutritional security, including gender-differentiated nutritional status, have hardly been analyzed. We examine the determinants of adoption of combinations of multiple climate smart agricultural innovations and their impact on different nutrition outcomes. We find that adoption of climate smart innovations increases dietary diversity and improves calorie and protein availability. These benefits increase with adoption of combinations of innovations, relative to adopting an innovation in isolation. Gender-disaggregation results suggest nutritional outcome differentials between male and female headed households due to both differences in household characteristics, including household resources, and differences in returns to resources. The study provides insight into the interaction between climate change adaptation and nutrition security among male and female headed households, with implication for the Sustainable Development Goals of ending hunger, achieving gender equality, and taking action on climate change.

1. Introduction

Food and nutritional insecurity is a defining feature of life for millions of Africans. Over the past decades, a number of agricultural interventions aimed at increasing food production have been implemented in Africa.[1] However, there is a potential trade-off between attempts to increase food production through modernization packages (which mainly combine mono-cropping of modern crop varieties with agro-chemicals) and the resulting risks of reduced household food diversity and dietary intake (Beuchelt & Badstue, 2013; Masset, Haddad, Cornelius, & Isaza-Castro, 2011; Wainaina, Tongruksawattana, & Qaim, 2017). Thus, the past interventions have had profound effects on human health in terms of micronutrient deficiencies known as the 'hidden hunger' – a trend towards a simplification of diets and accompanying nutritional degradation (Fanzo, Hunter, Borelli, & Mattei, 2013).

Climate change further imposes threats to food systems by impacting the quantity, quality and affordability of food. Thus, several studies recommend adaptation options as an essential vehicle to better the livelihoods of vulnerable segments of the population (Nelson et al., 2009; Campbell, Thornton, Zougmore, Asten, & Lipper, 2014; Makate, Wang, Makate, & Mango, 2016). Accordingly, the Ethiopian government has launched a vision to build a climate resilient green economy (CRGE) by 2025 (FDRE, 2011).[2] One of the pillars for the CRGE strategy is the adoption and diffusion of climate smart agricultural practices (CSAP) for improving agricultural production and income for higher food and nutrition security and strengthening farmers' resilience to climate change while reducing emissions (FDRE, 2011).[3] However, the degree to which the proposed CSAP have brought about the desired nutrition and food security effects is largely unknown.

CSAP (such as cropping system diversification, soil and water conservation, etc.) underpin ecosystem functioning and are salient for future progress in agricultural production through improved

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[1] The most significant of those, the Green Revolution approach, has focused on increasing calorie availability by boosting a handful of crop species – particularly rice, wheat and maize (Gómez et al., 2013).

[2] The CRGE vision is an economy that is middle-income and resilient to the negative impacts of climate change, with no net increase in greenhouse gas emissions relative to a baseline year.

[3] The CRGE strategy for the agricultural sector has identified about 41 promising climate change adaptation options to support both crop and livestock farming systems and build resilience against the risks of current climate variability and future climate change (FRDE 2011).

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yields and nutritional quality (Snapp, Blackie, Gilbert, Bezner-Kerr, & Kanyama-Phiri, 2010; Tilman, Cassman, Matson, Naylor, & Polasky, 2002). CSAP can improve household food security and nutrition status under climate variability by increasing agricultural income (through higher yields or lower production costs) or by freeing up labor for alternative economic activities (Wainaina et al., 2017). Production of diversified food, especially among subsistence farmers, is also an important pathway through which CSAP might improve nutrition (Jones etal., 2014; Beuchelt & Badstue, 2013). Cropping system diversification has the potential to cushion smallholders against food insecurity, contribute to dietary diversification, and increase farm income (Goshu, Kassa, & Ketema, 2012; Mandal & Bezbaruah, 2013; Njeru, 2013; Teklewold, Kassie, Bekele, & Köhlin, 2013; Makate et al., 2016; Wainaina et al., 2017).

Most previous studies on the adoption and welfare impacts of CSAP have focused on adoption of a single practice (e.g., Qaim & Kousre, 2013; Zeng et al., 2015; Makate et al., 2016). However, farmers are faced with a bundle of adaptation measures that may be adopted simultaneously, with complementary effects. Adopting a combination of practices can help farmers diversify production and improve productivity in the face of overlapping constraints such as biotic stressors, low soil fertility, and changes in climatic conditions (Dorfman, 1996; Khanna, 2001; Moyo & Veeman, 2004). Consequently, there is a growing and important body of literature on the adoption and impact of combination of practices on productivity and household welfare (Deressa, Hassan, Ringler, Alemu, & Yesuf, 2009; Teklewold et al., 2013; Makate, Makate, & Mango, 2017; Wainaina et al., 2017; Teklewold, Mekonnen, Kohlin, & Di Falco, 2017; Tambo & Mockshell, 2018). Some of these studies argue that a combination of practices may improve soil fertility, reduce soil degradation, adapt to local climatic change, and improve yields, income and food security (Wainaina et al., 2017; Teklewold et al., 2017; Tambo & Mockshell, 2018).

We contribute to this literature by analyzing the impact of adoption of a portfolio of CSAP on gender-disaggregated household food diversity and dietary intake in a smallholder farming system in Ethiopia. Gender inequalities in food and nutrition security have long been salient feature of rural households, and the concern for this under changing climate have long been the subject of empirical work (FAO, 2011; Beuchelt & Badstue, 2013). Many women in developing countries, especially those in female-headed households have less access to information, financial services and other resources needed to improve food and nutrition security. Empirical evidence has shown that female-headed households in Malawi had increased dietary diversity in the presence of high levels of crop and livestock diversity (Jones, Shrinivas, & Bezner-Kerr, 2014). Similar trends were observed between dietary diversity and vegetable production diversity in Tanzania and Kenya (Herforth, 2010). The challenge in gender inequalities in nutrition security is likely intensified due to incidence of climate variability. Hence, empirical evidence addressing gender differences in dietary diversity and nutritional consumption by disaggregating between male and female headed households; and the role CSAP has played to this gender difference in dietary intake contributes to critical policy debates.

This paper has two objectives. The first is to analyze the effect of climate-related and other socio-economic factors that condition farmers' decisions to adopt a combination of potential CSAP – crop diversification, soil and water conservation, and modern inputs (such as improved crop seeds and inorganic fertilizer). The second is to examine the heterogeneous impact of adopting various combinations of these practices on household nutrition among male and female headed households. An endogenous switching treatment effects approach is used to deal with unobserved heterogeneity and possible endogeneity bias (Bourguignon, Fournier, & Gurgand, 2007). The empirical assessment uses a recent panel data set that combines household characteristics with geo-referenced data on historical temperature and rainfall as well as various farm characteristics in the Nile Basin of Ethiopia. For Ethiopia and beyond, this understanding can help the design of policies to empower women, enhance adaptation decisions, and improve household nutrition.

The rest of the paper is organized as follows. The next section describes the study areas and sampling. Section 3 presents data descriptions. This is followed in Section 4 by presentation of the econometric framework, estimation of average treatment effects, and the empirical specifications of the model. In Section 5, we discuss estimation results. The final section concludes.

2. Study areas and sampling

Data used in this study are from a comprehensive panel of farm household survey data collected in the 2016 and 2017 cropping seasons covering five regional states of the Ethiopian part of the Blue Nile Basin: Amhara, Oromia, Tigray, Benshangul-Gumuz and Southern Nations, Nationalities, and Peoples (SNNP). The basin covers about two-thirds of the country's land mass and contributes nearly 40% of its agricultural products and 45% of its surface water (Erkossa, Haileslassie, & MacAliste, 2014). The areas selected represent different agro-ecological settings and are characterized by highly rugged topography with altitudes ranging from 800 to over 3000 m above sea level. The farming system of the basin can be broadly categorized as a mixed crop-livestock farming system, where over 90% of the cultivated area is covered by a cereal based farming system (Erkossa et al., 2014).

The sampling frame considered the traditional typology of agro-ecological zones in the country (i.e., *Dega* (cool, humid, highlands), *Weina-Dega* (temperate, cool sub-humid, highlands), *Kolla* (warm, semi-arid lowlands), and *Bereha* (hot and hyper-arid)). The sample was chosen through a multistage proportionate random sampling process. The procedure was employed to select villages from each district, and households from each village. The sampling frame selected *woredas*[4] in such a way that each class in the sample matched the proportions for each class in the entire Nile Basin. First, twenty woredas from the five regional states were selected (i.e., three from each of Tigray and Benshangul-Gumuz, six from Amhara, seven from Oromia, and one from SNNP). This resulted in a random selection of fifty farmers from each woreda. After cleaning inconsistent responses, our unbalanced sample is composed of a total of 917 farm households in 2016, while the follow-up survey in 2017 covers 904 households[5].

3. Household survey and data descriptions

3.1. Farm household survey

In both 2016 and 2017, a structured questionnaire was prepared, and the sampled respondents were interviewed using trained and experienced enumerators knowledgeable of the local language. The survey cover various modules: consumption modules, technology modules, production modules; and access to services (e.g., distance to extension and market services), production constraints modules, asset ownership, and climate change module. Accordingly, households were asked to provide a detailed description of their household, farm, and village characteristics, including access to input and output markets, household composition, edu-

[4] An administrative division equivalent to a district.

[5] The attrition (about 1.4%) is relatively small given the sample size and these are true attrition – either the household left the village or the respondent passed away.

cation, asset ownership including livestock ownership, various sources of income, participation in credit and off-farm activities, membership in formal and informal organizations, current shocks/stresses experienced in crop production, participation and confidence in extension services, crop production, land tenure, perceptions of climate change, and climate change adaptation practices. Food consumption data covering a 12 month period were elicited at the household level, consisting 40 food items. Quantities consumed include food from own production, market purchases, in-kind food transfers, and out-of-home meals and snacks. A wide range of farm-specific attributes such as soil fertility, depth, slope, farm size in hectares, and walking distance of the plot from the household dwelling were also collected. The survey also recorded geo-referenced household level latitude and longitude coordinates using handheld Global Positioning System (GPS) devices, which allow for the linking of household-level data to historical temperature and precipitation data.

3.2. Data descriptions

3.2.1. Outcome variables

Two sets of household nutrition indicators are employed in this study: diet diversity and per adult equivalent nutrient intake (such as calories and protein). We construct the household dietary diversity index using the Simpson Index (SI) of food diversity (Nguyen & Winters, 2011; Jones et al., 2014).[6] This measure reflects household access to a variety of foods, and is also a proxy for nutritional adequacy of individual diets (Ruel, 2003). Dietary diversity is a vital element of diet quality and the consumption of a variety of foods across and within food groups and across different varieties of specific foods more or less guarantees adequate intake of essential nutrients and important non-nutrient factors. Giving emphasis to the relative importance of each food group, diversity is measured not only by the number of food groups but also by their distribution, so that maximum diversity occurs when consumption shares are equally distributed among food groups. Mathematically, SI is defined as a function of household's consumption share of each food item:

$$SI = 1 - \sum_{i=1}^{n} w_i^2$$

where w_i is the calorie share of the food item in the total amount of calories consumed.

The SI ranges from zero to one; the higher the index, the more diversified the diet. Total calorie consumption is calculated by summing consumption levels on food items in the 2016 and 2017 years. The food items are grouped into the following categories: (i) cereals, (ii) pulses, (iii) oil crops, (iv) vegetables, (v) fruits, (vi) meat/egg, (vii) fish, (viii) dairy products, and (ix) beverages (FAO, 2011).

In addition to dietary diversity, we also compute calorie and protein consumption per adult equivalent per day from the survey data as measures of dietary intake. The quantity of consumed food items in 2016 and 2017 is converted into calorie and protein using locally relevant food composition tables from the Ethiopian Health and Nutrition Institute.

Sample statistics of the outcome (per adult equivalent consumption of calorie and protein, and degree of dietary diversity measured by Simpson Index) variables across the 2016 and 2017 years are presented in Table 1. The average per capita calorie consumption is about 2700 kcal for both years. This is higher than the average daily per capita calorie requirement needed to maintain the health of the population (2100 kcal), and also higher than

[6] This is a metric that accounts for the richness and evenness of components into a single measure (Jones et al., 2014).

Table 1
Household dietary intake and food diversity across years.

	year		
	2016	2017	Total
Calorie intake per adult equivalent, Kcal per day	2496.19_a	2895.85_b	2694.95
	(871.80)	(837.75)	(877.72)
Protein intake per adult equivalent, gm per day	42.72_a	66.50_b	54.45
	(33.28)	(19.57)	(53.14)
Iron intake per adult equivalent, mg per day	18.75_a	26.86_b	22.78
	(16.12)	(21.56)	(19.44)
Simpson index* (based on calorie share)	0.719_a	0.697_b	0.709
	(0.13)	(0.15)	(0.14)
Number of food groups	6.16 (0.90)	5.24 (1.40)	5.70 (1.26)

Note: Values in the same row and sub table not sharing the same subscript are significantly different at $p < 0.05$ in the two-sided test of equality for column means. Cells with no subscript are not included in the test. Tests assume equal variances.
* Simpson Index: $SI = 1 - \sum_{i=1}^{n} w_i^2$, where w_i is consumption share.

the national average calorie consumption – 1950 kcal (FAO, 2010). However, in about 25 percent of the sample, farm households consume fewer calories than this daily physiological requirement.

The average dietary protein consumption per day per person is about 55 g. This is almost equal to the national average dietary protein consumption (57 gm per person per day). The average Simpson index value is about 0.70. The large number of these index values shows that households exhibit a high level of diversity. Dietary diversity is higher in 2017 than in 2016. All differences between the two years are statistically significant at the 5% level.

We also noted a change in consumption of number of food groups between 2016 and 2017 years (Table 2). While about 95% of households consumed more than four food groups in 2016, about 75% of households consumed more than four food groups in 2017. Moreover, about half of the study farmers in 2016 consumed more than seven food groups in 2016, but only about 20% of the households consumed more than seven food groups in 2017. Interestingly, we also observed higher persistence in consumption of a lower number of food groups than consumption of a higher number of food groups. For instance, about 5% of study farm households consumed lower than four food groups in 2016. Of these households, about 36% still consumed lower than four food groups in 2017. About 42% of the study households consumed more than seven food groups in 2016 but only about 24% of these households continue to consume more than seven food groups in 2017.

3.3. Choice of CSAP variables

We follow Wainaina et al. (2017) on the choice of practices to select a mix of modern external inputs and natural resource management practices. We consider a bundle of CSAP as a component the following three practices: crop diversifications (D), soil and water conservation (S) and modern external inputs (improved crop seeds and fertilizer) (I). The first practice, crop diversification, is measured using a crop diversification index based on the total number of crops cultivated on the household's farm. Crop diversification is a strategy that maximizes the use of land, water and other resources and avoids risk and uncertainty due to climatic and biological vagaries. As in Makate et al. (2016), we create a binary variable from this crop diversification index. This is an agricultural production systems that departs from a simple cereal based farming system to an ecologically diversified cropping system that contributes to avoiding poor diet diversity, micronutrient deficiencies and the resulting malnutrition (Frison, Smith, Johns, Cherfas, & Eyzaguirre, 2006; Negin, Remans, Karuti, & Fanzo, 2009; Makate et al., 2016). Higher production diversity may be associated with forgone income from specialization; hence, adoption of crop diver-

Table 2
Transition matrix for food diversity between 2016 and 2017 years.

Food diversification in 2017 year	Food diversification in 2016 year				Total
	Less than 4	5	6	More than 7	
Less than 4	7.1 (36.4)	21.0 (36.2)	40.6 (25.9)	31.3 (18.5)	24.8
5	5.5 (31.8)	15.4 (30.0)	39.4 (28.5)	39.8 (26.7)	28.1
6	3.6 (20.5)	10.4 (20.0)	38.6 (27.4)	47.4 (31.1)	27.5
More than 7	2.8 (11.4)	10.2 (13.9)	36.2 (18.2)	50.9 (23.8)	19.6
Total	4.9	14.4	38.8	41.9	N = 904

Numbers in parenthesis are %ge of households who change consumption of different food groups in 2017 with in number of food groups consumed in 2016 year. Pearson $\chi^2(9) = 28.7860$ P = 0.001.

sification could lead to income loss, potentially also entailing lower diet diversity and quality. However, farmers' engagement in production and marketing of highly productive staple food items might improve household income and facilitate exchange of goods, with an ultimate effect of diversifying and smoothing consumption relative to what they can produce on the farm (Ruel, 2003; FAO, 2012; Darrouzet-Nardi & Masters, 2015).

The second practice is soil and water conservation practices. This is a method for improving soil moisture by storing and enhancing infiltration and reducing runoff and evaporation. Soil and water management practices (such as terracing, bunds) that change slope profile can reduce runoff speed – especially in erosion-prone highlands – thus reducing soil erosion (FAO, 2014). The practice is key to ensuring that agricultural production can withstand the stresses caused by climate change and is one of the best bet strategies for adapting agricultural production to climate change and variability (Ngigi, Savenije, Thome, Rockstro, & de Vriesd, 2005).

The third practice is modern inputs. Food security in an era of climate change may be possible if farmers transform agricultural systems via the use of modern inputs such as improved crop seed and fertilizer (Bryan, Ringler, Okoba, Koo, Herrero, & Silvestri, 2011). Appropriate use of fertilizer and modern seeds is required both to enhance crop productivity and to produce sufficient crop residues to ensure soil cover under smallholder conditions (Vanlauwe et al., 2013). As CSAP, the introduction of improved crop varieties and judicious use of fertilizer are primarily intended to increase yields, thus addressing food security and income needs (Bellon & Taylor, 1993). Adoption of these practices can improve household food diversity and dietary intake if farmers have access to agricultural markets; for instance, growing higher yielding varieties could lead to additional crop sales (Smale, Moursi, & Birol, 2015). However, Kumar (1994) studies the relationship between adoption of hybrid seed use and dietary diversity among smallholder maize farmers and finds that, while staple food consumption was greater in areas with higher rates of hybrid maize adoption, dietary diversity may have declined due to greater reliance by farmers on their own production and fewer purchased food types.

Table 3 presents the combinations of these practices. The farmer could choose from eight combinations of the three practices. For example, adoption of diversification (D), soil and water conservation (S), and modern inputs (I) is denoted as $D_1S_1I_1$; adoption of none of the practices is $D_0S_0I_0$; and so on. However, in our dataset we didn't observe $D_0S_0I_0$. We notice substantial differences in adoption of different combinations of practices. About 44% of the households adopted a combination of all three practices ($D_1S_1I_1$). While 28%–38% of farmers adopted a combination of two CSAPs, only 14% to 16% of farmers used a single CSAP in isolation. Thus, most farmers adopted a combination of CSAP. Simultaneous adoption of the three practices is slightly reduced from 47% in 2016 to 41% in 2017. Adoption of a combination of the three practices is significantly higher in male-headed households (47%) compared with female-headed households (25%).

3.4. Control variables

In our econometric analysis, we explore a rich set of literature on technology adoption to select a comprehensive set of drivers that are known to affect farmers' technology adoption decisions (Bandiera & Rasul, 2006; Hassan & Nhemachena, 2008; Deressa et al., 2009; Deressa, Hassan, & Ringler, 2011; Wollni, Lee, & Janice, 2010; Kassie, Teklewold, Jaleta, Marenya, & Erenstein, 2015; Di Falco, Veronesi, & Yesuf, 2011; Di Falco and Veronesi, 2013; Beuchelt & Badstue, 2013; Teklewold et al., 2017; Asfaw, Di Battista, & Lipper, 2016; Makate et al., 2016; Makate et al., 2017; Wainaina et al., 2017; Tambo & Mockshell, 2018). Following this literature, in Table 4 we present the control variables used in

Table 3
Adoption rates of combinations of climate smart agricultural practices (CSAP) by year and gender status.

Choice (k)	Package[Ψ]	Components of package of CSAPs			Over all	Year		Gender	
		Crop Diversification (D)	Soil and water conservation (S)	Modern inputs (I)		2016	2017	MHHs	FHHs
1	$D_0S_0I_0$	–	–	–	–	–	–	–	–
2	$D_1S_0I_0$	√	–	–	0.152	0.206	0.096	0.170	0.055
3	$D_0S_1I_0$	–	√	–	0.136	0.162	0.108	0.123	0.204
4	$D_0S_0I_1$	–	–	√	0.156	0.181	0.131	0.148	0.197
5	$D_1S_1I_0$	√	√	–	0.283	0.214	0.353	0.270	0.353
6	$D_1S_0I_1$	√	–	√	0.383	0.340	0.426	0.408	0.249
7	$D_0S_1I_1$	–	√	√	0.323	0.349	0.298	0.307	0.412
8	$D_1S_1I_1$	√	√	√	0.437	0.466	0.408	0.473	0.249

[Ψ] Each element in the CSAP combinations consist of a binary variable for a practice/Crop diversification (D), Soil and water conservation (S) and Modern inputs (I)/, where the subscript refers 1 = if adopted and 0 = otherwise.

Table 4
Definitions and summary statistics of the variables used in the analysis.

Variable	Descriptions	Combinations of CSAP							All
		$D_1S_0I_0$	$D_0S_1I_0$	$D_0S_0I_1$	$D_1S_1I_0$	$D_1S_0I_1$	$D_0S_1I_1$	$D_1S_1I_1$	
Household and farm characteristics									
Gender	1 = if gender of household head is male	0.94	0.76	0.80	0.80	0.90	0.80	0.91	0.84
Age	Age of household head (years)	53.23	52.22	53.59	52.55	53.57	52.85	53.90	53.46
Education	Total family size (number)	0.32	0.37	0.35	0.36	0.33	0.36	0.32	0.34
HHsize	Education level of household head (years)	8.01	6.67	6.81	6.61	7.24	6.85	7.39	7.01
Plotdist	Average plot distance from home, min	13.38	10.93	12.41	15.75	15.53	14.40	15.67	14.83
Plotsize	Average plot size, ha	0.25	0.33	0.30	0.45	0.27	0.35	0.26	0.33
Parcel	Number of parcels	7.98	3.40	4.77	3.76	7.54	3.77	7.54	5.48
Tenure	Share of own lands	0.74	0.65	0.66	0.79	0.80	0.82	0.79	0.77
Higferland	Share of high fertile lands	0.31	0.26	0.29	0.29	0.32	0.30	0.35	0.31
Flatland	Share of flat slope lands	0.56	0.46	0.49	0.60	0.61	0.60	0.63	0.59
Deepland	Share of deep soil lands	0.35	0.27	0.29	0.29	0.36	0.33	0.39	0.34
Resource constraints									
Farmsize	Farm size, Ha	1.99	1.30	1.48	1.65	2.00	1.36	1.91	1.66
Tlu	Livestock size (in tropical livestock unit)	5.67	3.80	4.50	4.03	5.71	4.21	5.63	4.76
Credtcons	1 = if credit constraint	0.47	0.49	0.47	0.51	0.52	0.56	0.53	0.53
Asset	Asset value ('000 Birr)	34.99	109.78	110.15	36.14	34.16	37.62	37.08	48.80
Offarm	1 = if participated in off-farm activities	0.29	0.34	0.33	0.32	0.31	0.36	0.30	0.32
Market access and extension									
Distoutmkt	Distance to output market, km	6.66	6.81	6.70	7.21	6.95	7.54	6.78	7.08
Distinpmkt	Distance to input market, km	5.42	4.84	4.70	5.28	5.28	5.32	4.99	5.17
Extcontin	Index for extension contact	0.60	0.45	0.48	0.46	0.57	0.56	0.62	0.54
Extconfind	Index for confidence on extension agent	0.88	0.92	0.92	0.93	0.90	0.91	0.89	0.91
Social capital and social protection									
Remitance	1 = if received remittances	0.08	0.13	0.14	0.13	0.10	0.14	0.10	0.11
Suport	1 = if received farm support	0.08	0.08	0.07	0.05	0.07	0.06	0.08	0.07
Aid	1 = if received aid	0.05	0.15	0.12	0.11	0.07	0.16	0.09	0.10
Kinship	Number of relatives living outside the village	32.78	25.36	27.72	24.79	36.33	29.61	40.72	32.61
Member	Number of groups the household is a member	9.79	8.81	9.02	6.67	7.66	8.80	8.74	8.16
Climate and shocks									
Rainindex	Rainfall index (1 = best)	0.61	0.52	0.53	0.60	0.60	0.59	0.60	0.59
Plotindex	Plot disturbance index (1 = worst)	0.10	0.09	0.09	0.09	0.11	0.11	0.11	0.10
Relygovt	1 = if believe in government support in case of crop failure	0.61	0.55	0.57	0.49	0.60	0.59	0.62	0.58
AV_Rain	Monthly rainfall in mm (1983–2015)	147.68	157.41	154.72	156.02	143.88	147.13	139.65	148.53
CV_Rain	Coefficient of variation of rainfall	0.85	0.78	0.80	0.80	0.86	0.85	0.89	0.84
Temp	Daily temperature in °C (1983–2015)	17.76	18.50	18.30	18.78	17.74	18.21	17.71	18.15
N	Number of observation								

the empirical analysis, their description and summary statistics for the full sample and disaggregated by gender and the sub-groups of the combination of practices. Explanatory factors include natural capital (soil depth, slope, fertility), social capital and network (membership in community-based institutions, kinship network), shocks (self-reported rainfall shocks and plot-level crop production disturbances), physical capital (farm size/livestock), access to services and constraints (distance to main market, access to credit, extension service and climate information), human capital (family size, household head education, gender and age), plot distance to dwelling, geographic location and climate variables (temperature, intensity and variability of rainfall). Below we focus on describing these variables in relation to climate change adaptation literature.

Using geo-referenced points recorded through GPS devices, we develop a set of climate variables to show the short- and long-term variation of precipitation and temperature shocks that are expected to affect the choice of combination of practices. We derived long-term mean rainfall and temperature and coefficients of variation of rainfall variables and included them in the technology choice model. The combined rain gauge and satellite based monthly climate data (1983–2015) was obtained from the National Meteorology Agency (NMA). In Ethiopia, available weather stations are unevenly distributed and suffer from gaps in the time series. These impose severe limitations to the availability of climate information and services for different applications. Cleaning climate observations and combining station measurements with the complete spatial coverage of satellite estimates could help to fill these gaps and improve data availability over locations with few or no meteorological observations (Dinku, Asefa, Hailemariam, & Connor, 2011). A collaborative effort has been made by the International Research Institute for Climate and Society at Columbia University with the NMA of Ethiopia and the University of Reading, UK, through combining station measurements with the complete spatial coverage of satellite estimates (Dinku et al., 2011). 30-year time series of rainfall and temperature data have been produced at 10 daily timescales for every 10-km grid over the country. Temperature data were obtained from the Climate Research Unit (Harris, Jones, Osborn, & Lister, 2014), while the rainfall data were obtained from Africa Rainfall Climatology version 2 (ARC-2) dataset (Novella & Thiaw, 2013). These datasets consist of daily, gridded $0.1° \times 0.1°$ estimates with a spatial domain of 40°S to 40°N in latitude, and 20°W to 55°E in longitude encompassing the African continent.

Fig. 1 illustrates the relationships between diet diversification and climate variables, including rainfall amount as well as coefficient of variation in rainfall during the growing season. As can be seen, there are differences in the distributions of diet diversification with changing rainfall amount and rainfall variability. We observed an inverted U-shaped relationship between rainfall intensity and diet diversity, in which farmers are less likely to consume diversified diets when faced with either a high or low amount of rainfall. We also noted an inverse relationship between rainfall variability and diet diversity, in which farmers face low diversity of foods in areas with high rainfall variability

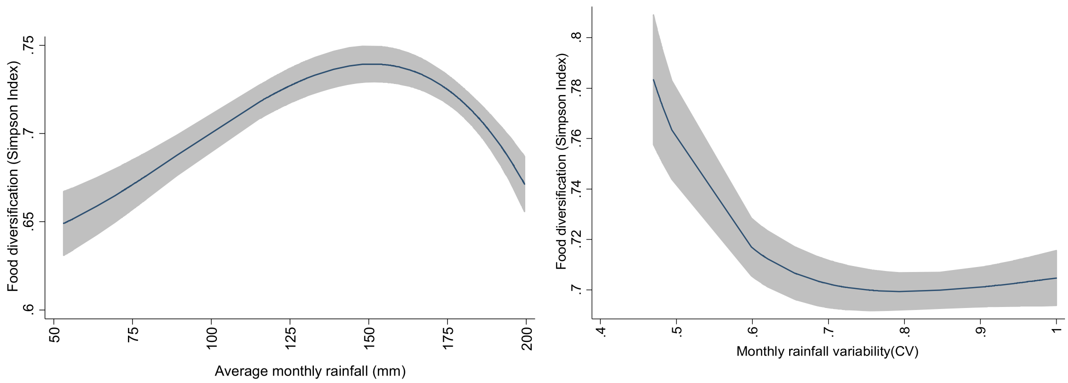

Fig. 1. Climate and dietary diversity.

Cognizant that meteorological stations are sparse and hence reliable rainfall data at micro-level is scarce in developing countries like Ethiopia (Dinku et al., 2011), we also considered self-reported rainfall shocks. We followed Quisumbing (2003) to construct the subjective rainfall index based on respondents' rainfall satisfaction in terms of timeliness, amount, and distribution. The individual rainfall index was constructed to measure the farm-specific experience related to rainfall in the preceding seasons, based on such questions as whether rainfall came on time at the start of the growing season, whether there was enough rain at the beginning and during the growing season, whether the rain stopped on time and whether there was rain at harvest time. Responses to each of these questions (either yes or no) were coded as favorable or unfavorable rainfall outcomes. By averaging over the number of questions asked (five questions), we created an index that provides a value close to one for the best outcome and zero for the worst outcome.

We also created a farm-level shocks index capturing the most common shocks affecting crop production: pest and disease pressure; drought; flood; hailstorm; and erratic rainfall. Based on agronomy and climate literature, these shocks are hypothesized to affect the choice of practices and production risk. Farmers' responses to the presence of each of these shocks (either yes or no) were coded as unfavorable or favorable disturbance outcomes. By averaging over the number of shocks about which we asked (five questions), we created an index that provides a value close to one for the highest level of shocks.

We control for the possible role of farmers' perceptions of relying on government support when events beyond the farmer's control occur and cause output or income to drop. Whether in the form of social safety nets or formal insurance, farm insurance can build confidence among farmers so that they invest in adaptive practices despite uncertainty, and can help farm households maintain productive capacity by reducing the need to liquidate assets that might arise in case of shocks (Barrett, 2005). A better understanding of this issue can be obtained by examining the effects of farmers' perceptions about government assistance on their decisions to adopt different types of climate-smart practices.

To account for the effect of farm features on choice of practices, we control several plot-specific attributes, including soil fertility, soil depth, plot slope, spatial distance of the plot from farmer's home (in minutes walking) and tenure security. On average, 75% of land owners operate on about four parcels, each about 0.25 ha, and these plots are often not spatially adjacent (as far as 15 min walking time from the farmer's residence). The variable distance to plot is an important determinant of adaptation practices through its effect on increasing transaction costs on the farthest plot, particularly costs for transporting bulky materials/inputs associated with adaptation practices.

With respect to socio-demographic characteristics, we control for education level, family size, and age and gender of the household head. On average, male-headed households (MHHs) and female-headed households (FHHs) make up 84% and 16% of all the households in the sample, respectively. Out of the total number of female-headed households involved in this study, 78% are *de jure* female headed households, where the household is headed by widows and unmarried, separated or divorced women.

As a measure of household resource constraints, we considered household wealth indicators such as farm size, household total expenditure, credit access and livestock size (measured in tropical livestock units, TLU). Household wealth is expected to have a positive association with implementation of adaptation practices due to its effect of relaxing liquidity constraints.

We also study the ways in which individuals relate to wider social networks and the effects of these networks on adaptation decisions. In this study, we distinguished two forms of social capital and network variables: the number of groups (institutions) in which the household is a member; and kinship network, defined as the number of close relatives living outside the village. In the absence of formal channels, social networks are considered a means to facilitate the exchange of information, enable farmers to access inputs on schedule, and overcome credit constraints, all of which can build resilience and reduce vulnerability to climate change (Fafchamps & Minten, 2002; Barrett, 2005). With regard to system-level determinants, we control for access to extension service by considering whether the farmer has had contact with the extension agent. However, access to extension service *per se* may not impact technology adoption, because the quality of information provided to farmers depends on the skill of extension workers. We thus control for farmers' confidence regarding the skill of extension workers in providing the required services.

3.5. Econometric estimation strategy

As mentioned above, the simultaneous nature of the adoption of the three components of CSAP (modern input, crop diversification, and soil and water conservation) leads to eight possible combinations or packages of practices. At household level, farmers may adopt different combination of practices in a given cropping season. From an econometric view point, the choice of various combinations of CSAPs and the implications of adopting the various combinations of CSAP on household's nutrition outcome are analyzed by applying a two-stage estimation procedure (Bourguignon et al., 2007).

In the first stage, a multivariate probit model is used to analyze the determinants of the adoption decisions. Because all farmers have a choice of adopting one or more than one of the combinations of practices, the multivariate model is modified to take into account this simultaneous nature of the adoption decision. This approach recognizes that the same unobserved characteristics of farmers could influence the adoption of the various combinations of practices. Therefore, the multivariate model is more efficient than the univariate methods of analyzing adoption of each combination independently.

In the second stage of the estimation, the impacts of adopting various combinations of practices on nutrition outcome are analyzed. In examining the determinants of household nutrition for each sub-group, this study acknowledges that differences between those farm households that did and did not adopt CSAP may be due to selection bias. That is, adoption of these combinations of practices may not be random; instead, farmers may make adoption decisions based on information that is not available to the econometrician. Then, this information would affect both adoption and outcome equations, possibly generating inconsistent parameter estimates associated with unobserved heterogeneity when using standard econometric approaches (e.g., ordinary least-squares). Besides the non-randomness of selection in CSAP adoption, another important econometric issue is heterogeneity of the impacts of the combination of CSAP. The standard econometric method of assessing the effects of technology is to use a dummy indicator variable for the different combinations of CSAP over a pooled sample of observation. This assumes adoption could have only an intercept shift effect and common slope coefficients for the different groups of adopters. However, the set of factors and characteristics that influence the outcome could vary depending on the adoption status (Di Falco et al., 2011; Di Falco and Veronesi, 2013; Teklewold et al., 2013; Kassie et al., 2015).

In the panel data context, the presence of unobserved heterogeneity in the outcome equations, if correlated with observed explanatory variables, can also lead to inconsistent estimates. The endogenous switching regression (which involves a two-step estimation approach) combined with panel data can help tackle these problems. Our two-step approach first estimates the multivariate probit model using Mundlak (1978) approach to obtain estimates of the time-variant individual heterogeneity (inverse Mills ratios) that cause selection bias[7]. The outcome equations are estimated by fixed effects, including inverse Mills ratios estimates from the first stage as additional explanatory variables. The use of Mundlak in the first step and a fixed effects approach in the second step captures the time-invariant individual heterogeneity underlying endogeneity, and the inverse Mills ratios take care of time-varying heterogeneity. The Mundlak approach allows for inclusion of the means of the time-varying explanatory variables in the adoption equations as additional explanatory variables in the multivariate probit model, as a proxy for removing the time-invariant individual effects. Modeling this dependence allows for unbiased estimation of the parameters, regardless of whether the explanatory variables and the individual effects are independent in the equations (Ebbes, Wedel, Steerneman, & Boeckenholt, 2005).

The observed outcome of a combination of CSAP adoption can be modeled following random utility formulation. Consider the i^{th} farm household ($i = 1, \ldots, N$) that is facing a decision on whether or not to adopt the available combination CSAP. Let U_k represent the benefit of adopting the k^{th} combination of CSAP, where k denotes the different combinations of CSAP as shown in Table 3; and let U_j represent the benefits to the farmer from any combinations of CSAP other than the k^{th} CSAP. The farmer decides to adopt the k^{th} CSAP if its utility, U_k, outweighs the utility that could be obtained from any other alternative, U_j; such that $U_k > \max(U_j)$, where k = 1, …, 7 and k ≠ j. The utility that the farmer derives from the adoption of the k^{th} CSAP is a latent variable determined by observed household, farm, and climate variables and expressed as follows:

$$U^*_{itk} = X'_{it}\beta_k + \alpha + \varepsilon_{itk} \; (k = 1, 2, \ldots, 7) \tag{1}$$

where X'_{it} is a matrix of household and farm characteristic and climate variables, β_k are parameters to be estimated, α is unobserved time-constant heterogeneity, and ε_{itk} is the disturbance term.

Using the indicator function, the unobserved preferences in Eq. (1) translate into the observed binary outcome equation for each choice as follows:

$$I_{itk} = \begin{cases} 1 & \text{if } U^*_{itk} > 0 \\ 0 & \text{otherwise} \end{cases} \quad (k = 1, 2, \ldots, 7) \tag{2}$$

In the multivariate model, where the adoption of several combinations of CSAPs is possible, the error terms jointly follow a multivariate normal distribution (MVN) with zero conditional mean and variance normalized to unity (for identification of the parameters). Eq. (2) will be estimated for each CSAP set.

In the second step, the relationship between the outcome variable and a set of control variables Z is estimated by a fixed effect model for the chosen combination of practices. The outcome equation for each package of CSAP k is given as:

$$Q_{itk} = \delta Z_{itk} + \theta_k + u_{itk} \;\; \text{if } I_{it} = k \text{ for } k = 1, \ldots, K \tag{3}$$

here, $Q'_{itk}s$ are vectors of outcome variables (per capita consumption of calories and protein, and Simpson index) of the i^{th} farmer for CSAP category k at time t and the error term ($u'_{itk}s$) is distributed with $E(u_{itk}|X, Z) = 0$ and $var(u_{itk}|X, Z) = \sigma^2_j Q_{itk}$ is observed if and only if CSAP k is used; Z is a vector of covariates influencing nutrition outcomes, and θ is unobserved time-invariant household heterogeneity.

From the estimation results of the multivariate probit model (Eq. (2)), we derive the inverse Mills ratio (λ) variables that will be added as additional explanatory variables in the second-stage outcome Eq. (3) to capture individual heterogeneity underlying selection bias.[8] The second-stage equation of the endogenous switching regression in (3) is re-specified as:

$$Q_{itk} = \delta Z_{itk} + \sigma_k \hat{\lambda}_{itk} + \theta_k + u_{itk} \text{ if } I_{it} = k \text{ for } k = 1, \ldots, K \tag{4}$$

where σ_j is the parameter of coefficients for $\hat{\lambda}_{itj}$ showing the covariance between $\varepsilon's$ and $u's$.

3.6. Estimation of average adoption effects

In this section, we show how to estimate the average adoption effect of a combination of CSAP from the econometric approach outlined above. The estimates that are most commonly of interest are the average adoption effect on the adopter (ATT) and the average treatment effect on the non-adopter (ATU). The ATT and ATU answers the question of how the average outcome would change if everyone who adopted one particular combination of practices had instead adopted another particular combination of practices.

The average treatment effect on the treated (ATT) is the estimand that is most commonly of interest to obtain an unbiased estimate of the average effect of combination of more practices. The ATT answers the question of how the average outcome would change if everyone who used a combination of fewer practices

[7] The inverse Mill's ratio is defined as the ratio between the standard normal probability distribution function and the standard normal cumulative distribution function evaluated at each $z_{it}\delta$ for h_{itj}.

[8] See Bourguignon et al. (2007) for the derivation of selection bias correction terms from the choice model.

had instead used a combination of more practices. In observational studies, where control over the assignment of the adoption of CSAP is less likely, the CSAP choice status is likely to be dependent on outcomes and thus a biased estimator of the average effect of adoption on the population. However, the ATT is used to compare the expected nutritional outcome in the case of a combination of more practices with the counterfactual nutritional outcome of a combination of fewer practices. The expected net nutritional outcome under the actual and counterfactual hypothetical cases is computed as follows, by applying Eq. (4):

Actual average nutritional outcome for combination of high number of CSAP adopters:

$$E(Q_{ik}|I_i = k) = Z_{ik}\delta_k + \sigma_k\lambda_{ik} \quad (5)$$

Counterfactual outcome if adopters of a combination of a high number of CSAP had decided to adopt a combination of fewer CSAP:

$$E(Q_{ij}|I_i = k) = Z_{ik}\delta_j + \sigma_j\lambda_{ik} \quad (6)$$

Actual average nutritional outcome for combination of few number of CSAP adopters:

$$E(Q_{ij}|I_i = j) = Z_{ij}\delta_j + \sigma_j\lambda_{ij} \quad (7)$$

Counterfactual outcome if adopters of a combination of a smaller number of CSAP had decided to adopt a combination of a higher number of CSAP:

$$E(Q_{ik}|I_i = j) = Z_{ij}\delta_k + \sigma_k\lambda_{ij} \quad (8)$$

Eqs. (5) and (7) represent the expected nutritional outcome of adopters of a combination of a high (low) number of CSAP that were actually observed in the sample, whereas Eqs. (6) and (8) denote the counterfactual expected nutritional outcome if adopters of a high (low) number of CSAP had decided to adopt a low (high) number of CSAP. These expected values are used to compute unbiased estimates of the effects of adoption of combinations of CSAP. The average effect of adoption of CSAP conditional on a high number of CSAP (the ATT) is defined as the difference between Eqs. (5) and (6):

$$ATT = (Q_{ik}|I_i = k) - E(Q_{ij}|I_i = k) = Z_{ik}(\delta_k - \delta_j) + \lambda_{ik}(\sigma_k - \sigma_j) \quad (9)$$

Similarly, the average adoption effect of CSAP conditional on adoption of a low number of CSAP (the ATU) is computed as the difference between Eqs. (7) and (8):

$$ATU = (Q_{ik}|I_i = j) - E(Q_{ij}|I_i = j) = Z_{ij}(\delta_k - \delta_j) + \lambda_{ij}(\sigma_k - \sigma_j) \quad (10)$$

3.7. Estimation of gender heterogeneity effects

The above frameworks can be used to estimate expected nutritional outcomes and the gender and heterogeneity effect relationships between female- and male-headed households. Following the above procedures, the subsequent conditional expectations for each outcome variable are computed by manipulating Eq. (3) in the actual and counterfactual scenarios:

$$E(Q_{mk}|g = m) = Z_{mk}\delta_{mk} \text{ for } k = 1, \ldots, K \quad (11)$$

$$E(Q_{fk}|g = m) = Z_{mk}\delta_{fk} \text{ for } k = 1, \ldots, K \quad (12)$$

$$E(Q_{mk}|g = f) = Z_{fk}\delta_{mk} \text{ for } k = 1, \ldots, K \quad (13)$$

$$E(Q_{fk}|g = f) = Z_{fk}\delta_{fk} \text{ for } k = 1, \ldots, K \quad (14)$$

where g represents gender group such that *f* and *m* denote female-headed households (FHH) and male-headed households (MHH), respectively.

The "actual" MHH and FHH nutritional outcomes are the ones actually observed in the data (Eqs. (11) and (14), respectively). The "counterfactual" scenarios show what the nutritional outcome for FHHs would be, if they had had the same characteristics as the MHHs, and vice versa (Eqs. (12) and (13), respectively). Alternatively, the counterfactuals show what the nutritional outcome of FHHs would be if the responses (coefficients) to their characteristics had been the same as the current returns on MHHs' resources, and vice versa. Using these conditional expectations, the average gender nutritional outcome differences for each combination of CSAP k for k = 1, ..., K is derived as follows.

The gender gap in household nutrition is the change in MHH's nutritional outcome (MQ_k) which is defined as if MHH had had the same characteristics as they do now, but had had the same returns to those characteristics as FHHs have now. This is given as the difference between (11) and (12):

$$MQ_k = E(Q_{mk}|g = m) - E(Q_{fk}|g = m) = Z_{mk}(\delta_{mk} - \delta_{fk}) \quad (15)$$

Similarly, the gender gap in nutritional outcome is the expected change in FHH's nutritional status (FQ_k) if FHH had had the same characteristics as they do now, but had had the same returns to those characteristics as the MHHs have now. This is given as the difference between (13) and (14):

$$MQ_k = E(Q_{mk}|g = f) - E(Q_{fk}|g = f) = Z_{fk}(\delta_{mk} - \delta_{fk}) \quad (16)$$

The difference between Eqs. (15) and (16) can also be used to compute heterogeneity effects (e.g., due to differences in the quality of households' resources, managerial skill, access to services, etc.). These heterogeneity effects show what the difference in nutritional outcome would have been if all households had had the current MHH responses and the current FHH responses to the observable characteristics. This provides information on whether the gender gap on nutritional outcome with the adoption of combinations of CSAP is larger or smaller due to MHH or FHH characteristics. MHHs and FHHs do in fact have different observable characteristics, and this would have an impact even if their responses to the characteristics had been the same.

4. Empirical results

4.1. Factors influencing adoption decisions

The results from fitting the MVP model of adoption of combinations of CSAP are reported in Table 5. The MVP model is estimated using the maximum likelihood method at household-level observations. The model fits the data reasonably well. The Wald test that all regression coefficients are jointly equal to zero is rejected [$\chi^2(385) = 3339$; $p = 0.000$]. As shown in Table 5, the estimated MVP coefficients differ substantially across the alternative CSAP combinations, indicating the appropriateness of separate analyses instead of aggregating them as one variable.[9] In order to formally test this, we estimated a constrained specification with all slope coefficients forced to be equal. The likelihood ratio test statistic decisively rejected the null hypothesis of equal-slope coefficients. This result strongly indicates the heterogeneity in adoption of combinations of CSAP. As expected, the likelihood ratio test [$\chi2(21) = 1174$, $p = 0.000$)] of the null hypothesis that the covariance of the error terms across equations are not correlated is also rejected, which supports estimations of MVP model.

Self-selection models that are estimated in a two-stage procedure have been criticized for being sensitive to misspecification

[9] The joint significance of the mean of time-varying explanatory variables in all choices [$\chi2(56) = 95.174$, p=0.000)] suggests that there is a correlation between observed and unobserved heterogeneity, justifying the use of Mundlak's approach.

Table 5
Coefficient estimates of the multivariate probit model with Mundlak's approach.

Variables	$D_1S_0I_0$		$D_0S_1I_0$		$D_0S_0I_1$		$D_1S_1I_0$		$D_1S_0I_1$		$D_0S_1I_1$		$D_1S_1I_1$	
	Coeff.	SD	Coeff.	SD	Coeff.	SD	Coeff.	SD	Coeff.	SD	Coeff.	SD	Coeff.	SD
Household and farm characteristics														
Gender	0.330**	0.152	0.057	0.113	0.019	0.113	0.033	0.113	−0.093	0.115	0.034	0.117	0.190*	0.119
Age	0.001	0.004	−0.003	0.004	0.002	0.003	−0.002	0.003	−0.001	0.003	−0.004	0.003	−0.001	0.003
Education	−0.023	0.106	0.068	0.098	−0.033	0.096	0.004	0.086	0.103	0.087	−0.073	0.090	0.055	0.091
HHsize	0.031	0.021	0.011	0.019	−0.004	0.018	0.001	0.018	−0.016	0.019	0.004	0.017	−0.006	0.019
Plotdist	−0.013***	0.004	−0.006**	0.003	−0.006*	0.003	0.004	0.002	−0.003	0.002	−0.007***	0.002	−0.001	0.002
Plotsize	−1.783***	0.646	−0.780***	0.252	−0.731**	0.290	0.367	0.263	−0.480	0.353	−0.394	0.234	0.183	0.393
Parcel	0.214***	0.032	−0.249***	0.025	−0.034	0.022	−0.273***	0.025	0.354***	0.029	−0.434***	0.030	0.427***	0.032
Tenure	−0.477***	0.142	−0.358***	0.133	−0.312**	0.124	0.031	0.142	0.230*	0.146	0.683***	0.140	0.028	0.141
Higferland	−0.007	0.154	−0.052	0.132	0.093	0.131	−0.097	0.124	−0.248**	0.126	0.254**	0.124	0.021	0.129
Flatland	−0.171	0.131	−0.276**	0.112	−0.250**	0.117	0.310***	0.107	−0.146	0.111	0.051	0.113	0.056	0.119
Deepland	−0.239*	0.142	0.018	0.129	−0.107	0.125	−0.061	0.114	−0.034	0.120	0.045	0.114	0.083	0.114
Resource constraints														
Farmsize	0.097	0.103	0.139***	0.043	0.081*	0.047	0.026	0.050	0.042	0.057	0.181***	0.057	−0.098*	0.058
Tlu	0.005	0.031	0.001	0.029	−0.041	0.029	−0.040*	0.025	0.009	0.023	0.044*	0.024	0.060**	0.027
Credtcons	−0.144	0.141	0.069	0.121	0.006	0.123	−0.076	0.112	0.116	0.116	0.194*	0.107	−0.064	0.130
Asset	0.001*	0.001	0.000	0.000	0.001	0.000	−0.001*	0.000	0.000	0.001	0.000	0.000	0.001**	0.001
Offarm	−0.063	0.161	−0.138	0.137	−0.083	0.140	0.240*	0.131	0.244*	0.134	0.032	0.131	−0.155	0.147
Market access and extension														
Distoutmkt	−0.003	0.009	−0.026**	0.013	−0.012	0.014	−0.007	0.009	0.001	0.006	0.002	0.007	−0.004	0.008
Distinpmkt	0.006	0.006	−0.009*	0.005	−0.016**	0.007	−0.001	0.005	0.006	0.008	−0.001	0.005	−0.005	0.006
Extcontin	−0.403*	0.226	0.199	0.196	−0.027	0.191	0.302*	0.189	−0.727***	0.191	0.640***	0.177	−0.017	0.192
Extconfind	0.074	0.303	0.237	0.292	0.166	0.277	0.069	0.254	0.036	0.235	0.051	0.218	−0.163	0.269
Social capital and social protection														
Kinship	−0.000	0.000	−0.001	0.001	−0.000	0.001	−0.000	0.000	0.000	0.000	−0.000	0.000	0.000	0.000
Member	−0.026**	0.011	−0.001	0.011	0.013	0.011	0.012	0.011	−0.040***	0.011	0.037***	0.010	−0.017	0.011
Remitance	−0.310**	0.150	0.017	0.118	0.113	0.112	0.263**	0.114	−0.096	0.114	0.107	0.119	−0.199	0.110
Suport	0.182	0.171	0.410***	0.143	0.164	0.153	0.013	0.159	−0.132	0.133	0.098	0.144	0.044	0.181
Aid	−0.077	0.182	0.184	0.157	0.139	0.156	0.249	0.161	−0.227	0.169	0.213	0.149	−0.030	0.172
Climate and shocks														
Rainindex	0.005	0.236	0.225	0.227	0.014	0.217	−0.327*	0.195	−0.227	0.200	0.262	0.187	−0.246	0.212
Plotindex	0.274	0.620	0.682	0.567	0.324	0.538	−0.718	0.485	0.083	0.513	0.467	0.506	0.260	0.531
Relygovt	0.138	0.094	−0.094	0.086	−0.036	0.082	−0.193**	0.078	0.225***	0.076	−0.128*	0.077	−0.206**	0.085
AV_Rain	0.015	0.026	−0.039**	0.016	−0.026	0.017	0.017	0.017	0.007	0.018	0.023	0.017	−0.036*	0.019
Rain-squar	−0.0001	0.0001	0.0001*	0.0001	0.0001	0.0001	−0.0001	0.0001	−0.0001	0.0001	−0.0001	0.0001	0.0001**	0.0001
CV_Rain	1.911	1.694	−2.671***	0.973	−2.376***	0.916	1.548*	0.969	0.898	1.175	3.688***	1.041	−0.839	1.214
Temp	0.943	0.918	−0.918	0.619	−0.608	0.620	0.507	0.670	−0.829	0.554	−1.022*	0.648	0.835	0.740
Temp-squar	−0.026	0.025	0.026	0.017	0.017	0.017	−0.013	0.018	0.023	0.015	0.029*	0.018	−0.023	0.020
Year-2017	−0.793***	0.150	−0.084	0.142	−0.025	0.144	0.763***	0.134	−0.092	0.134	0.242*	0.127	−0.459***	0.133
Constant	−10.571	9.131	14.480**	5.981	8.666	5.965	−7.076	6.317	6.879	5.520	2.425	6.337	−7.813	7.228
Joint significance of location variables: $\chi^2(12)$		31.37***	16.83		15.16		53.25***		35.32***		41.95***		210.9***	

Wald $\chi^2(3\,8\,5) = 3339$; $p > \chi^2 = 0.000$; N = 1821; Joint significance of time varying variables: $\chi^2(56) = 95.174$; $p > \chi^2 = 0.000$

Note: *, **, and *** indicate statistical difference at 10, 5, and 1% respectively. SE refers standard error.

(Wu & Babcock, 1998). Despite this, we established a set of selection instruments using climate variables and farm characteristics as exclusion restrictions included in the adoption equations but not in the outcome equations. We conduct a simple post-estimation test to check the validity of the instruments and the results confirm that, in nearly all cases, these variables are jointly significant in the adoption equations but not in the outcome equations. A simple correlation analysis between these instruments and outcome variables also shows that there is insignificant correlation.

The MVP model results show that accessibility of plots has a significant relationship with the adoption of combinations of CSAP (Table 5). Plot access, as measured by residence-to-plot distance, has a negative impact when the three practices are adopted in isolation – that is, the farther the plot, the less likely is adoption of any of the practices in isolation. This might be because of increased transaction costs on the farthest plot, particularly the cost of transporting bulky materials/inputs. The farthest plots usually receive less attention and less frequent monitoring in terms of, e.g., watching and guarding. However, this effect disappears when practices are adopted in combination. This is perhaps because distant plots might have some observed and unobserved beneficial plot characteristics so that farmers face a tradeoff for using these practices on nearby plots (Teklewold et al., 2013). The effects of plot size on adoption is mixed. The result indicates that the effect of plot size on adoption of CSAP depends on whether the practices are adopted in isolation or in combination. While we found an inverse relationship between plot size and adoption of the three practices in isolation, the effect of plot size is statistically insignificant when the practices are adopted in combination. The inverse relationship between farm size and use of crop diversification suggests that, under climate change, small land size can induce diversification that favors intensification, because improved soil fertility and water holding capacity increase yields and resilience to climate change. This result is consistent with earlier works by Kassie et al. (2015) in Ethiopia and Holden (2014) in Malawi.

As expected, adoption of crop diversification in isolation or in combination with modern inputs or with soil and water conservation and modern inputs is more likely for farm households that have more parcels of land. However, with increasing fragmentation of land, adoption of soil conservation is less likely even when combined with crop diversification. Farmers are more likely to adopt combinations of practices on their own plots. This is probably because of tenure security and the hypothesis of Marshallian inefficiency, i.e., lower efficiency or input use on rented plots as compared to owned plots (Kassie et al., 2015). Given the fact that the benefits from long-term investments (e.g., crop diversification and modern inputs, or soil and water conservation and modern inputs) accrue over time, this inter-temporal aspect suggests that secure land access or tenure will positively impact adoption decisions. This result also suggests that perceived plot characteristics (such as farm slope and soil fertility) also conditioned the adoption of combinations of CSAP, suggesting the importance of considering these characteristics in promoting these practices in the cropping systems.

Table 5 also shows the importance of social capital and networks variables in explaining the decision to adopt combinations of climate-smart practices. Farmers who are member of several groups are more likely to adopt a combination of modern inputs and soil/water conservation. With imperfect markets for credit and insurance, including high transaction costs and scarce or inadequate information sources, participation in such networks can improve information flows about new opportunities and potential shocks and can confer other benefits, such as better access to finance and inputs. It can also serve as an informal insurance mechanism in time of crisis (Quisumbing, 2003). However, we also found that membership in several institutions had a disincentive effect in the choice of crop diversification. The result is in agreement with the dark side of social capital, as in Di Falco et al. (2011), where social capital may reduce incentives for hard work and induce inefficiency, such that farmers may exert less effort to increase farm productivity through various adaptation strategies.

We found that farmers' perceptions of rainfall shocks are important in determining the adoption of combinations of CSAP. The results indicate that in areas/years where rainfall is worst in terms of timing, amount and distribution, it is more likely that a household adopts a combination of practices that is more climate smart. This finding suggests that smallholder farmers who are conscious of rainfall variability are using crop diversification in combination with soil and water conservation practices ($D_1S_1I_0$) as adaptation strategies to mitigate the risks of climate variability. This is important evidence of the synergy among climate-smart practices when adopted in combination as adaptations to climate change. For instance, households that don't believe that the government will provide support when crops fail[10] are more likely to adopt risk-*reducing* practices such as crop diversification and soil and water conservation practices ($D_1S_1I_0$), even in combination with risk *increasing* inputs ($D_0S_1I_1$) and ($D_1S_1I_1$)[11]. This result suggests that farmers may substitute the absence of farm insurance, whether in the form of social safety nets or formal insurance, with the adoption of risk reducing CSAP. The result is consistent with earlier work by Tadesse, Shiferaw, and Erenstein (2015), who found that the existence of social-safety networks may affect the demand for weather index insurance.

We found that climate variables are important in determining farmers' choice of CSAP. Changes in precipitation influence the probability of choosing soil and water conservation practices, either in isolation ($D_0S_1I_0$) or in combination with crop diversification and modern inputs ($D_1S_1I_1$). The U-shaped response indicates that decisions about soil and water conservation practices are responsive to rainfall extremes. Soil and water conservation is found to be an important practice in moisture stressed areas. The result corroborates with Deressa et al. (2009). As a risk-decreasing practice, the adoption of soil and water conservation is the most common response to declining rainfall. This is because soil and water conservation lead to sustainable improvements in efficient use of water and nutrients by improving nutrient balance and availability, infiltration and retention by the soil, as well as reducing water loss due to evaporation and improving the quality and availability of ground and surface water (Arslan, McCarthy, Lipper, Asfaw, & Cattaneo, 2013). In high rainfall areas, climate change can contribute to land degradation by exposing unprotected soil to more soil erosion. In this regard, soil conservation is an important adaptation practice due to its role of protecting the soil from water erosion.

The results also show the importance of variability of rainfall to the choice of a combination of CSAP. We found that, in areas where variability of rainfall is high, the adoption of a combination of soil and water conservation practices and modern inputs is more likely than adoption of either of the practices in isolation.

We also found a U-shaped relationship between temperature and adoption of a combination of soil and water conservation and modern inputs. Consistent with Deressa et al. (2009) and Di Falco et al. (2011), the result implies that the choice of soil and water conservation when combined with modern inputs can be considered as important options for adapting agricultural production under extreme temperature climatic conditions. This could be the case because soil and water conservation is a risk-reducing option, so that increased frequency of unfavorable weather conditions favors its adoption. Soil and water conservation is thus key to ensuring agricultural production and reduction of risks, whilst at the same time improving resilience to drought and dry spells. These are techniques for improving soil moisture by enhancing infiltration and reducing runoff and evaporation, hence achieving stability of crop production by maintaining soil conditions close to optimum for crop growth (Ngigi et al., 2005).

4.2. Adoption effects

In this section, we report and discuss the conditional average effects of the combination of crop diversification, soil and water conservation and modern inputs on dietary intake (per capita calorie and protein consumption) and diet diversity (Simpson index). Each estimated effect is reported in both aggregate and disaggregated levels. By presenting the aggregate size of the effects, it is possible to compare the magnitude of the effects between the treated and the non-treated groups for the whole sample. This is presented in Tables 6–8. The sub-category effects indicate the magnitude of the effect and help explain how the results are changed when samples are disaggregated by sub-groups of individuals. We have also examined this variation in the estimated effects among individuals disaggregated by gender (Tables 9–11). In these tables, the average adoption effects are computed as the difference between actual and counterfactual expected outcomes. That is, in each of these tables, we compare columns A and B. Column C presents the impacts of adoption of combinations of CSAP on nutritional outcome, computed as the difference between columns A and B. Moreover, while rows [a]–[c] compare the nutritional effect of adoption of a combination of more than one practice with adoption of a practice in isolation, rows [d]–[f] compare the nutritional outcome from adoption of a combination of three practices with nutritional outcome from adoption of a combination of two practices.

In general, there is considerable heterogeneity among the climate smart practices. Results show that adoption of a greater num-

[10] In some circumstances, the Ethiopian government provides assistance in case of crop failure, but this is not guaranteed.

[11] Crop diversification and soil and water conservation reduce production risk, while adoption of improved seeds and inorganic fertilizer, while offering the potential for higher yields, increase risk (Teklewold et al., 2017).

Table 6
Average adoption effects of combinations of crop diversification, soil and water conservation and modern inputs on household's food diversity (Simpson index).

Sample	Outcome	Adoption status		Average effects [C]
		Multiple adoption (k = 5, 6, 8) [A]	Single adoption (k = 2) [B]	
[a] Multiple Adopter	$E(Q_k\|I=5)$	0.675 (0.003)	0.599 (0.016)	0.075 (0.016)***
	$E(Q_k\|I=6)$	0.731 (0.002)	0.631 (0.011)	0.100 (0.012)***
	$E(Q_k\|I=8)$	0.785 (0.002)	0.619 (0.011)	0.166 (0.011)***
[b] Multiple Adopter		Multiple adoption (k = 5, 7, 8)	Single adoption (k = 3)	
	$E(Q_k\|I=5)$	0.675 (0.003)	0.521 (0.019)	0.153 (0.019)***
	$E(Q_k\|I=7)$	0.687 (0.004)	0.537 (0.019)	0.150 (0.019)***
	$E(Q_k\|I=8)$	0.785 (0.002)	0.614 (0.015)	0.170 (0.015)***
[c] Multiple Adopter		Multiple adoption (k = 6, 7, 8)	Single adoption (k = 4)	
	$E(Q_k\|I=6)$	0.731 (0.002)	0.525 (0.015)	0.207 (0.016)***
	$E(Q_k\|I=7)$	0.687 (0.004)	0.516 (0.018)	0.171 (0.018)***
	$E(Q_k\|I=8)$	0.785 (0.002)	0.547 (0.015)	0.238 (0.015)***
		Full adoption (k = 8)	Partial adoption (k = 5)	
[d] Full adopter	$E(Q_k\|I=8)$	0.785 (0.002)	0.690 (0.003)	0.094 (0.003)***
		Full adoption (k = 8)	Partial adoption (k = 6)	
[e] Full adopter	$E(Q_k\|I=8)$	0.785 (0.002)	0.731 (0.002)	0.053 (0.003)***
		Full adoption (k = 8)	Partial adoption (k = 7)	
[f] Full adopter	$E(Q_k\|I=8)$	0.785 (0.002)	0.706 (0.003)	0.079 (0.004)***

Note: figures in parenthesis are standard errors; *, ** and *** indicate statistical significance at 10%, 5% and 1% level.

Table 7
Average adoption effects of combinations of crop diversification, soil and water conservation and modern inputs on calorie consumption per adult equivalent (Kcal/day).

Sample	Outcome	Adoption status		Average effects [C]
		Multiple adoption (k = 5, 6, 8) [A]	Single adoption (k = 2) [B]	
[a] Multiple Adopter	$E(Q_k\|I=5)$	2622.36 (27.64)	2469.96 (89.49)	152.39 (93.67)***
	$E(Q_k\|I=6)$	2727.28 (32.66)	2563.19 (91.81)	164.09 (97.44)**
	$E(Q_k\|I=8)$	2705.79 (38.44)	2520.28 (84.17)	185.50 (92.53)**
[b] Multiple Adopter		Multiple adoption (k = 5, 7, 8)	Single adoption (k = 3)	
	$E(Q_k\|I=5)$	2622.36 (27.64)	2306.63 (114.17)	315.72 (117.47)***
	$E(Q_k\|I=7)$	2521.68 (21.58)	2131.09 (104.41)	390.58 (106.62)***
	$E(Q_k\|I=8)$	2705.79 (38.44)	2132.37 (93.92)	573.42 (101.48)***
[c] Multiple Adopter		Multiple adoption (k = 6, 7, 8)	Single adoption (k = 4)	
	$E(Q_k\|I=6)$	2727.28 (32.66)	2358.38 (97.62)	368.98 (102.94)***
	$E(Q_k\|I=7)$	2521.68 (21.58)	2319.13 (104.44)	202.55 (106.65)***
	$E(Q_k\|I=8)$	2705.79 (38.44)	2264.28 (90.36)	441.50 (98.19)***
[d] Full adopter		Full adoption (k = 8)	Partial adoption (k = 5)	
	$E(Q_k\|I=8)$	2705.79 (38.44)	2673.03 (22.10)	32.76 (44.34)
[e] Full adopter		Full adoption (k = 8)	Partial adoption (k = 6)	
	$E(Q_k\|I=8)$	2705.79 (38.44)	2766.21 (30.84)	−60.42 (49.28)
[f] Full adopter		Full adoption (k = 8)	Partial adoption (k = 7)	
	$E(Q_k\|I=8)$	2705.79 (38.44)	2691.18 (19.43)	14.61 (43.07)

Note: figures in parenthesis are standard errors; *, ** and *** indicate statistical significance at 10%, 5% and 1% level.

Table 8
Average adoption effects of combinations of crop diversification, soil and water conservation and modern inputs on protein consumption per adult equivalent (gm/day).

Sample	Outcome	Adoption status		Average effects [C]
		Multiple adoption (k = 5, 6, 8) [A]	Single adoption (k = 2) [B]	
[a] Multiple Adopter	$E(Q_k\|I=5)$	101.35 (0.80)	51.73 (3.83)	49.62 (3.91)***
	$E(Q_k\|I=6)$	100.63 (0.49)	66.29 (3.65)	34.34 (3.69)***
	$E(Q_k\|I=8)$	101.90 (1.06)	67.64 (3.36)	34.26 (3.52)***
[b] Multiple Adopter		Multiple adoption (k = 5, 7, 8)	Single adoption (k = 3)	
	$E(Q_k\|I=5)$	101.35 (0.80)	84.51 (3.85)	16.84 (3.93)***
	$E(Q_k\|I=7)$	82.89 (0.99)	82.52 (3.62)	0.38 (3.75)
	$E(Q_k\|I=8)$	101.90 (1.06)	79.48 (3.09)	22.42 (3.28)***
[c] Multiple Adopter		Multiple adoption (k = 6, 7, 8)	Single adoption (k = 4)	
	$E(Q_k\|I=6)$	100.63 (0.49)	65.61 (3.02)	35.02 (3.06)***
	$E(Q_k\|I=7)$	82.89 (0.99)	83.39 (3.90)	−0.50 (4.03)
	$E(Q_k\|I=8)$	101.90 (1.06)	69.97 (2.91)	31.94 (3.09)***
[d] Full adopter		Full adoption (k = 8)	Partial adoption (k = 5)	
	$E(Q_k\|I=8)$	101.90 (1.06)	64.11 (7.12)	37.79 (7.19)***
[e] Full adopter		Full adoption (k = 8)	Partial adoption (k = 6)	
	$E(Q_k\|I=8)$	101.90 (1.06)	100.53 (0.45)	1.38 (1.15)*
[f] Full adopter		Full adoption (k = 8)	Partial adoption (k = 7)	
	$E(Q_k\|I=8)$	101.90 (1.06)	78.34 (0.22)	23.56 (1.08)***

Note: figures in parenthesis are standard errors; *, ** and *** indicate statistical significance at 10%, 5% and 1% level.

Table 9
Gender differentials and average effects of various combinations of CSAP on household food diversity (Simpson index).

CSAP	Outcome	Household			Share of food diversity gaps due to[Ψ]:	
		MHH (D)	FHH (E)	Response effect (F = D-E)	Difference in FHHs and MHHs characteristics	Gender differences in responses to characteristics
$D_1S_0I_0$	$E(Q_2\|g = MHH)$	a] 0.629 (0.003)	c] 0.772 (0.012)	−0.143 (0.012)***		
	$E(Q_2\|g = FHH)$	b] 0.685 (0.014)	d] 0.723 (0.024)	−0.038 (0.023)*		
	Heterogeneity effect	−0.056 (0.014)***	0.049 (0.047)		0.60	0.40
$D_0S_1I_0$	$E(Q_3\|g = MHH)$	a] 0.637 (0.004)	c] 0.680 (0.013)	−0.043 (0.014)***		
	$E(Q_3\|g = FHH)$	b] 0.671 (0.009)	d] 0.693 (0.017)	−0.022 (0.019)*		
	Heterogeneity effect	−0.035 (0.009)***	−0.013 (0.025)		0.61	0.39
$D_0S_0I_1$	$E(Q_4\|g = MHH)$	a] 0.644 (0.004)	c] 0.702 (0.013)	−0.057 (0.014)***		
	$E(Q_4\|g = FHH)$	b] 0.692 (0.007)	d] 0.731 (0.014)	−0.039 (0.016)***		
	Heterogeneity effect	−0.047 (0.008)***	−0.028 (0.027)		0.55	0.45
$D_1S_1I_0$	$E(Q_5\|g = MHH)$	a] 0.600 (0.003)	c] 0.679 (0.006)	−0.079 (0.006)***		
	$E(Q_5\|g = FHH)$	b] 0.649 (0.007)	d] 0.699 (0.009)	−0.049 (0.011)***		
	Heterogeneity effect	−0.049 (0.007)***	−0.020 (0.012)**		0.50	0.50
$D_1S_0I_1$	$E(Q_6\|g = MHH)$	a] 0.650 (0.002)	c] 0.759 (0.005)	−0.109 (0.005)***		
	$E(Q_6\|g = FHH)$	b] 0.705 (0.006)	d] 0.752 (0.009)	−0.047 (0.011)***		
	Heterogeneity effect	−0.055 (0.005)***	0.008 (0.014)		0.54	0.46
$D_0S_1I_1$	$E(Q_7\|g = MHH)$	a] 0.602 (0.002)	c] 0.664 (0.006)	−0.062 (0.007)***		
	$E(Q_7\|g = FHH)$	b] 0.645 (0.005)	d] 0.692 (0.009)	−0.047 (0.011)***		
	Heterogeneity effect	−0.043 (0.005)***	−0.028 (0.013)**		0.48	0.52
$D_1S_1I_1$	$E(Q_8\|g = MHH)$	a] 0.639 (0.002)	c] 0.781 (0.004)	0.142 (0.005)***		
	$E(Q_8\|g = FHH)$	b] 0.708 (0.006)	d] 0.771 (0.010)	−0.062 (0.012)***		
	Heterogeneity effect	−0.069 (0.005)***	0.011 (0.014)		0.53	0.47

Note: figures in parenthesis are standard errors; *, ** and *** indicate statistical significance at 10%, 5% and 1% level.
Ψ Because FHHs are expected to move to the MHH food diversity function trajectory, and because discrimination consists of a bias against women (Kassie et al., 2015), we derived the gendered overall food diversity gaps as: $\delta_{mk}(Z_{mk} - Z_{fk}) + Z_{fk}(\delta_{mk} - \delta_{fk})$.

Table 10
Gender differentials and average effects of various combinations of CSAP on per capita calorie consumption (Kcal/day).

Sample	Outcome	Household		
		MHH (D)	FHH (E)	Response effect (F = D-E)
$D_1S_0I_0$	$E(Q_2\|g = MHH)$	2519.19 (26.15)	2510.05 (137.64)	9.14 (140.10)
	$E(Q_2\|g = FHH)$	2769.81 (128.82)	2803.87 (226.17)	−33.46 (260.28)
	Heterogeneity effect	−250.61 (110.17)**	−293.22 (558.44)	
$D_0S_1I_0$	$E(Q_3\|g = MHH)$	2410.50 (38.23)	2555.34 (72.08)	−114.85 (81.59)**
	$E(Q_3\|g = FHH)$	2483.47 (66.17)	2646.47 (79.39)	−163.00 (103.35)*
	Heterogeneity effect	−72.97 (77.66)	−91.43 (136.24)	–
$D_0S_0I_1$	$E(Q_4\|g = MHH)$	2399.97 (36.67)	2328.95 (61.99)	71.02 (72.03)
	$E(Q_4\|g = FHH)$	2508.98 (82.89)	2668.70 (87.97)	−159.72 (120.88)*
	Heterogeneity effect	−109.01 (84.12)*	−339.76 (131.42)***	–
$D_1S_1I_0$	$E(Q_5\|g = MHH)$	2526.57 (21.26)	2658.68 (32.74)	−132.11 (39.04)***
	$E(Q_5\|g = FHH)$	2612.21 (50.53)	2735.76 (54.35)	−123.55 (74.21)**
	Heterogeneity effect	−85.64 (49.60)**	−77.08 (71.22)	–
$D_1S_0I_1$	$E(Q_6\|g = MHH)$	2629.67 (17.43)	2394.81 (37.41)	234.85 (41.27)***
	$E(Q_6\|g = FHH)$	2760.90 (54.54)	2889.74 (72.76)	−128.84 (90.93)*
	Heterogeneity effect	−131.24 (54.57)***	−494.93 (112.99)***	–
$D_0S_1I_1$	$E(Q_7\|g = MHH)$	2474.45 (21.32)	2680.56 (39.69)	−205.81 (45.06)***
	$E(Q_7\|g = FHH)$	2646.22 (45.75)	2791.82 (49.18)	145.61 (67.17)**
	Heterogeneity effect	−171.77 (48.21)***	−111.57 (82.72)*	–
$D_1S_1I_1$	$E(Q_8\|g = MHH)$	2568.08 (14.72)	2483.08 (72.19)	84.99 (73.68)*
	$E(Q_8\|g = FHH)$	2671.59 (54.09)	2873.73 (144.21)	−202.14 (154.02)
	Heterogeneity effect	−103.52 (49.69)**	−390.65 (233.45)**	–

Note: figures in parenthesis are standard errors; *, ** and *** indicate statistical significance at 10%, 5% and 1% level.

ber of practices provides a higher Simpson index (diet diversity) compared with adoption in isolation or adoption of fewer practices (Table 6). In all counterfactual cases, farm households who actually adopted more practices would have had lower food diversity if they had not adopted this greater number of practices (see column B of Table 6).[12] The additional effect on diet diversity of adopting a combination of the three practices compared with adoption of one practice in isolation is greater than the effect of adopting a combination of two practices compared with adopting a single practice. For instance, for farm households who adopted a combination of soil and water conservation and crop diversification ($D_1S_1I_0$) and modern inputs and crop diversification ($D_1S_0I_1$), adopting $D_1S_1I_0$ and $D_1S_0I_1$, respectively, provides a Simpson index of 0.075 and 0.100 more than adopting crop diversification only. However, this Simpson index rises to 0.166 if farm households are adopting crop diversifications in combination with modern inputs and soil and water conservation, compared to adopting crop diversification only. We also found that adopting more practices increases food diversity more than adopting fewer practices. The results from the last three rows of Table 6 highlight that adopting three practices provides significantly higher dietary diversity than adopting two practices.

[12] A similar adoption effect is observed for the average treatment effects of the untreated. The result is not reported here for the sake of space.

Table 11
Gender differentials and average effects of various combinations of CSAP on per capita protein consumption (gm/day).

Sample	Outcome	Household		
		MHH (D)	FHH (E)	Response effect (F = D-E)
$D_1S_0I_0$	$E(Q_2\|g = MHH)$	44.70 (0.92)	37.44 (2.89)	7.26 (3.04)**
	$E(Q_2\|g = FHH)$	48.08 (3.53)	55.48 (10.38)	−7.40 (10.96)
	Heterogeneity effect	−3.38 (3.82)	−18.04 (11.95)***	
$D_0S_1I_0$	$E(Q_3\|g = MHH)$	40.42 (1.56)	50.30 (2.84)	−9.88 (3.24)***
	$E(Q_3\|g = FHH)$	49.90 (2.13)	55.39 (2.97)	−5.49 (3.66)*
	Heterogeneity effect	−9.48 (3.04)***	−5.08 (5.34)	–
$D_0S_0I_1$	$E(Q_4\|g = MHH)$	39.08 (0.89)	40.53 (2.75)	−1.46 (2.89)
	$E(Q_4\|g = FHH)$	49.21 (2.09)	55.22 (2.75)	−6.01 (3.45)**
	Heterogeneity effect	−10.13 (2.19)***	−14.69 (5.67)***	–
$D_1S_1I_0$	$E(Q_5\|g = MHH)$	47.09 (0.79)	50.88 (1.93)	−3.79 (2.09)**
	$E(Q_5\|g = FHH)$	54.96 (1.75)	68.55 (2.45)	−13.59 (3.01)***
	Heterogeneity effect	−7.87 (1.82)***	−17.66 (4.07)***	–
$D_1S_0I_1$	$E(Q_6\|g = MHH)$	49.68 (0.70)	42.87 (4.53)	6.81 (4.59)*
	$E(Q_6\|g = FHH)$	60.13 (2.74)	72.00 (4.23)	−11.87 (5.04)***
	Heterogeneity effect	−10.45 (2.32)***	−29.13 (13.44)**	–
$D_0S_1I_1$	$E(Q_7\|g = MHH)$	44.93 (0.87)	57.99 (6.81)	−13.07 (6.87)**
	$E(Q_7\|g = FHH)$	55.23 (2.01)	67.54 (3.12)	−12.69 (3.71)***
	Heterogeneity effect	−10.30 (1.99)***	−9.55 (13.64)	–
$D_1S_1I_1$	$E(Q_8\|g = MHH)$	47.08 (0.57)	61.71 (15.87)	−14.63 (15.88)
	$E(Q_8\|g = FHH)$	59.94 (2.31)	70.11 (4.02)	−10.17 (4.64)**
	Heterogeneity effect	−12.86 (1.94)***	−8.40 (50.38)	–

Note: figures in parenthesis are standard errors; *, ** and *** indicate statistical significance at 10%, 5% and 1% level.

This result supports Smale et al. (2015), who found that adoption of hybrid seeds is significantly associated with food group diversity in Malawi. Similarly, the significant relationship between crop diversity and diet diversity is probably more closely related to consumption from the household's own produced food than consumption of market-purchased food (Herforth, 2010). This is in line with Herforth (2010), Jones et al. (2014) and Makate et al. (2016), who examined the relationship between farm diversity and dietary diversity among households in some sub-Saharan African countries (Tanzania, Kenya, Malawi and Zimbabwe) and concluded that there is a strong relationship between dietary diversity and farm production diversity. Increased diversification of crops will not only allow farmers to have a greater number of options to face the uncertain weather conditions associated with the increased climate variability but will enhance nutritional possibilities as well (Lotze-Campen, 2011). As in Makate et al. (2016), this makes crop diversification a more important climate-smart option, as improving food security and diet options will help build smallholder farmers' resilience to intensifying climate change and variability effects.

Table 7 presents the average adoption effect of CSAP on per capita calorie consumption. In spite of some heterogeneity depending on the type of practice, adoption of a combination of practices provides more per capita calorie consumption compared to adoption of practices in isolation. The gains in per capita calorie consumption from shifting adoption of any of the practices in isolation to adoption of the three practices jointly is higher than the shift to adoption of a combination of two practices. For instance, the results in row [a] of Table 7 indicate that adoption of crop diversification provides more per capita calorie consumption when combined with soil and water conservation (152 kcal.) or modern input (164 kcal.) than adoption of diversification in isolation. The potential calorie gain from adopting a combination of the three practices over adopting crop diversification alone is statistically significantly higher by 22 percentage points than the gain from adopting a combination of crop diversification and soil and water. Similarly, the calorie gain from adopting a combination of the three practices over adopting crop diversification alone is statistically significantly higher by 13 percentage points than the gain from adopting crop diversification and modern inputs. However, as shown in the last three rows of Table 7, we didn't find statistically significant evidence of the difference in per capita calorie consumption between adoption of the combination of three practices and adoption of a combination of any of the two practices.

We also determine the adoption effects of combinations of CSAP on per adult equivalent consumption of protein. The result is presented in Table 8. Similar to the above result, we found that the protein consumption effect is higher when the practices are used in combination than in isolation, and adoption of more practices provides more per capita protein consumption than adoption of fewer practices. As in Tambo et al. (2018) and Wainaina et al. (2017), these results confirm the role of productivity enhancing, resource conserving and risk minimizing practices in improving household nutrition. Thus, a combination of modern inputs, soil and water conservation and cropping system diversification can be considered as the most practical and sustainable way to alleviate nutrient deficiency.

4.3. Gender differences in nutritional outcomes

The result of the gender decomposition analysis for the different nutritional outcomes is presented in Tables 9–11. We analyze the difference in household dietary intake and diet diversity into that part attributable to differences in underlying socio-economic characteristics such as household, farm and climatic characteristics (called the "heterogeneity effect") and that attributable to the "response or returns" to these characteristics, i.e., the gender-differentiated impact of these characteristics on nutrition status (called "gender gaps"), using estimates from the switching regression. We estimate the average heterogeneity effects on the nutritional outcome for FHHs with each combination of CSAP, when both the MHHs and FHHs characteristics face the MHH's returns to resource use (i.e., comparing Eqs. (11) and (13)). Similarly, we also estimate the average gender effects (response to resource use) on the nutritional status of FHHs, if FHHs' characteristics had the same returns as MHHs (i.e., by comparing Eqs. (13) and (14)). In almost all cases, the decomposition analysis reveals an overall gender difference in different combinations of CSAP categories due to gender gaps and heterogeneity gaps.

Table 9 presents the considerable average gender return and heterogeneity effects on household diet diversity (Simpson index).

We find that, with the adoption of most of the combination of practices, the food diversity index of FHHs is significantly higher, on average, than the food diversity status of MHHs under both actual and counterfactual conditions. For instance, comparing the actual values of expected diet diversity index (i.e., comparing estimates from Eqs. (11) and (14)) reveals that the gendered diet diversity gaps are 15, 9 and 14%, respectively, when households adopt crop diversification, soil and water conservation, or modern inputs in isolation. Similarly, the gap when household adopts a combination of all three practices is 21%. However, when the household adopts crop diversification only, the counterfactual estimate indicates that, with the same response levels of resource use as MHHs, the FHHs' diet diversity index would have increased by 9% (0.629 vs 0.685), 5% (0.637 vs 0.671) and 7% (0.644 vs 0.692), respectively, when the household adopted crop diversification, soil and water conservation, or modern inputs in isolation. This is the heterogeneity effect. Where households adopted two CSAP (that is, $D_1S_1I_0$, $D_1S_0I_1$ and $D_0S_1I_1$), the heterogeneity effect shows that the food diversity status of FHHs is also significantly increased. Moreover, the gender heterogeneity gap in household food diversity status further widens to 11% for FHHs when households adopted the three CSAP jointly. Similarly, with the counterfactual condition that the FHHs characteristics had had MHH's returns, the food diversity index of FHHs would increase by 5% (0.685 vs 0.723), 3% (0.671 vs 0.693) and 6% (0.692 vs 0.731) when the household adopted crop diversification, soil and water conservation, or modern inputs in isolation, respectively. Again, while we found a positive gender gap in diet diversity for FHHs for all of the practices, whether adopted in isolation or in combination, the largest gap is observed from adoption of a combination of all the practices.

The above results highlight that the gender gap (the gap in response to household characteristics) does not fully explain the overall gender difference in household nutritional outcome. The decomposition results in Table 9 indicate that, when the household adopted CSAP in isolation, 55 to 60% of the diet diversity gap is explained by differences in FHHs' and MHHs' heterogeneous observable characteristics, and the remaining 40 to 45% is attributable to gender differences in responses to these characteristics. On the other hand, for the adoption of the three practices in combination, 53% of the total gap in diet diversity results from gender differences in the responses to household characteristics, while 47% is attributable to differences in the responses to these characteristics. The result supports Kassie et al. (2015), who suggest the policy implication that improving FHHs' access to resources and increasing their responses to the resources is essential to improving their nutritional outcome status. In agreement with the above result, the decomposition analysis further reveals marked gender difference in per capita calorie consumption (Table 10) and per capita protein consumption (Table 11).

5. Conclusion

Under climate change, one of the most formidable challenges that African governments confront is how to secure adequate food that is healthy, safe and of high quality for all, in an environmentally sustainable manner. This study aims to help in filling the knowledge gaps on how to achieve household nutritional security by broadening our understanding of the determinants of adoption of multiple climate-smart agricultural practices and investigating the link between adoption of various combinations of climate-smart agricultural and household nutrition security among male- and female-headed households. The rationale for testing the impact of combinations of practices is that CSAP is usually considered as an integrated adaptation approach to the implementation of agricultural development programming policies that endeavor to improve productivity, livelihood and environmental outcomes under changing climatic conditions. The study uses panel endogenous switching regression in a counterfactual framework to account for unobserved individual heterogeneity and selection bias causing endogeneity. In this study, rather than using the traditional gender dummy, the impact evaluation methodologies allow decomposition of the gender nutrition security gap (household diet diversity, dietary intakes of micro-nutrients) into the portion that is caused by observable resources and characteristics and the part that is caused by returns to the resources. This is helpful to identify the key points of intervention that can help define high impact initiatives in the climate smart agriculture-nutrition nexus.

Our results indicate that farmers' decisions about alternative combinations of practices and related farm income in the Nile basin of Ethiopia depend on climate. When a climate is hot and rainfall is variable, farmers are more likely to adopt a combination of climate-smart practices than a single practice. The role of climate variables in the choice of combinations of CSAP suggests the need for agro-ecological targeting of practices.

The farmers' decision to adopt a particular combination of CSAP is affected by several policy relevant socio-economic and environmental factors. The results on the effect of plot access (spatial plot distance from home), plot size, fragmentation and tenure security on adoption of combinations of CSAP can be used as inputs in Ethiopia's land redistribution and land certification policy process. The model results also revealed that the likelihood of adoption of combinations of CSAP is influenced by plot level shocks, social capital and networks. The effect of these variables can be used to target policies aimed at increasing adoption rates of CSAP. The significant role of social capital and networks suggests the need for establishing and strengthening local institutions, service providers and extension systems to accelerate and sustain adoption. In a country where there is information asymmetry and both input and output markets are missing or incomplete, local institutions can play a critical role in providing farmers with timely information, inputs (e.g., labor, credit, and insurance), and technical assistance.

There is no doubt that CSAP offers benefits in increasing household nutrition security. But this benefit is increasing with increasing adoption of combinations of CSAP rather than adoption of the practices in isolation. We found a very strong relationship between adoption of combinations of crop diversification, soil and water conservation and modern inputs and household dietary intake (per adult equivalent daily consumption of calories and protein), and household food diversity. Interestingly, with the adoption of combinations of CSAPs, the per capita nutrition consumption and dietary diversity is increasing compared with the adoption of a single CSAP.

The results disaggregated by gender of the household head show there is heterogeneity between female- and male-headed households. We found significant evidence of household nutrition outcome differentials between FHHs and MHHs due to both household characteristics, such as resource endowments, and gender differences in responses to these characteristics. These results suggest that elimination of gender differentials in access to resources would not lead to equality in nutrition security status, unless accompanied by changes that improve return to resources.

Declaration of Competing Interest

The authors declare that there is no conflict of interest.

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References

Arslan, A., McCarthy, N., Lipper, L., Asfaw, S., & Cattaneo, A. (2013). *Adoption and intensity of adoption of conservation farming practices in Zambia, ESA Working paper No. 13-01*. FAO.

Asfaw, S., Di Battista, F., & Lipper, L. (2016). Agricultural technology adoption under climate change in the Sahel: Micro-evidence from Niger. *Journal of African Economies, 25*, 637–669.

Bandiera, O., & Rasul, I. (2006). Social networks and technology adoption in Northern Mozambique. *Economics Journal, 116*, 869–902.

Barrett, C. B. (2005). On the relevance of identities, communities, groups and networks to the economics of poverty alleviation. In C. B. Barrett (Ed.), *The social economics of poverty: On identities,communities, groups and networks*. London: Routledge.

Bellon, J., & Taylor, E. (1993). "Folk" soil taxonomy and the partial adoption of new seed varieties. *Economic Development and Cultural Change, 41*(763), 786.

Beuchelt, T. D., & Badstue, L. (2013). Gender, nutrition- and climate-smart food production: Opportunities and trade-offs. *Food Security, 5*, 709–721.

Bourguignon, F., Fournier, M., & Gurgand, M. (2007). Selection bias corrections based on the multinomial logit model: Monte-Carlo comparisons. *Journal of Economic Surveys, 21*, 174–205.

Bryan, E., Ringler, C., Okoba, B., Koo, J., Herrero, M. & Silvestri, S. (2011). Agricultural management for climate change adaptation, greenhouse gas mitigation, and agricultural productivity: insights from Kenya. International Food Policy Research Institute (IFPRI) Working paper 01098. Washington DC.

Campbell, B., Thornton, P., Zougmore, R., Asten, P., & Lipper, L. (2014). Sustainable intensification: What is its role in climate smart agriculture? *Current Opinion in Environmental Sustainability, 8*, 39–43.

Darrouzet-Nardi, A. F., & Masters, W. A. (2015). Urbanization, market development and malnutrition in farm households: Evidence from the Demographic and Health Surveys, 1986–2011. *Food Security, 7*, 521–533.

Deressa, T. T., Hassan, R. M., Ringler, C., Alemu, T., & Yesuf, M. (2009). Determinants of farmers' choice of adaptation methods to climate change in the Nile Basin of Ethiopia. *Global environmental Change, 19*, 248–255.

Deressa, T. T., Hassan, R. M., & Ringler, C. (2011). Perception of and adaptation to climate change by farmers in the Nile basin of Ethiopia. *The Journal of Agricultural Science, 149*, 23–31.

Di Falco, S., & Veronesi, M. (2013). How African agriculture can adapt to climate change? A counterfactual analysis from Ethiopia. *Land Economics, 89*, 743–766.

Di Falco, S., Veronesi, M., & Yesuf, M. (2011). Does adaptation to climate change provide food security? A micro-perspective from Ethiopia. *American Journal of Agricultural Economics, 93*, 825–842.

Dinku, T., Asefa, K., Hailemariam, K., & Connor, S. J. (2011). Improving availability, access and use of climate information. *World Metrology Organization Bulletin, 60*, 80–86.

Dorfman, J. H. (1996). Modelling multiple adoption decisions in a joint framework. *American Journal of Agricultural Economics, 78*, 547–557.

Ebbes, P., Wedel, M., Steerneman, T., & Boeckenholt, U. (2005). Solving and testing for regressor-error (in)dependence when no instrumental variables are available: With new evidence for the effect of education on income. *Quantitative Marketing and Economics, 3*, 365–392.

Erkossa, T., Haileslassie, A., & MacAliste, C. (2014). Enhancing farming system water productivity through alternative land use and water management in vertisol areas of Ethiopian Blue Nile Basin (Abay). *Agricultural Water Management, 132*, 120–128.

Fafchamps, M., & Minten, B. (2002). Returns to social network capital among traders. *Oxford Economic Papers, 54*, 173–206.

Fanzo, J., Hunter, D., Borelli, T., & Mattei, F. (2013). *Diversifying food and diets: Using agricultural biodiversity to improve nutrition and health* (1st ed.). London and New York: Earth Scan.

FAO (2012). *Making agriculture work for nutrition: Synthesis of guiding principles*. Rome: Italy.

FAO (2014). *Adapting to climate change through land and water management in Eastern Africa: Results of pilot projects in Ethiopia*. Rome, Italy: Kenya and Tanzania.

FAO. (2010), Food Balance Sheets, Rome, Italy.

FAO. (2011). Climate change, water and food security. Rome. Italy.

FDRE (2011). *Ethiopia's Climate-Resilient Green Economy: Green Economy Strategy*. Addis Ababa: Federal and Democratic Republic of Ethiopia.

Frison, E., Smith, I. F., Johns, T., Cherfas, J., & Eyzaguirre, P. B. (2006). Agricultural biodiversity, nutrition, and health: Making a difference to hunger and nutrition in the developing world. *Food Nutrition Bulletin, 25*, 143–155.

Gómez, M., Barrett, C., Raney, T., Andersen, P., Meerman, J., Croppenstedt, A., ... Thompson, B. (2013). Post-green revolution food systems and the triple burden of malnutrition. *Food Policy, 42*, 129–138.

Goshu, D., Kassa, B., & Ketema, M. (2012). Does crop diversification enhance household food security? Evidence from Rural Ethiopia. *Advances in Agriculture, Sciences and Engineering Research, 2*, 503–515.

Harris, I., Jones, P. D., Osborn, T. J., & Lister, D. H. (2014). Updated high-resolution grids of monthly climatic observations – The CRU TS3.10 Dataset. *International Journal of Climatology, 34*, 623–642.

Hassan, R., & Nhemachena, C. (2008). Determinants of African farmers' strategies for adapting to climate change: Multinomial choice analysis. *African Journal of Agricultural and Resource Economics, 2*, 83–104.

Herforth, A. (2010). Nutrition and the Environment: Fundamental to Food Security in Africa. In P. Pinstrup-Andersen (Ed.), *The African food system and its interaction with human health and nutrition*. Ithaca, NY, US: Cornell University Press in cooperation with the United Nations University.

Holden, S.T., (2014). Agricultural household models for Malawi: Household heterogeneity, market characteristics, agricultural productivity, input subsidies, and price shocks. A baseline report. In: CLTS Working Paper No. 5/2014.

Jones, A. D., Shrinivas, A., & Bezner-Kerr, R. (2014). Farm production diversity is associated with greater household dietary diversity in Malawi: Findings from nationally representative data. *Food Policy, 46*, 1–12.

Kassie, M., Teklewold, H., Jaleta, M., Marenya, P., & Erenstein, O. (2015). Understanding the adoption of a portfolio of sustainable intensification practices in eastern and southern Africa. *Land Use Policy, 42*, 400–411.

Khanna, M. (2001). Sequential adoption of site-specific technologies and its implications for nitrogen productivity: A double selectivity model. *American Journal of Agricultural Economics, 83*, 35–51.

Kumar, S. K. (1994). *Adoption of hybrid maize in Zambia: Effects on gender roles, food consumption and nutrition. Research Report 100*. Washington, DC: International Food Policy Research Institute.

Lotze-Campen, H. (2011). Climate change, population growth, and crop production: An overview. In S. S. Yadav, R. J. Redden, J. L. Hatfield, H. Lotze-Campen, & A. E. Hall (Eds.), *Crop adaptation to climate change*. New Jersey: Wiley.

Makate, C., Makate, M., & Mango, N. (2017). Sustainable agriculture practices and livelihoods in pro-poor smallholder farming systems in southern Africa. *African Journal of Science, Technology, Innovation and Development, 9*, 269–279.

Makate, C., Wang, R., Makate, M., & Mango, N. (2016). *Crop diversification and livelihoods of smallholder farmers in Zimbabwe: adaptive management for environmental change*. Springer Plus. DOI: 10.1186/s40064-016-2802-4.

Mandal, R., & Bezbaruah, M. P. (2013). Diversification of cropping pattern: Its determinants and role in flood affected agriculture of Assam Plains. *Indian Journal of Agricultural Economics, 68*, 169–181.

Masset, E., Haddad, L., Cornelius, A., & Isaza-Castro, J. (2011). *A systematic review of agricultural interventions that aim to improve nutritional status of children*. London: EPPI-Centre, Social Science Research Unit, Institute of Education, University of London.

Moyo, S., & Veeman, M. (2004). Analysis of joint and endogenous technology choice for protein supplementation by smallholder dairy farmers in Zimbabwe. *Agro Forestry System, 60*, 199–209.

Mundlak, Y. (1978). On the pooling of time series and cross section data. *Econometrica, 64*, 69–85.

Negin, J., Remans, R., Karuti, S., & Fanzo, J. C. (2009). Integrating a broader notion of food security and gender empowerment into the African Green Revolution. *Food Security, 1*, 351–360.

Nelson, G. C., Rosegrant, M. W., Koo, J., Robertson, R., Sulser, T., Zhu, T., ... Lee, D. (2009). *Climate change: Impact on agriculture and costs of adaptation*. Washington DC: IFPRI Food Policy Report.

Ngigi, S. N., Savenije, H. H. G., Thome, J. N., Rockstro, J., & de Vriesd, F. W. T. P. (2005). Agro-hydrological evaluation of on-farm rainwater storage systems for supplemental irrigation in Laikipia district, Kenya. *Agricultural Water Management, 73*, 21–41.

Nguyen, M. C., & Winters, P. (2011). The impact of migration on food consumption patterns: The case of Vietnam. *Food Policy, 36*(71), 87.

Njeru, M. E. (2013). Crop diversification: A potential strategy to mitigate food insecurity by smallholders in sub-Saharan Africa. *Journal of Agricultural, Food Systems and Community Development, 3*, 63–69.

Novella, N., & Thiaw, W. (2013). African rainfall climatology version 2 for famine early warning systems. *Journal of Applied Meteorology and Climatology, 52*, 588–606.

Qaim, M., & Kouser, S. (2013). Genetically modified crops and food security. *PLoS ONE, 8*, e64879. https://doi.org/10.1371/journal.pone.0064879.

Quisumbing, A. (2003). Food aid and child nutrition in rural Ethiopia. *World Development, 7*, 1309–1324.

Ruel, M. T. (2003). Operationalizing dietary diversity: A review of measurement issues and research priorities. *Journal of Nutrition, 133*, 3911S–3926S.

Smale, M., Moursi, M., & Birol, E. (2015). How does adopting hybrid maize affect dietary diversity on family farms? Micro-evidence from Zambia. *Food Policy, 52*, 44–53.

Snapp, S. S., Blackie, M. J., Gilbert, R. A., Bezner-Kerr, R., & Kanyama-Phiri, G. Y. (2010). Biodiversity can support a greener revolution in Africa. *Proceedings of the National Academy of Sciences of the United States of America, 107*, 20840–20845.

Tadesse, M., Shiferaw, B., & Erenstein, O. (2015). Weather index insurance for managing drought risk in smallholder agriculture: Lessons and policy implications for sub-Saharan Africa. *Agricultural and Food Economics, 3*. https://doi.org/10.1186/s40100-015-0044-3.

Tambo, J. A., & Mockshell, J. (2018). Differential impacts of conservation agriculture technology options on household income in Sub-Saharan Africa. *Ecological Economics, 151*, 95–105.

Teklewold, H., Mekonnen, A., Kohlin, G., & Di Falco, S. (2017). Does adoption of multiple climate smart practices improve climate resilience of farmers? Empirical evidence from the Nile Basin of Ethiopia. *Climate Change Economics, 8*. https://doi.org/10.1142/S2010007817500014.

Teklewold, T., Kassie, M., Bekele, S., & Köhlin, G. (2013). Cropping systems diversification, conservation tillage and modern seed adoption in Ethiopia: Impacts on household income, agrochemical use and demand for labor. *Ecological Economics, 93*, 85–93.

Tilman, D., Cassman, K. G., Matson, P. A., Naylor, R., & Polasky, S. (2002). Agricultural sustainability and intensive production practices. *Nature, 418*, 671–677.

Vanlauwe, B., Wendt, J., Giller, K. E., Corbeels, M., Gerard, B., & Nolteg, C. (2013). A fourth principle is required to define Conservation Agriculture in sub-Saharan Africa: The appropriate use of fertilizer to enhance crop productivity. *Field Crops Research*. https://doi.org/10.1016/j.fcr.2013.10.002.

Wainaina, P., Tongruksawattana, S., & Qaim, M. (2017). Synergies between different types of agricultural technologies in the Kenyan small farm sector. *The Journal of Development Studies*. https://doi.org/10.1080/00220388.2017.1342818.

Wu, J. J., & Babcock, B. A. (1998). The choice of tillage, rotation, and soil testing practices: Economic and environmental implications. *American Journal of Agricultural Economics, 80*, 494–511.

Wollni, M., Lee, D. R., & Janice, L. T. (2010). Conservation agriculture, organic marketing, and collective action in the Honduran hillsides. *Agricultural Economics, 41*, 373–384.

Zeng, D., Alwang, J., Norton, G. W., Shiferaw, B., Jaleta, M., & Yirga, C. (2015). Ex post impacts of improved maize varieties on poverty in rural Ethiopia. *Agricultural Economics, 46*, 515–526.