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An Evaluation of Nutritional Security Impacts of Climate-Smart Adaptation Practices among Smallholder Farmers of Eastern Oromia, Ethiopia

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ABSTRACT

Climate impact mitigation through improved agricultural practices is one means by which agricultural productivity increases to meet the growing food demands in the world. This study evaluated the impacts of climate-smart practices on rural households' nutrition security. The study used both primary and secondary data sources. Primary data was collected from sample respondents in the 2020/21 production year. Descriptive statistics and econometric models were employed for data analysis. Multinomial logit result indicated that the probability of adopting climate-smart agricultural practices is influenced by the education level of the head, extension contact, livestock holding, membership coop, market information, advice on land management, climate change information, farmers training, climate change perception, and weather road distance. The result from Generalized propensity score (GPS) estimation indicated that adopting package one of climate-smart practices increases household nutritional status by16%. Likewise, adopting packages two and three of climate-smart practices increases the household level nutritional status by 37% and 76% respectively over that of treatment level one of the climate-smart practices and is significant at a 1% statistical probability level. This study has found evidence that the adoption of climate-smart on the households' nutrition security status. Therefore, the result of this study would be expected to significantly contribute as policy and strategic inputs for policymakers in designing rural livelihood improvement policies and to the beneficiary in enhancing their welfare and living standard.

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Introduction

Background of the Study

Agricultural business is difficult activity mostly for developing countries where producers are highly dependent on the climate, degraded soil, and has little access to improved inputs and markets (Kuhl, 2020; Sova et al., 2018). Agriculture is characterized by long droughts, pests, disease epidemics, long maturity time, flooding, and low productivity (Asfaw and Branca, 2018; Mensah et al., 2020; Muchuru and Nhamo, 2019; Senyolo et al., 2021).

Nowadays there is a global interest for agriculture to increase food access through sustainable agricultural practices and adjusting natural and social capitals without affecting the farming environments (Pretty et al., 2018). Ethiopia has a population of 112 million where four out of five live in rural areas and have subsistence farming as source of livelihoods (World Bank, 2018).The proportion of households with insufficient calorie intake (<2550 Kcal per adult equivalent per day) accounts for 31%, with 24% located in urban areas and 33% in rural areas (FAO, 2019).

Climate change causes a series of effect to the economic growth of developing countries including Ethiopia. Climate change also reduces crops and livestock yields, food security and the whole wellbeing of rural households of Ethiopia (Endalew et al., 2014; Campbell et al., 2016; Lewis, 2017). In addition lack of information, price systems, reduced yields, and food insecurity are identified as multiple factors affecting growth (Hansen et al., 2019; Etwire and Kuwornu, 2020).

The study area Eastern Hararge, Oromia mostly affected by the climate change effects of land degradation, population pressure, loss topsoil, deforestation, poor afforestation, unsustainable agricultural practices, use of manure and crop residues for fuel, and overgrazing (Tesfa and Mekuriaw, 2014; Abebe and Sewnet, 2018). Flooding and high erosion rate affect several regions of Ethiopia (Gessesse et al., 2015; Hurni et al., 2016; Asfaw and Neka, 2017). Adoption and use of climate-smart agricultural practices are suggested mechanisms for increasing productivity, increasing the resilience capacity of crops and livestock to climate change, and reducing the emission of greenhouse gas (James et al., 2015; FAO, 2016; Teklewold et al., 2017).

More of the last studies on the adoption of climate-smart practices have focused on the adoption of single practices and their effect on food security status and not focused on multiple practices and their effect on nutrition security (Zeng et al., 2015, Makate et al., 2016). Therefore, there is a literature gap and growing demands in the literature on the adoption and impact of a combination of practices on household productivity and well-being (Makate et al., 2017, Wainaina et al., 2017, Teklewold et al., 2017, Tambo and Mockshell, 2018). Even in Ethiopia, the integrated use of fertilizers, improved seeds, and irrigation in agriculture are still below 1% (Bachewe et al., 2018). Thus, this study evaluates the impact of climate-change adoption practices on the nutrition security of rural households in Eastern Oromia, Ethiopia.

The specific objectives of the study

- Identify determinants of smallholder farmers' adoption of climate-smart practices
- Evaluate the impacts of the adoption of climate-smart practices on rural households' nutrition security.

Materials and Methods

Description of the Study Area

This study was conducted in the Girawa, Haramaya, and Meta districts of the east Hararghe zone of Oromia Regional State, Ethiopia. Its altitude ranges from 1200 to 3405m above sea level with minimum and maximum rainfall of 400 and 1200 mm respectively. The total area covered by this zone is about 22,622.6 km2. The zone has three agro-ecological zones, highland (>2300), midland (1500–2300), and lowlands (<1500) meters (m.a.s.l.) (AEHZ, 2018). Girawa district has an estimated total population of 300,661 (CSA, 2019). The estimated total population of Haramaya is 352,031, out of which 172,495 are females (HDAO, 2019)**.** The total population of the Meta district is 318,458; of whom 160,334 were men and 158,124 were women (MAO, 2019).

Sources of Data and Methods of Data Collection

The study used both primary and secondary sources of data. The primary data was collected by the trained enumerators. Three districts were selected purposively due to their potential area for cereal crops and problems of rural households' nutrition security. From that three districts, eight kebeles were selected using simple random sampling. The sample size was determined through the application of the Kothari (2004) sample size determination formula and finally, a total of 461 sample households were interviewed.

Methods of Data Analysis

The study employed descriptive statistics and econometric models for data analysis.

Measure of nutritional status

Household Dietary diversity score was used to measure nutrition security status using the types of different food groups consumed by a given household over the last 24hours. This is used as a measure of overall food access, including total dietary intakes as well as diet quality (Kennedy et al., 2010; Leroy et al., 2015). Dietary diversity scores are relatively inexpensive to obtain, and so can be collected over large populations to monitor the progress of intervention and measure disparities over time. Different measures often yield diversity scores that are highly correlated with each other and other measures of nutrition security (Kennedy et al., 2010; Lovon and Mathiassen, 2014). As a crosscut the number of food groups or dietary diversity can be categorised as low dietary diversity (≤3 food groups); medium dietary diversity (4 to 5 food groups) and high dietary diversity (≥6 food groups) for household level study (FAO, 2015).

Multinomial logit selection model

The study employed a multinomial logit selection model to measure the decision to adopt a combination of climate-smart agricultural practices as one of the random utility frameworks. Following Kassie et al.(2015,2018) consider the latent model (U_{jit}) below which describes the behavior of the i'th farmers in adopting multiple agricultural practices $j(= 1,2,3,4)$ at time t over any alternative multiple agricultural practices combination m:

$$U_{jit}=\alpha_j X_{jit}+\omega_j X_{ji}+\varepsilon_{jit}$$

$$\text{With } U=\int_J^1 \ldots \begin{matrix} \text{if } U_{jit}>\max_{m\neq 1}(u_{mit}) \text{ or} \tau_{jit}<0 \\ \text{if } u_{jit}>\max_{m\neq j}(u_{mit}) \text{ or } \tau_{jit}<0 \end{matrix} \text{ for all } m\neq j \quad (1)$$

Where X_{jit} is a vector of observed exogenous covariates that the households level characteristics, $\alpha_j$and ω_j are vectors of parameters to be estimated, and ε_{jit} is the random error term.

Estimation of the multinomial logit selection model could be inconsistent due to the correlation of unobserved factors with explanatory variables. To overcome this we use Mundlak's (1978) and Wooldridge's (2010) approach where the means ($\bar{x}_{ji}$) of all time-varying covariates are included as additional covariates in the multinomial logit selection model. Unlike the adoption decision which is observable, the utility derived from the adoption of multiple climate-smart practices is unobservable. Therefore, eq(1) entails that the i'th farmer will adopt a combination of multiple climate-smart practices to maximize expected benefits if the practice provides greater utility than an alternative combination m: e.g., if $\tau_{jit}(U_{mit} - U_{jit}$)<0, assuming that are independent and identically Gumbel distributed (Bourguignon et al., 2007). As indicated by Mc-Fadden (1973), the probability that a farmer i will choose practice j can be expressed as a multinomial logit selection model with:

$$P_{jit} = (\tau_{jit} < 0\ X_{jit}) = \frac{\exp(\alpha_j x_{jit+}\omega_j x_{ji})}{\sum_{m\neq 1}^{1} exp(\alpha_m X_{mit}+\omega_m X_{mi})} \quad (2)$$

Thus the multinomial logit selection model in the above equation is estimated using mlogit command in Stata statistical software (STATA 14.2)

The Generalized Propensity Score Function

In multiple treatment impact evaluation, the Generalized Propensity Score (GPS) method is a viable method for estimating the dose-response function (Herrano and Imbens, 2004). The method yields efficient and accurate results in the social studies research (Kloe et al., 2012; Cassie et al., 2014; Liu and Floraux, 2014; Li and Fraser, 2015). A sample of a large population of random sample is shown by imaging and with the help of i = 1,…, N. The dose-response function, called Yi-T, T-T, is that for each component under the treatment level T. In the case of binary solutions, t = 0, 1. However, in the case of continuous treatment such as the numbers of adopted climate-smart practices, t is intermediate [t0, t1], t0> 0 (Herrano and Imbens, 2004). Because the utility of GPS focuses on the effects of average dose-response and treatment for the households using agricultural practices and households that do not use climate-smart practices are not included in the study (Guardabascio and Ventura, 2013).

The goal is to estimate the average potential effect or dose-response, (t) = E[yi (t)], which represents the normal function of dietary diversity. Nutrition status is estimated to all possible practices of climate-smart farming, and to these (T) farming practices. Notable variables in the model are the vectors of the covariates Xi. The first step, as Dean and Imbans (2004) point out, is the general distribution of GPS of participants (t (r, r) = E [Y / T = t, r = r]). Agricultural practices parameters will be estimated using the maximum likelihood of the functions the, β0, β1 and δ2 (conditional distribution of contributions) (3).

$$T_i|Xi \sim N[\beta_0 + \beta_{1X_{i,}}\delta^2] \quad (3)$$

As the main purpose for estimating the GPS is to ensure balancing of covariates across categories of practices, a test for sufficient covariate balancing property of the estimated GPS was conducted before proceeding to step two. Following the estimation of the parameters of the participation function in Eq. (3), GPS was estimated using Eq. (4).

$$R_i = \frac{1}{\sqrt{2\pi\delta^2}} exp[-\frac{1}{2\delta^2}(T_i - \beta_0 - \beta_0 X_i)^{\ 2}] \quad (4)$$

The second step involved modeling the conditional expectation of household nutrition security status (Y_i) as a quadratic function of observed treatment (T_i), estimation of GPS (R_i), and analysis of the interaction between the two using Eq. (5).

$$\beta(t,r) = g([Y_i|T_{i,}R_i]) = \alpha_0 + \alpha_1 T_i + \alpha_2 Ti^2 + \alpha_3 R_i + \alpha_4 Ri^2 + \alpha_5 T_i R_i \quad (5)$$

Since the outcome variable of the study is continuous, *g* was estimated using a normal regression model. Finally, the average dose-response function at a particular value of the treatment *t* was estimated by averaging the (estimated) conditional expectation $\mu(t)$ over the GPS at that level of climate-smart practices ($\mu(t) = E[\beta(t, r(t, X))]$, $t \forall$ T) using Eq. (6).

$$\mu(t) = E[\acute{\dot{Y}}(t)] = \frac{1}{N}\sum_{i=1}^{N} g^{-1}[\alpha_0 + \alpha_1 . t + \alpha_2 t^2 + \alpha_3 . r(t,x_i) + \alpha_4 . r(t,x_i)^2 + \alpha_5 . tr(t,x_i) \quad (6)$$

α is the vector of parameters estimated in step two and $r(t, X_i)$ is the predicted value of $r(t, X_i)$ at level *t* of the treatment. The entire dose-response function was obtained by estimating this average potential outcome for each level of practice.

Estimation of inverse probability weighting (IPW)

If the generalized propensity score j sample farmers given as;

$$e_j(X) = Pr\ (Z\ X) \quad (7)$$

The inverse probability weighting of the average treatment effect is given by;

$$W(X_i) \ldots W_J(X_J) = \left(\frac{1}{e_{j(X_i)}}\right) \ldots\ldots \left(\frac{1}{e_{j(X_i)}}\right). \quad (8)$$

$$P_j ATE_j = \frac{\sum_{i=1}^{n} 1(Z_i=j) Y_i\, e_j(X_i)}{\sum_{1}^{n} 1(Z_i=j_i) e_j(X_i)} - \frac{\sum_{i=1}^{n} 1(Z_i=j^{'})\ YY_i(\ ej^{'}\ (X_i)}{\sum_{i=1}^{n} 1(Z_i=j^{'}) e^{'}\ (X_i)} \quad (9)$$

Where the inverse probability weighting for the average treatment effect on the treated sample is calculated following Morgan et al (2008); Austin (2011) as:

$$W_{ATT} = Z + (\frac{e^{(1-z)}}{1-e}) \quad (10)$$

Where PATE_j Weighted average treatment effect, W_{ATT} is the weighted average treatment on treated.

Definition of variables and hypothesis

Dependent variables: The dependent variable is continuous in nature and measured as the number of adopted climate-smart agricultural practices.

Outcome variables: Nutrition security are outcome variable in impact estimation. Table 1 below presents the detail of variables definitions, measurements, and hypotheses

Results and Discussion

Descriptive Statistical Results

Descriptive statistics results of continuous variables

Descriptive statistics results of continues variables among the different climate-smart adoption practices are presented in Table 2. The discussion about the descriptive statistics of each variable is presented below;

Level of education: The total sample's average years of formal schooling were found to be 3.4 years. The average education level for less than one package-adopters, one package practice adopters, two package practices adopters, and all three packages of climate-smart agriculture practices adopters were found to be 1.74, 2.7, 4.1, and 4.8 years respectively. The F-test results of groups mean difference comparison shows that there is a statistically significant mean difference among the four groups at 1% probability level. This shows that more educated household adopts more climate-smart agricultural practices than less educated household.

Extension contacts: Extension service refers to advice, training, demonstration, and input distribution to farmers. According to the survey results, farmers have an average of 3.6 days of extension contact per year. The average extension contact for less than one package adopter, one package practice adopter, two package practices adopters, and three package practice adopters were found to be 3.2, 3.3, 3.7, and 5.14 times per year respectively. The F-test results of groups mean difference comparison shows that there is a statistically significant mean difference among the four groups at a 1% probability level. A result further shows that households with more extension contact adopt more climate-smart agricultural practices others.

Livestock holding: The sample households' mean livestock holding in Tropical Livestock Unit (TLU) was found to be 2.57. The average livestock holding for less than one package adopters, one package practice adopters, two package practices adopters, and all three package practice adopters were found to be 1.84, 2.57, 2.68, and 3.07 years respectively. The F-test results of groups mean difference comparison shows that there is a statistically significant mean difference among the four groups at a 1% probability level. This showed that the sample households that did adopt more packages of the number of climate-smart agriculture practices had significant mean differences in livestock holding (Table 2).

Distance to weather road: Market access is a determinant of the profitability and sustainability of agricultural products, as well as a proxy for agricultural marketing services. The average weather road distance for less than one package adopter, one package practice adopter, two packages adopter and all three package practice adopter were found to be 36.86, 32.77, 29.4,5, and 29.27 minutes respectively. According to the F-test results of group mean difference comparison, there was a statistically significant mean difference between the four in terms of weather road distance at the 1% probability level.

Total farm income: The average total farm income for the entire sample is 36395.04 Birr. The average livestock income for less than one package adopter, one package adopter, two packages adopter, and all three packages of practice adopters are found to be 22193, 33201.26, 35841.5, and 56980.54 birrs respectively. The F-test results of group mean difference comparison shows that there was a statistically significant mean difference in farm income among the four treatment levels at the 1% probability level. This showed that the sample households that did adopt more packages of climate-smart agriculture practices had significant mean differences in total farm income.

Characteristics of sample households (Dummy variables)

Membership status: According to the survey results, 48.6 percent of the total sample was found to be members of farmer groups and cooperatives, while the remaining 51.4 percent did not participate. The comparison across different groups of climate-smart practices, about 6.3 %, 14.1, 17.1, and 11.4 percepts of the households who did adopt less than one package, adopted one package, adopted two packages, and adopted all three packages of climate-smart practices had participated in the memberships. At a 1% probability level, the chi-square test revealed a statistically significant mean difference between the four treatment levels in terms of the membership status of the household head. This demonstrated that participating households use more climate-smart practices than less participating households.

Table 1. Definitions, measurements, and hypotheses of used variables

Variables	Measurement	The expected effect
Dependent variables		
Climate change adaptation practices	Number of climate change adaptation practices used	
Outcome variables		
Dietary diversity	Numbers of food types consumed per day	
Independent variables		
Age	Age of head in years	+/-
Gender	1 male headed, 0 female headed	+
Family size	Family size in numbers	+
Land area	Cultivated land area in hectors	+
Education	Education level of head grade completed	+
Training	1 if trained 0 otherwise	+
Extension	Number of contact in cropping season	+
Distance to main road	Distance to the main road in kms	-
Climate information	1 if accessed 0 if not	+
Perception climate change	1 if perceived 0 otherwise	+
Training on land mgt	1 if participated 0 otherwise	+
Livestock holding	Total livestock holding in TLU	+
Coop memberships	1 if member 0 if not	+
Market information	1 if accessed 0 if not	+
Soil fertility status	1 if fertile 0 otherwise	-
Non/off- farm income	1 if accessed 0 if not	+
Access to credit	1 if accessed 0 if not	+

Table 2. Descriptive statistical results for sample households continues variables

Variables	Treatment level one	Treatment level two	Treatment level three	Treatment level four	All sample	F- Value
	Mean	Mean	Mean	Mean	Mean	
Age	41	40	39.9	41	40.5	0.40
Family size	6.4	6.1	6.13	6.3	6.2	.39
Cultivated	0.614	0.451	.464	.521	0.4903	1.68
Livestock	1.84	2.57	2.68	3.07	2.57	4.72***
Labor	206.4	212.46	205.95	225.53	211.71	1.25
Extension	3.2	3.17	3.7	5.14	3.68	10.41***
Education	1.7	2.7	4.1	4.8	3.4	14.96***
Crop income	19537.7	29353.4	31005.45	51981.4	32218.2	5.26***
Lincome	2655.08	3845.87	4836.06	4999.46	4177.1	4.58***
Fincome	22193.5	33201.87	35841.6	56980.5	36395.37	5.92***
Kilocalories	1920.3	3088.13	5090.7	7971.2	4375.4	34.18***
Dietary div	4.05	4.5	4.98	5.75	4.8	12.14***
Weather road	36.86	32.77	29.45	29.27	31.74	4.95***

Source: Own computation results,** and *** means significant at 5% and 1% respectively

Training: According to the study findings, 63.6 percent of the total sample households participated in farmer training, while the remaining 36.4 percent did not. The comparison across different groups of climate-smart practices, about 6.3, 21.5, 21.9, and 13.9% of the households who did adopt less than one package, adopted one package, adopted two packages, and adopted all three packages of practices had participated in the farmers training. This demonstrated that participating households use more climate-smart practices than less participating households (Table 3).

Training on land management: According to the study findings, 49.2 percent of the total sample households received technical advice on sustainable land management, while the remaining 50.8 percent did not. The comparison across different groups of climate-smart practices, about 5.4, 16.9, 16.9, and 10.4% of the households who did adopt less than one package, adopted one package, adopted two packages, and adopted all three packages of practices had received technical advice on land management. The chi-square tests shows that there was a statistically significant mean difference in technical advice among the four treatment levels at the 1% probability level (Table 3).

Non/off farm income: According to the findings of the study, 13.9 percent of the total sample household participated in non/off-farm income, while the remaining 86.1 percent did not. The comparison across different groups of climate-smart practices, about 3.3, 6.1, 2.8 and 1.7% percepts of the households who did adopt less than one package, adopted one package, adopted two packages and adopted all three packages of practices had participated in the non/off-farm income. At the 5% probability level, the chi-square tests show that there is a statistically significant mean difference between the four treatment levels in terms of access to non/off farm income.

Access to market information: According to the study findings, 61.8 percent of the total sample household accessed market information, while the remaining 38.2 percent did not. The comparison across different groups of climate-smart practices, about 7.2, 22.1, 21.7, and 10.8% of the households who did adopt less than one package practices, adopted one package, adopted two packages of practices, and adopted all three packages of practices accessed market information. At a 5% probability level, the chi-square tests show that there is a statistically significant mean difference in market information among the four treatment levels. This indicates that households that had access to market information adopted more climate-smart practices than households that did not.

Climate change information: According to the study findings, 66.6 percent of the total sample household accessed climate change information, while the remaining 33.4 percent did not. The comparison across different groups of climate-smart practices, about 6.3, 22.1, 24.1, and 14.1% of the households who did adopt less than one package, adopted one package, adopted two packages, and adopted all three packages of practices accessed market information. At the 1% probability level, the chi-square tests show that there was a statistically significant mean difference between the four treatment levels in terms of climate change information. This shows that households that accessed climate change information adopted more climate-smart practices than households that did not.

Perception about climate change: According to the study's findings, 64.4 percent of the total sample households accessed market information, while the remaining 35.6 percent did not. The result of the comparison across different groups of climate-smart practices indicated that about 7.2, 21, 23.6, and 12.6% of the households who did adopt less than one package practices, adopted one package practices, adopted two package practice and adopted all three package practices perceived existence of climate change. The chi-square tests show that there was a statistically significant mean difference in climate change perception among the four treatment levels at the 1% probability level. This shows that households that perceived climate change adopted more climate-smart practices than households that did not perceive climate change.

Econometric Results

Adoption decision of climate-smart agricultural practices

The multinomial logit model result indicated that the probability of adopting the packages of climate-smart agricultural practices was significantly influenced by the following eleven explanatory variables.

Table 3. Descriptive statistical results for sample households' categorical variables

Variables		Treatment level one		Treatment level two		Treatment level three		Treatment level four		Total		X^2 value
		Num	%	Num	%	num	%	Nu	%	Num	%	
Coop Memberships	No	41	8.9	101	21.9	68	14.8	27	5.9	237	51.4	17.7***
	Yes	29	6.3	65	14.1	79	17.1	51	11.1	224	48.6	
	Total	70	15.2	166	36	147	31.9	78	16.9	461	100	
Advise on land mgt	No	45	9.8	88	19.1	69	15	32	6.9	234	50.8	9.28***
	Yes	25	5.4	78	16.9	78	16.9	46	10	227	49.2	
	Total	70	15.2	166	36	147	31.9	78	16.9	461	100	
Training on irrigation	No	46	10	73	15.8	58	12.6	36	7.8	213	46.2	13.7***
	Yes	24	5.2	93	20.2	89	19.3	42	9.1	248	53.8	
	Total	70	15	166	36	147	31.9	78	16.9	461	100	
Access to training	No	41	8.9	67	14.5	46	10	14	3	168	36.4	29.1***
	Yes	29	6.3	99	21.5	101	21.9	64	13.9	293	63.6	
	Total	70	15	166	36	147	31.9	78	16.9	461	100	
Access to n/of income	No	55	11.9	138	29.9	134	29.1	70	15.2	397	86.1	8.551**
	Yes	15	3.3	28	6.1	13	2.8	8	1.7	64	13.9	
	Total	70	15.2	166	36	147	31.9	78	16.9	461	100	
Access to market info	No	37	8	64	13.9	47	10.2	28	6.1	176	38.2	8.983**
	Yes	33	7.2	102	22.1	100	21.7	50	10.8	285	61.8	
	Total	70	15.2	166	36	147	31.9	78	16.9	461	100	
Social status	No	48	10.4	94	20.4	77	16.7	36	7.8	255	55.3	8.253**
	Yes	22	4.8	72	15.6	70	15.2	42	9.1	206	44.7	
	Total	70	15.2	166	36	147	31.9	78	16.9	461	100	
Access to climate change info	No	41	8.9	64	13.9	36	7.8	13	2.8	154	33.4	36.9***
	Yes	29	6.3	102	22.1	111	24.1	65	14.1	307	66.6	
	Total	70	15.2	166	36	147	31.9	78	16.9	461	100	
Climate change perception	No	37	8	69	15	38	8.2	20	4.3	164	35.6	21.9***
	Yes	33	7.2	97	21	109	23.6	58	12.6	297	4.4	
	Total	70	15.2	166	36	147	31.9	78	16.9	461	100	

Sources: Own survey result, 2021. ** and *** means significant at 5% and 1% % respectively

Education of household head: At the 1% probability level, the education level of household heads was found to have a significant and positive effect on the probability of adopting two and three packages of climate-smart practices, respectively. The marginal effects of 0.024 and 0.014 for education level indicated that, after controlling for other variables, the probability of adopting two and three packages of climate-smart practices increased by 2.4 and 1.4 percent, respectively, as the education level of the household head increased by one year. According to Daniel and Muluget (2017) and Workneh (2015), education allows farmers to perceive, interpret, and respond to new information much faster than farmers with lower education levels. This finding was consistent with the findings of Ademe et al. (2019), Etim et al. (2019), and Luu et al. (2020).

Extension Contact: At 1% probability, extension contact was found to have a significant and positive effect on the probability of adopting one or three packages of climate-smart practices. The marginal effects of 0.032 and 0.027 for extension contact indicated that, while other factors remained constant, the likelihood of adopting one and three packages of climate-smart practices increased by 3.2 and 2.7 percent as extension contact increased by one advisory contact, respectively. Access to extension agents' services will raise farmers' awareness and provide them with more information about the importance of technology adoption (Akpan et al., 2012, Martey et al., 2014). This finding supports the findings of Teklewold et al. (2017), who discovered that it is the quality of the extension workers, not the extension contact that influences the adoption decision. This result was also consistent with the findings of Nhat et al. (2019), Etim et al. (2019), and Tekeste (2021).

Access to farmers' training: At a 1% probability level, this variable has a positive and significant relationship with the likelihood of implementing three packages of climate-smart practices. Keeping other factors constant, the marginal effects of 0.102 for extension contact indicated that the probability of adopting the three packages of climate-smart practices increased by 10.2 percent as the household accessed farmers training. Farmers who have access to training are more likely to obtain technological and climate-related information about crop and livestock production. This finding was consistent with those of Tesfaye (2017) and Zakarias et al (2020).

Training on land management: At a 1% probability level, this variable has a positive and significant relationship with the likelihood of adopting two packages of climate-smart practices. The marginal effects of 0.172 for access to training on land management practices indicated that, after controlling for other factors, the probability of adopting the two packages of climate-smart practices increased by 17.2 percent as the household accessed training on land management practices. This is because of technical knowledge and the advantages of land management practices for crop and livestock production. This finding was consistent with the findings of Tesfaye (2017) and Zakarias et al (2020)

Livestock holdings: At a 5% probability level, this variable has a positive and significant relationship with the likelihood of adopting all three packages of climate-smart practices. The marginal effects of 0.019 for livestock holding indicated that, when all other factors were held constant, the likelihood of adopting the three packages of climate-smart practices increased by 1.9 percent as household livestock holding increased by one tropical livestock unit. The presence of livestock in rural families reduces the amount of time, energy, and money spent on composting. This finding was consistent with the findings of (Ademe et al., (2019), Etim et al. (2019), and Luu et al. (2020).

Memberships of Coop: Participation of household heads in cooperatives was found to have a significant and positive effect on the probability of adopting two and three packages of climate-smart practices at the 1% probability level. The marginal effects of 0.147 and 0.097 for memberships indicated that, after controlling for other factors, the likelihood of adopting two and three packages of climate-smart practices increased by 14.7 and 9.7 percent, respectively, as the household participated in cooperative memberships. Being membership in at least one agricultural group, and trusting in fellow community members had a positive effect on the choice of climate-smart agricultural practices (Hailemariam et al., 2019). (Hailemariam et al., 2019). This finding was consistent with those of Etim et al. (2019) and Tekeste (2021).

Climate change information: At the 1% probability level, this variable was found to be positively related to the likelihood of adopting two and three packages of climate-smart practices, respectively. The marginal effects of 0.132, 0.175, and 0.073 for climate change information indicated that, while other factors remained constant, the probability of adopting one, two, or three packages of climate-smart practices increased by 13.2, 17.5, and 7.3 percent as the household accessed climate change information, respectively. This result agrees with the findings of (Nhat et al., 2019 and Ademe et al., 2019). Mulwa et al. (2017) and Issahaku and Abdulai (2019) discovered that exposing farmers to climate information increases their knowledge and awareness of climate change, as well as their climate-smart agriculture skills and practices.

Perception of climate change: At 5% and 1% probability levels, this variable has a positive and significant relationship with the likelihood of adopting one or two packages of climate-smart practices. The marginal effects of 0.130 and 0.167 for climate change perception indicated that, while other factors remained constant, the likelihood of adopting one and two packages of climate-smart practices decreased and increased by 13 and 16.7 percent, respectively, as the households perceived climate change. Farmers who are aware of climate change are more likely to adopt climate-friendly practices. The findings were consistent with those of Nyang'au et al (2021).

Market information: This variable has a positive and statistically significant relationship with the likelihood of implementing the two packages of climate-smart practices. Keeping other factors constant, the marginal effects of 0.093 for market information indicated that as the household head accessed market information, the probability of adopting the two packages of climate-smart practices increased by 9.3 percent. Farmers can obtain relevant information about climate-smart practices through market information. This result was consistent with the findings of Ademe et al. (2019), Etim et al. (2019), and Luu et al. (2020).

Distance to weather road: At a 5% probability level, this variable was found to be negatively and statistically significant with the probability of adopting the packages of climate-smart practices. The marginal effects of -0.004 and -0.002 for weather road distance imply that all else being equal, the likelihood of adopting two and three packages of climate-smart practices decreases by 0.4 and 0.2 percent as the distance to the weather road increases by one unit. This finding was consistent with those of Tekeste (2021), Nhat et al. (2019), Hailemariam et al. (2019), and Aryal et al. (2018). (2018).

Impact Evaluation Results

Impacts of the adoption of climate-smart practices

Current works of literature indicate that assessing the impact of climate-smart practices on nutrition security by taking climate-smart practices as a binary treatment is not enough in a context where there are heterogeneous adoption practices at the household level due to different factors. Hence, this study estimates the impact of climate-smart practices on-farm households' nutrition security. The GPS model (dose-response function) is estimated for climate-smart practices as a continuous dependent variable – which takes 1, 2, 3, and 4 values.

GPS is a non-parametric method used to correct for selection bias in a continuous treatment setting by comparing units that are similar in terms of their observable determinants of extents of time spent. Hence, it does not require control groups (Magrini et al*.,* 2014). The intensity of adopted climate-smart practices which is the "number of practices" that indicates a probability of adoption, which ranges from 0 to 1, was captured by dividing the number of adopted climate-smart practices of each household by the maximum number of adopted practices. Here missing important variables may create mismatching and biased estimators because the GPS does not directly account for the unobservable variables that may affect both households' nutrition security and the number of adopted climate-smart practices. Alike to PSM analysis, GPS focuses on the estimation of nutrition security impacts by using household households' dietary diversity scores.

Before estimating the generalized propensity score, it is required to group the numbers of adopted climate-smart practices into four clusters at 25%, 50%, and 75% following the procedure suggested by Kluve et al (2007). Four groups of comparable size were formed on the basis of the proportion of the numbers of adopted practices, i.e. group one (less than 0.25); group two (greater than 0.26 and less than 0.50), and group three (greater than 0.51 to 0.75) and group four (greater than 0.76 to 1). Group one presents the households with the relatively a lower number of adopted practices that consisting of 70 households; the second group indicates the household with medium numbers of adopted practices which contain 166 households and the third group indicates relatively high numbers of adopted practices that consists of 142 sample households and group four indicates relatively higher numbers of adopted practices that consists of 77 sample households.

Table 4. Determinants of the adoption of climate-smart agricultural practices

Variables	One package		Adopters of two packages		Adopters of all three packages	
	ME	SE	ME	SE	ME	SE
Family size	-0.016	0.011	0.006	0.010	0.010	0.006
Gender	-0.139**	0.066	0.066	0.060	0.034	0.035
Age	0.001	0.002	-0.002	0.002	0.001	0.001
Of/n income	0.130*	0.077	-0.108	0.068	-0.042	0.041
Education	-0.026***	0.008	0.024***	0.007	0.014***	0.004
Extension	-0.032***	0.011	0.011	0.010	0.027***	0.006
Membership	-0.221***	0.051	0.147***	0.049	0.097***	0.032
Social status	-0.013	0.055	0.039	0.051	0.042	0.032
Training	-0.057	0.056	0.026	0.053	0.102***	0.031
Water train	-0.063	0.054	0.172***	0.049	0.001	0.031
Livestock	0.003	0.014	-0.004	0.013	0.019**	0.008
C.change ino	-0.132**	0.056	0.175***	0.050	0.073**	0.031
Mkt info	-0.057	0.055	0.093*	0.051	0.027	0.031
Perception	-0.130**	0.055	0.167***	0.050	0.016	0.032
W.road dist	0.004*	0.002	-0.004**	0.002	-0.002*	0.001
Land area	-0.018	0.084	0.004	0.081	0.058	0.038

LR chi2(48) = 245.99; Number of obs = 461; Prob > chi2 = 0.0000; Log likelihood = -481.69957; Pseudo R2 = 0.2034; Sources: Own survey result, 2022. *** , **and * means significant at 1%,5% and 10% probability levels respectively

Table 5. Distribution of estimated generalized propensity score

Variable	Mean	Std. Dev.	Min	Max
All sample	.2821324	.2024226	.0045064	.7307587
25%	.2821324	.2024226	.0045064	.7307587
50&	.5882531	.1603005	.0775026	.739016
75%	.5848511	.1702425	.0478257	.7390129
100%	.4624792	.200764	.0455838	.7372773

Sources: Own survey result, 2022.

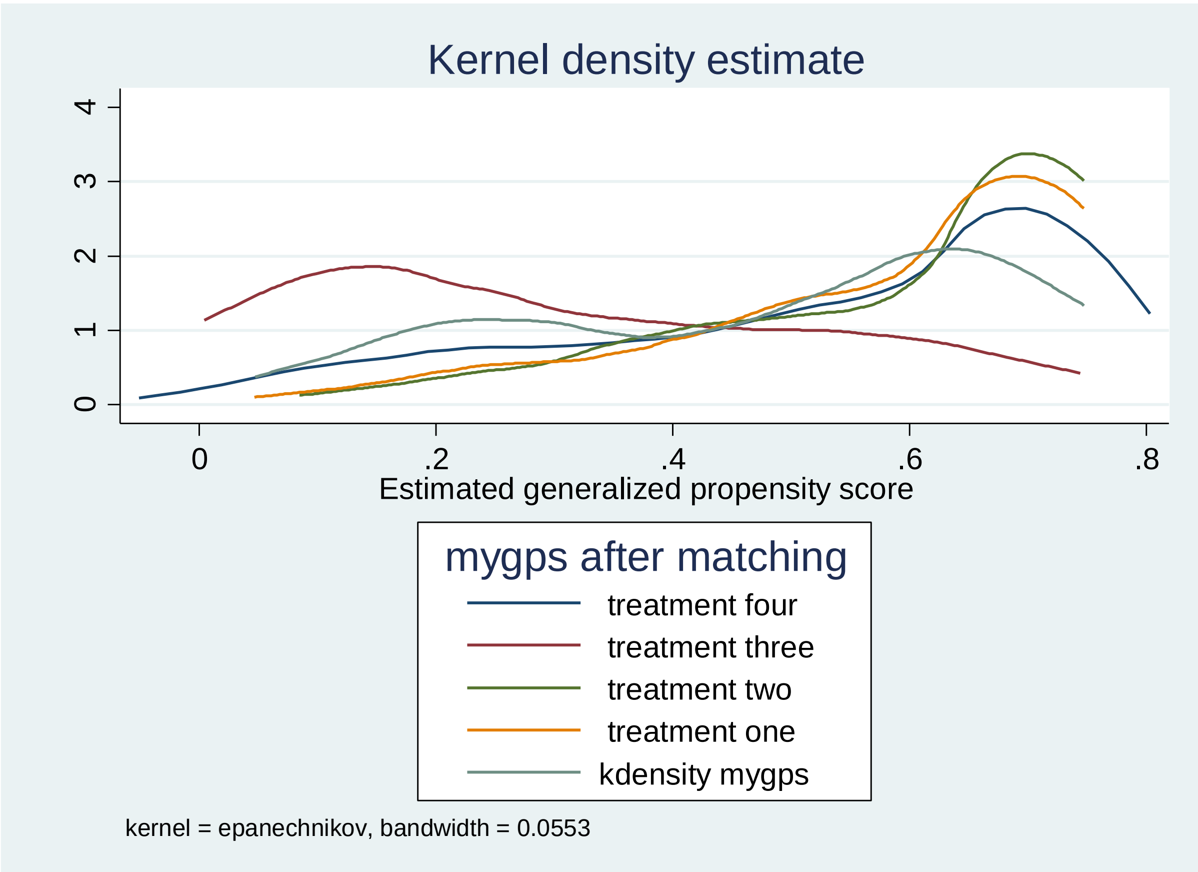

Figure 1. Kernel density of GPS-score with common (off) support regions
Sources: Own computational result, 2022.

The common support region is the area that contains the minimum and maximum propensity scores of groups one, two, three, and four households, respectively. It requires deleting all observations whose propensity scores are smaller than the minimum and larger than the maximum of all groups, respectively (Caliendo and Kopeinig, 2005).

Consequently, the common support region would then lie between 0.0478257 and 0.7307587 by discarding 9 households from below and 53 households from above, and a total of 399 households were found on the common support region for GPS estimation. Figure 1 below portrays the distribution of the treated households with respect to the estimated GPS scores and the household on the common support. The kernel distribution shows that most of the households are found on the left side of the distribution, which suggests a lower proportion of probability of adopting climate-smart practices.

Test for covariate balance

The main purpose of estimating the GP score is to check the balancing of the covariates and not to obtain a precise prediction of determinants of the f probability of adopting climate-smart practices. Accordingly, testing of balancing property by comparing the covariates across groups with and without GPS correction was done. Finally, strong evidence was found that showed the satisfaction of the balancing property at a level lower than 1% statistical error after GPS adjustment.

Tables 6 and 7 present the result of the standard two-sided t-test of covariate balance for each group before and after GPS adjustment. The results point out that the covariate balance has improved by making the adjustment for the GPS. The equality of mean across groups without GPS adjustment indicated as there were five covariates with a significant mean difference, whereas after GPS correction it was reduced to two significant mean difference variables.

Table 6. Test for covariate balance before GPS adjustment

Variable	[<0.25]			[0.26, 0.50]			[0.51, 0.75]			[0.76, 1]		
	MD	SD	t-value	MD	SD	t-value	MD	SD	t-value	MD	SD	t-value
Famsize	0.12	0.44	0.26	0.15	0.25	0.60	0.11	0.27	0.42	-0.20	0.41	-0.47
GEND	-0.05	0.07	-0.64	0.06	0.04	1.59	0.01	0.04	0.23	-0.07	0.07	-1.12
age1	0.18	1.96	0.09	0.28	1.07	0.26	0.69	1.17	0.59	-1.87	1.79	-1.04
OFIN	0.07	0.05	1.36	-0.02	0.03	-0.55	0.04	0.04	0.97	0.05	0.06	0.83
edu1	-0.24	0.57	-0.41	0.20	0.30	0.68	-0.61	0.31	-2.00	0.25	0.48	0.53
NEXT	-0.15	0.46	-0.33	0.18	0.25	0.70	-0.14	0.28	-0.53	0.07	0.41	0.18
SFS	0.14	0.09	1.63	-0.03	0.05	-0.62	0.00	0.05	0.08	-0.02	0.08	-0.31
SSH	0.02	0.09	0.23	-0.03	0.05	-0.63	0.02	0.05	0.43	-0.10	0.08	-1.32
TLU	4.23	13.47	0.31	-2.85	7.28	-0.39	9.55	7.77	1.23	-2.14	11.68	-0.18
TRIN	0.06	0.07	.78	-0.05	0.04	-1.19	0.04	0.05	0.76	-0.10	0.08	-1.28
DAIR	0.05	0.08	0.65	-0.01	0.05	-0.28	0.03	0.05	0.57	-0.07	0.08	-0.97
LSHH	0.59	0.34	1.72	-0.32	0.19	-1.70	0.18	0.20	0.87	-0.34	0.30	-1.13
CCINFO	0.07	0.06	1.17	0.01	0.04	0.37	-0.09	0.04	-2.11	-0.07	0.07	-1.00
PCC	-0.05	0.07	-0.68	0.05	0.04	1.25	-0.08	0.05	-1.65	0.00	0.08	0.02
DWR	1.91	2.54	0.75	-1.32	1.43	-0.93	-1.71	1.54	-1.11	0.63	2.30	0.28
Cultland	-0.05	0.08	-0.55	0.08	0.05	1.54	0.04	0.06	0.75	0.01	0.09	0.15

Source: Own computation results, 2022.

Table 7. Balancing Test after Gps Adjustment

Variable	[<0.25]			[0.26 0.50]			[0.51 0.75]			[0.76, 1]		
	MD	SD	t-value	MD	SD	t-value	MD	SD	t-value	MD	SD	t-value
Famsize	0.16	0.45	0.35	0.19	0.25	0.74	0.06	0.27	0.23	-0.17	0.41	-0.41
GEND	-0.05	0.07	-0.66	0.05	0.04	1.32	0.02	0.04	0.40	-0.07	0.07	-0.98
age1	0.85	1.98	0.43	0.22	1.11	0.19	0.65	1.18	0.55	-1.63	1.79	-0.91
OFIN	0.07	0.06	1.18	-0.03	0.03	-1.00	0.05	0.04	1.23	0.05	0.06	0.82
edu1	0.08	0.59	0.14	0.22	0.31	0.70	-0.65	0.32	-2.03	0.34	0.48	0.71
NEXT	-0.24	0.48	-0.49	0.26	0.27	0.96	-0.21	0.27	-0.78	0.16	0.41	0.39
SFS	0.13	0.09	1.55	-0.03	0.05	-0.68	0.01	0.05	0.14	-0.01	0.08	-0.16
SSH	0.03	0.09	0.38	-0.04	0.05	-0.83	0.02	0.05	0.38	-0.10	0.08	-1.32
TLU	6.39	13.85	0.46	-2.20	7.60	-0.29	9.10	7.83	1.16	-1.64	11.75	-0.14
TRIN	0.10	0.08	1.30	-0.05	0.04	-1.12	0.03	0.05	0.71	-0.09	0.08	-1.21
DAIR	0.05	0.09	0.64	0.01	0.05	0.20	0.00	0.05	0.06	-0.08	0.08	-1.09
LSHH	0.64	0.35	1.55	-0.36	0.19	-1.57	0.14	0.20	0.71	-0.32	0.30	-1.05
CCINFO	0.07	0.06	1.16	0.01	0.04	0.24	-0.08	0.04	-1.92	-0.08	0.07	-1.02
PCC	-0.03	0.07	-0.41	0.05	0.04	1.21	-0.07	0.05	-1.52	0.00	0.08	-0.04
DWR	1.77	2.61	0.68	-1.52	1.47	-1.04	-1.56	1.56	-1.00	0.45	2.32	0.19
Cultland	-0.03	0.08	-0.38	0.08	0.05	1.54	0.04	0.06	0.74	0.01	0.09	0.13

Source: Own computation results, 2022.

Table 8. Impacts of climate-smart practices on household level nutrition quality

Treatment level	Dose response	Robust S.E	Treatment effect	Robust S.E
0.50	.1253034	.0849779	0.1551987**	0.0767776
0.75	.3273202***	.0942655	0.3711003***	0.0894554
1	.6162376***	.1188418	0.6937098***	0.1289761

Source: own survey result, 2022 *** means significant at 1% probability levels

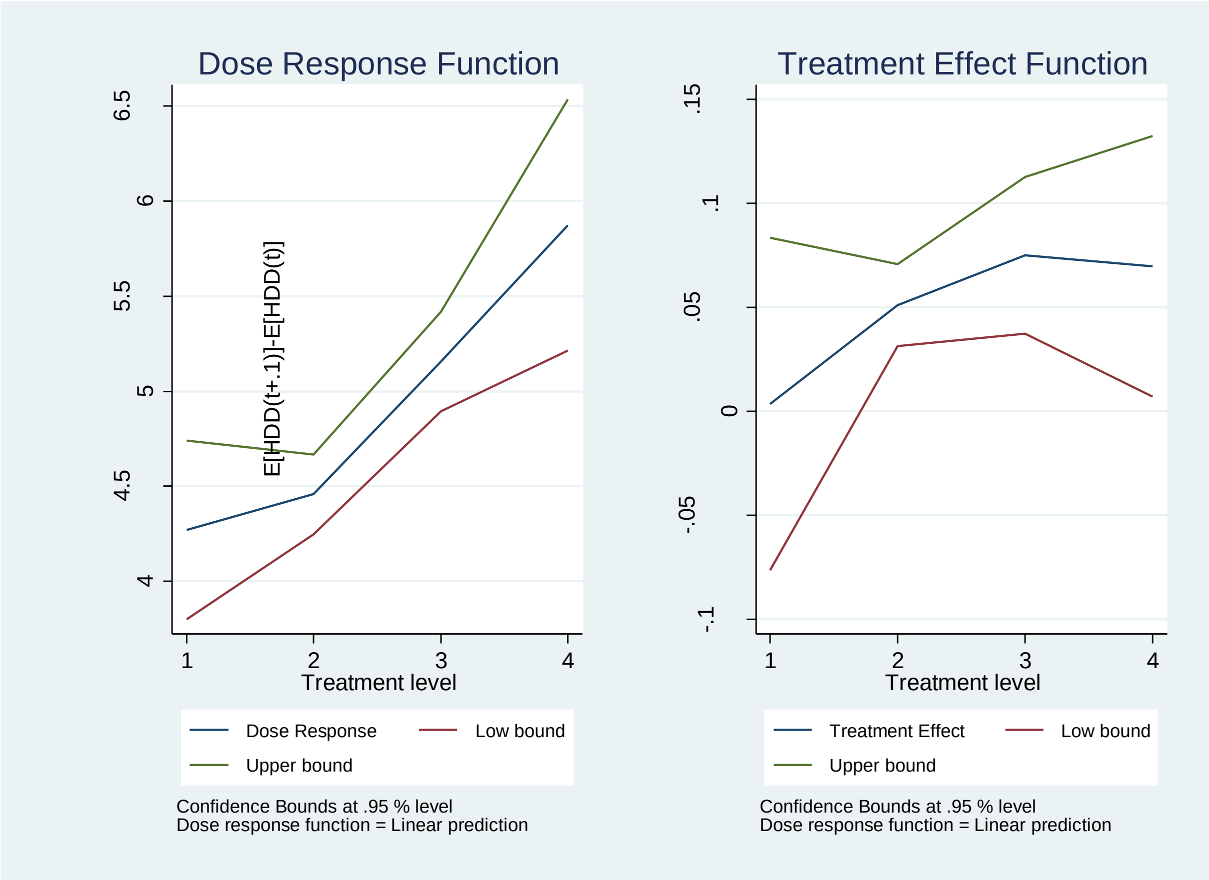

Figure 2. Dose-response and treatment effect of climate-smart practices on nutrition quality

Results of the Dose-Response Function

The final step of GPS, estimating the GPS-adjusted dose-response function was undertaken to evaluate the impact of climate-smart practices on household nutrition status. Here the estimated GPS was adjusted by inverse probability weight to reduce the selection bias. The study used household dietary diversity consumed over the last 24hours to measure nutritional status.

Impact of climate-smart practices on-farm household nutritional status

As Table 8 illustrates, as the adopted number of climate-smart practices increased from a treatment level of 25% to 50% the farm households' nutritional status increased by 16%. Similarly, as the number of adopted practices increases further to treatment levels of 75% and 100% the farm household nutritional status also increases by 37% and 69% over that less number of adopter households and is significant at a 1% statistical probability level. Similarly, Figure 2 confirms the positive relation of climate-smart practices with the average effect (dose-response) on the farm households' nutritional status of the farm households of eastern Oromia, Ethiopia.

Conclusion and Recommendations

Conclusion

This study was carried out to examine the impact of climate-smart agricultural practices on-farm households' nutrition security in the districts of East Hararghe Zone Oromia, Ethiopia. For this study, both primary and secondary data were used. The primary data source was gathered from 461 sample households using semi-structured questionnaires. In doing so, generalized propensity score matching was used. The multinomial logit model was employed to model climate-smart practices. The GPS model was estimated for climate-smart practices as a continuous dependent variable to estimate the impacts of continuous outcome variables.

The estimated results of a multinomial logit model show that the probability of adopting climate-smart agricultural practices was significantly influenced by the head's education level, extension contact, livestock holding, cooperative membership, market information, traniing on land management, climate change information, access to training, climate change perception, and weather road distance.

According to the impact evaluation results, implementing one package of climate-smart practices improves household nutritional status by 16%. Similarly, adopting two and three packages of climate-smart practices improves household nutritional status by 37% and 76%, respectively, compared to less than one package adopter households, and this difference is statistically significant at the 1% statistical probability level.

Recommendations

The large packages of climate-smart management practices had the greatest impact on food security. Policy interventions to increase agricultural productivity and reduce farmers risk exposure should consider alleviating farmers' difficulties in adopting packages crops and livestock practices. Enhancing quality climate change information accessible to smallholder farmers will increase their adoption of integrated practices. In fact that effective adoption of climate-smart practices requires some knowledge and skills, improving farmers' education, training and accessing extension services should be some of the policy measures that will facilitate adoption. The study also suggest enhancing smallholder farmers awareness on climate change and land degradation and expansion of rural social capitals like farmers' cooperative, farmer groups. Improving the smallholder farmers' accessibility to information systems both on climate change and markets suggested. Therefore this is an encouraging policy implication for policymakers to give due attention to the identified variables.

Conflicts of Interest

There are no conflicts of interest related to the authorship and publication of this research manuscript.

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