

Farmers' technology adoption decision and use intensity in the agricultural sector: Case of Masha Woreda (Double Hurdle Model)

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Abstract

This research aimed to critically analyze the determinants of technology adoption and the use intensity by small farm households in the study area (Masha District). Six kebeles were randomly selected from the district, and 251 sample households were proportionally and randomly identified from the selected kebeles. The data collected from the sample households have been analyzed using both descriptive as well as inferential analysis. For inferential analysis, the Double Hurdle Model was adopted to estimate the technology adoption decision as well as use intensity of small farm households in the study area. The findings show that technology adoption decisions were associated with household-specific characteristics such as sex, education, extension, and family size, increasing the likelihood of technology adoption. In contrast, the age of the household head has a negative contribution to it. On the other hand, institutional factors such as access to extension service and access to credit facilities have a significant impact where the latter has contributed negatively to the farmers' decision regarding technology adoption.

Keywords: *Agricultural, Double-Hurdle, Masha Woreda, Technology adoption*

JEL Classification: Q12, Q16

INTRODUCTION

The African Union report recognized that there had been little improvement in agricultural production and factor productivity in Africa (New Partnership for Africa's Development, 2014). Though Agricultural growth in Africa is generally achieved by land-intensive production and by mobilizing a larger agricultural labor force, the two production factors (labor and land) remain stagnant in terms of productivity. On average, cereal yields are 50 percent less than those obtained in Asia per a given plot. In the last three decades, Africa's population has doubled, which implies the continent now has more mouths to feed and less per-capita land to cultivate. However, agricultural output has been unable to keep growing side by side. It resulted in food self-insufficiency, which puts the continent into a net importer of cereals from the rest of the world.

The dimension of African's agricultural growth has been recognized to be different from Asia and South America. Through intensification, agricultural growth was registered in Asia. Simultaneously, growth in South America was driven largely by improvements in labor productivity resulting from mechanization. Opposed to these, area expansion was responsible for increasing production in the agricultural sector and

the predominant intensification of cropping systems in sub-Saharan countries (New Partnership for Africa's Development, 2014; Brink & Eva, 2009). As SSA is generally endowed with abundant land and most of this arable land is still unexploited, area expansion in the decades to come may not seem problematic. But since in rural SSA, there is an uneven distribution of land. A considerable share of its rural population resides in smallholder farming areas densely populated and face land shortages (OECD/FAO, 2016; Jayne & Tschirley, 2014).

In countries with constrained land size, area-driven growth may come at the expense of fallows. The rapid growth of rural populations and associated land would result in continuous cropping in many African countries, with fallows largely disappearing in densely populated areas. The repeatedly cultivated plot of land would remain productive only when appropriate technologies such as fertilizers, improved seed varieties, soil amendment practices, and other related investments are promoted and coupled with continued teaching and awareness creation to maintain and improve soil quality (Stoorvogel & Smaling, 1990; Drechsel et al., 2001; Tittonell & Giller, 2012). To re-state the above arguments, if Africa needs to attain food self-sufficiency and sustainable development, it needs to improve its technology adoption practice. Thus, those backward cultivation practices should progressively be transformed into relatively modern methods, while any attempt to boost production and productivity should be environmentally friendly.

The agriculture sector in the Ethiopian economy is the largest contributor to Gross Domestic Production (GDP), the lion's share contributor in employs generation (about 80% of the population), and the main income-generating sector for the majority of the rural population as well as a prominent contributor in foreign currency generation. Cereals, pulses, and oilseeds are the major crops grown in Ethiopia accounted for about 42% of the total agricultural GDP.

METHODS

The study area

Masha Woreda is one of the three woredas in the Sheka Zone of the South Nation Nationalities and Peoples Region (SNNPR). Masha Woreda shares borders on the South by the Andracha Woreda on the West and North by Oromia regional state and on the East by Keffa zone (CSA, 2007).

Concerning demographic characteristics, Masha Woreda has a total population of 40810, of whom 20,116 are men and 20,694 women. About 6787 or 16.63% of its population is urban dwellers. Religion wise majority of the inhabitants (56.5%) were Protestant followers, followed by Ethiopian Orthodox Christian (32.82%), while the remaining 7.15% practiced traditional belief and 1.56% were Muslim (Census 2007 Tables). It receives a mean annual rainfall of about 2000mm, and its mean monthly temperature ranges between 18 – 21°C. The woreda's total area is 217,527.15 hectares (CSA, 2007; Benyam & Fayera, 2018).

Data types, sources, and methods of data collection

This study used the data both from primary and secondary sources. Primary data was collected directly from randomly selected farmers using a structured questionnaire. In contrast, the secondary data was obtained from different published, and unpublished government reports, especially from Sheka Zone agricultural and rural development office. The secondary data is used for triangulation purposes to validate the primary data obtained from the farmers. Data is collected through group discussion with concerned parties like Woreda agriculture and natural resource management offices, site supervisor, and key informant interview with Development agents.

Sampling techniques and sample size

Regarding the method used to draw the sample units from the target population (farmers in Masha Woreda), a multi-stage sampling technique was adopted. In the first stage, Sheka Zone is purposively selected based on the observed degree of reluctance in technology adoption by the farm households. From the three woredas in the zone, Masha Woreda is randomly selected in the second stage. In stage three, out of 19 kebeles in the woreda, five kebeles (Yina, Degelle, Wello, Ateso, and Gatimo) are randomly selected, and the final stage (stage 4) deals with selecting a total of 251 farm households proportionally from the kebeles chosen as a representative sample. The final questionnaire was distributed to these farm households. These 5 kebeles have 2,613 farm households, and the sample size is determined by using the statistical formula forwarded by Yemane (1967) by choosing the precision level to be 7 percent.

Table 1. Distribution of sample households in selected kebeles

Kebeles	Total farm household	Sample size
Yina	463	45
Degele	590	57
Wello	710	68
Ateso	450	43
Gatimo	400	38
Total	2613	251

Data analysis

The researcher used both descriptive and inferential analysis methods to answer the research question and associated objectives mentioned above regarding the data analysis techniques. The descriptive analysis makes use of the usual methods such as computing mean and frequency distributions using tables and graphs basically to support the inferential analysis. In the inferential analysis, the Double Hurdle model is used to estimate factors influencing the farmers' decision and intensity to adopt agricultural technologies in the study area.

Most adoption studies have used the Tobit model to estimate adoption relationships with limited dependent variables. However, the Tobit model is very restrictive for statistical reasons, making this model unsuitable for certain empirical applications. The Tobit model is also statistically restrictive because it assumes that the same set of variables determine both the probability of non-zero adoption and intensity use level. That is why recent empirical studies have shown the Tobit model's inadequacy in cross-sectional analysis, stressing alternative approaches' relevance.

Therefore, this study's appropriate model is the Double-Hurdle model initiated by Cragg (1971). The DH model assumes that farm households face two hurdles in any agricultural decision-making process, such as participation decision (the decision to adopt) followed by intensity (the production level decision). Hence, the Double Hurdle model allows for the simultaneous consideration of the determinants of technology adoption decision of the HHs and the determinants of use intensity through two separate stages. The Double Hurdle Model uses both probit and truncated regression at different stages. The first stage involves running a probit regression to determine factors affecting farm households' decision to participate in technology adoption. While in the second stage, truncated regression is used to analyze the intensity of adoption on the individuals who passed the first Hurdle (i.e on those participating in the technology market).

The Double Hurdle model helps a subset of the data pile up at some value without causing bias in estimating the continuous dependent variable's determinants in the second stage. Hence, it can be possible to obtain all the data in the remaining sample for

the participants. Thus, there are no restrictions regarding explanatory variables in each decision in the double Hurdle model. Stated differently, it is possible to separately analyze the determinants of adoption decisions and the extent of adoption decisions. Due to this separability, the estimates of production decisions can be obtained by using probit regression. The level of adoption decision can be analyzed using a truncated regression. According to Burke, the separability in estimation may not be mistaken.

The general form of the Double Hurdle model employed for analyzing farm households' decision for adoption and intensity of adoption of technologies in term of area coverage in hectare based:

$$D_i = z'\gamma + e_i \dots\dots\dots (1)$$

$$y_i^* = x'\beta + \zeta_i \dots\dots\dots (2)$$

$$y_i = \begin{cases} y_i^* & \text{if } z'\gamma + \varepsilon_i > 0 \text{ and } x'\beta + \zeta_i > 0 \\ 0 & \text{if } z'\gamma + \varepsilon_i \leq 0 \text{ and } x'\beta + \zeta_i > 0 \text{ or} \\ & \text{if } z'\gamma + \varepsilon_i > 0 \text{ and } x'\beta + \zeta_i \leq 0 \text{ or} \\ & \text{if } z'\gamma + \varepsilon_i \leq 0 \text{ and } x'\beta + \zeta_i \leq 0 \end{cases} \dots\dots\dots (3)$$

where, $(\varepsilon, \zeta) \sim BVN(0, \Sigma), \Sigma = \begin{pmatrix} 1 & \sigma\rho \\ \sigma\rho & \sigma \end{pmatrix}$

Z and x respectively are the set of explanatory variables that enter the first and second hurdles. Di represents a latent variable indicating the household's participation decision, while Y* is a latent variable and measures the intensity of adoption. Lastly, y indicates the actual (observable) amount of intensity which can only be observed if the household is a potential adopter (D>0) as well as the actual adopter (Y*>0).

The sample version of the likelihood function for Equation (3) can be given as:

$$L = \prod_0 1 - F(\varepsilon > -Z\gamma, \zeta > -x\beta) \prod_+ F(\varepsilon > -Z\gamma, \zeta > -x\beta) f(\zeta | \varepsilon > -Z\gamma, \zeta > -x\beta) \dots\dots\dots (4)$$

Where F(.) and f(.) indicating cumulative distribution function (CDF) and probability density function (PDF), respectively.

Since the error terms in the two decisions follow a bivariate normal distribution, their distribution can be shown as

$$f(\zeta | \varepsilon > -Z\gamma, \zeta > -x\beta) = \frac{\int_{-z\gamma}^{\infty} f(\zeta) f(\varepsilon | \zeta) d\zeta}{\int_{-z\gamma}^{\infty} \int_{-x\beta}^{\infty} f(\varepsilon, \zeta) d\varepsilon d\zeta} = \frac{f(\zeta) \int_{-z\gamma}^{\infty} f(\varepsilon | \zeta) d\varepsilon}{\Phi(z\gamma, x\beta / \sigma, \rho)} \dots\dots\dots (5)$$

As the conditional distribution of Di conditional on Y=Y* follows a normal distribution with mean $Z\gamma + \sigma\rho^{-1}(y_i - x\beta)$ and variance of $1 - \rho^2$, the Equation (5) can be further simplified as:

$$f(\zeta | \varepsilon > -Z\gamma, \zeta > -x\beta) = \frac{\Phi\{(z\gamma + \rho/\sigma(y - x\beta))/\sqrt{1 - \rho^2}\} \frac{1}{\sigma} \phi(y - x\beta)/\sigma}{\Phi(z\gamma, x\beta / \sigma, \rho)} \dots\dots\dots (6)$$

Hence the above sample likelihood function becomes;

$$L = \prod_0 1 - \Phi(Z\gamma, x\beta / \sigma, \rho) \prod_+ (\Phi\{(z\gamma + \rho/\sigma(y - x\beta))/\sqrt{1 - \rho^2}\} \frac{1}{\sigma} \phi(y - x\beta)/\sigma) \dots\dots\dots (7)$$

Given the Equation (7), whether to adopt Cragg's Double Hurdle model or a simple Tobit model depends on its value ρ and γ . That is if $\rho = 0$, the above equation gives the likelihood function for Cragg's model. On the other hand, if $\gamma = \beta/\sigma$, the appropriate model turns out to be Tobit. Whether the two hurdles (whether to adopt and how much to adopt) are independent can be tested using the likelihood ratio test

The general form of the Double-Hurdle Model employed for analyzing for

smallholders farm households' decision for adoption and intensity production of technologies in term of area coverage in hectare based.

Measurement and definitions of variables for adoption of the dependent variables of the Double-Hurdle Model. The model's dependent variable takes a censored value depending on the farmers' decision to adopt or not adopt the improved technologies and the intensity of adoption if they decide to adopt the technology. In this case, it indicates the amount of fertilizer per hectare cultivated in the year 2018. A farmer is said to be an adopter if he/she uses inorganic fertilizer on his/her farmland.

The Independent variables and their definitions in the Double Hurdle Model: Adoption literature provide a long list of factors that may influence agricultural technologies' adoption. Generally, farmers' decision to use improved agricultural technologies and the intensity of the use in a given period is hypothesized to be influenced by a combined effect of various factors such as farm household-specific characteristics, socioeconomic and physical environments in which farmers operate.

Based on the previous study done on the adoption of improved crop technologies and the experience of the study area's farming system, farm household-specific characteristics' such as marital status and age of the household head, education level of the household head, religion of the farmer are considered. As institutional factors, access to roads, access to credit facilities, and extension services are considered. Additionally, variables such as previous output level and farm size were selected as potential variables hypothesized to affect the adoption decision and extent of adoption.

RESULTS AND DISCUSSION

Needless to state, the agriculture sector in Ethiopia is and continues to be the base of the country's economy, accounting for more than one-third of gross domestic product (GDP) and more than 80 percent of exports, as well as total employment (NBE, 2018). Ethiopia's agriculture is highly exposed to natural phenomena and beleaguered by periodic drought, soil degradation caused by overgrazing, deforestation, and poor infrastructure. Yet agriculture is the country's most promising resource and a possible means for self-sufficiency in food.

The controversy of Ethiopia's resource structure (labor and land abundance) and self insufficiency in food remains unsolved regardless of policy directions by the government. The country has continued to import food items from the rest of the world, though 80 percent of the labor force has been engaging in the sector,

Descriptive analysis

As shown from Table 2, out of 251 sampled farm households, 166 individuals are agricultural technology adopters, and the remaining 85 individuals are non-users. Average outputs produced by technology users are about 82.38 quintals per hectare with a standard deviation of 53.82. Those who didn't use any technology on average produce approximately 26.95 quintals per hectare with an associated deviation of 21.59.

Table 2. Mean output by adoption status

Adoption	Freq.	Mean output	Std. deviation
Non participant	85	26.95	21.59
Participant	166	82.38	53.82
Combined	251	63.61	52.53
Difference	-	-55.43	-
Ho: mean diff = 0 .00		Prob = 0.000	

The mean productivity difference between the two groups is about 55.43 quintal per hectare, and this difference is statistically meaningful, as can be checked using a t-test. The non-users can be treated as the ones who are less ready to take the risk (risk-

averse farmers) as the mean deviation for the users is relatively higher as compared to the mean deviation of the output for non-users. The argument is in line with the fact that technology in any sector is riskier and more return.

Farmers are reluctant to practice new technology on their farms as they are afraid to take the risk because they want to be safe and avoid failure. But those who are constantly involved in risk-taking activities have the probability of becoming successful. Therefore, the risk-return trade-off associated with new technology adoption can be considered one factor behind some farmers' reluctance to adopt agricultural technologies on their farmland.

Across their educational attainment, farmers' technology use improves. That means farmers with higher educational attainment are ready to use agricultural technology than individuals with lower educational backgrounds. On the other hand, there is no evidence that education improves agricultural productivity for non-users of technology.

Illiterate non-adopters, on average, produce 34.36 quintals per hectare, and this output declines to 33 quintals for 1-4th grand individuals. As education increases, the mean output level of the non-adopters is almost constant with no major change. Opposed to non-adopters, technology adopters' average productivity improves with educational attainment. Illiterate farmers' average productivity is about 61.46 quintal per hectare, and this figure rises to 94.86 quintals per hectare for grand 12 and above.

Table 3. Average output distribution across various attributes

Education	Non-Adopter		Adopter	
	freq	Mean output	Freq.	Mean output
Illiterate	25	34.36	13	61.46
1-4	4	33	7	90.14
5-8	23	21.13	38	58.87
9-12	27	24.30	59	90.86
>12	6	26.33	49	94.86
Total	85	26.95	166	8238
Marital status				
Single	3	35	3	94
Married	77	26.92	148	85.12
Divorced	4	20.75	12	53.42
Widowed	1	30	3	51.67
Extension Access				
Yes	36	26.69	146	89.67
No	49	27.14	20	92.20
Credit Access				
No	40	30.85	63	72.17
Yes	45	23.49	103	88.63
Sex				
Female	6	19.67	10	46.10
Male	79	27.51	156	84.71

In terms of marital status, single farmers are the most productive group with an average output of 35 quintals per hectare for non-adopters and 94 quintals per hectare for adopters, followed by married farmers (whose average output ranges about 27 quintals for non-users and 85 quintals for users).

On the other hand, access to extension services improves the decision to participate in the technology adoption. In contrast, it doesn't significantly affect the average productivity for both adopters and non-adopters. As shown from Table 3, out of 85 non-adopter farmers, 58% of farmers do not have access to extension, whereas only

42% have access to extension services. In terms of the average productivity of non-adopters, the one who has access to extension service produces 27 quintals per hectare. This figure is almost similar to the farmers who do not have access to extension service.

On the other hand, out of the total technology adopters (166 farmers), 88% of farmers have access to extension service, and the remaining 12% of farmers have not. In terms of their average productivity, farmers who adopt technology and have access to extension service on average produce 90 quintals per hectare. Farmers with no access to an extension on average produce 92 quintals per hectare.

Regarding farmers' access to credit facilities, out of the sampled households, 41% of farm households do not have access to credit facilities, whereas 59% have access to credit. In terms of technology use, out of the non-users, 47% have no access, whereas 53% have access to credit facilities. On the other side, 38% have no access to credit among the technology users, and 62% have access to it. One can conclude from the above figure that access to credit is not the inessential determinants of technology adoption decision in the study area as about 47 % of non-adopters have access to it and still decides not to adopt the technology on their farmland

The adoption decision of farm households are split gender-wise in Table 3, and accordingly, 6.37% of the farm households are female-headed. The remaining 93.63% of farm households are male-headed. Out of the total female-headed farm households, 37.5% are non-adopters, and 62.5% engage in technology adoption. In terms of average productivity, male-headed households are more productive than female-headed households in the study (27.51 vis-à-vis 19.67 quintals for non-adopters and 84.71 vis-à-vis 46.1 quintals per hectare for adopters).

Inferential analysis (Double Hurdle Model)

In this part, the data is estimated using the DH model after taking care of all the prior tests on the collected and managed data. To address the researcher's objective of measuring the decision and use intensity of technology in the study area, the researcher chooses the Double Hurdle model because of its superiority, as discussed in the previous sections.

The Double Hurdle estimates are reported in Table 4. Accordingly, the overall significance of the model is checked given the likelihood ratio test statistics (LR $\chi^2(6) = 104.52$) and its respective p-value ($P > \chi^2=0.00$), which indicates the model is statistically meaningful. The goodness of fit, 52 percent of the dependent variable's deviation, is explained by the model (Pseudo $R^2=0.52$).

Table 4. Determinants of technology adoption (DH Model)

Agri_Tech	1 st Hurdle		2 nd Hurdle	
	Coefficients	P-values	Coefficients	P-values
Sex	0.48**	0.02	0.07	0.86
Education	0.04	0.35	0.07**	0.01
Extension	0.39**	0.01	1.11*	0.00
Age	-0.01*	0.00	-0.01	0.75
Family Szs	0.07*	0.00	0.01	0.74
Credit	-0.21**	0.02	-	-
Farm Sz	-0.03	0.17	0.07	0.14
Ln_sigma	-0.60	0.92	0.00	
/sigma	0.55	0.03	-	
N = 251	LR $\chi^2(6) = 104.52$	$P > \chi^2=0.00$	pseudo $R^2=0.52$	

* Significant at 1% level, ** significant at 5% level, *** significant at 10% level. Significance levels are based on the significance levels of the underlying marginal effects.

Sex of the household doesn't significantly affect farm households' decision to adopt the agricultural technologies, whereas once the household decides to adopt the technology, to what extent it has to be used is partially determined by the sex of the household. Accordingly, compared to female-headed households, male-headed households have a higher likelihood of participating in technology adoption. On the other hand, the household's education level is estimated to affect farm households' decision to participate in the technology market. It doesn't have any significant impact on the intensity of technology use in the study area. Farm households with better educational attainment have a relatively higher probability of participating in the technology market, while the variable is statistically significant at 5 percent.

Other variables such as extension access and family size positively impact the use intensity of agricultural technology in the study area. In contrast, the household head and credit access age have a negative and significant impact on the use intensity of the technology in the study area. All variables but access to credit have their respective expected sign, and access to credit is negative, against the theory and intuition.

Empirically access to extension services is among the key determinants of technology adoption. Extension agents have a critical role in providing information to farmers about the access and the benefits of new technology and giving guidance on the farmland how and how much to use. Extension agents are assumed to serve as a bridge between technology innovators (research and development) and users of the same technology through facilitating information flow and reducing the transaction cost (Genius et al., 2010), (Mwangi & Kariuki, 2015). Apart from this finding, access to credit has been believed to facilitate technology adoption (Mohamed & Temu, 2008) by promoting the adoption of risky technologies by lessening the financial constraint of farm households and boosting household-risk bearing ability (Simtowe & Zeller, 2006).

Land size owned by the farm households is generally believed to play a significant role in the farmers' technology adoption decision (Mwangi & Kariuki, 2015). Many researchers have argued that land size is one determinant of technology adoption as land size can influence other factors determining the adoption decision (Lavison 2013).

Opposed to many studies that have reported a positive impact of farm size and technology adoption (Kasenge, 1998; Gabre-Madhin & Haggblade, 2001 Ahmed, 2004; Uaiene *et al.*, 2009) this study has revealed no significant impact of land size on farmers' adoption decisions as well as the intensity of adoption. This finding is generally against the arguments of previous researches that farmers who have ownership of large farm sizes are likely to use new technology as they can be able to put aside part of their land to practice a new technology to avoid crop failure if used in their entire land. On the other hand, large farm size facilitates the use of other farm technologies (such as tractors) as it requires economies of scale to make sure profitability (Feder and Zilberman, 1985). But the latter argument doesn't work, especially for the study area, as land size in the study area is more or less distributed symmetrically and relatively small.

Impact of adoption on productivity

Farmers in the study area claim that technology has an adverse impact on their land productivity, as one reason behind the low rate of technology adoption. Cobb-Douglas production function was estimated to test the impact of technology on productivity, while technology use is entered as one explanatory variable.

The objective is to empirically test whether the claims by most of the small farm households in the study area about the ineffectiveness of agricultural technology in the study area by estimating the production function, including the technology adoption as

one of the determinants of productivity. They argue that the technology the government supplies them is incompatible with the soil's nature and contributes adversely to their land productivity. Apart from this claim, as shown in Table 4, fertilizer use is one of the statistically significant determinants of productivity in the study area. Accordingly, as compared to non-users, output increases by about 85 percent for technology users.

Table 4. Determinants of productivity

Output	Coefficients	Std. Error	P-values
M. status	-0.04	0.12	0.72
Religion	-0.00	0.08	0.98
Lnd size	0.13*	0.02	0.00
Education	0.09**	0.04	0.04
Extension	0.46*	0.12	0.00
Age	-0.01	0.05	0.38
Family Szs	0.07*	0.02	0.00
Distance_Road	0.01	0.49	0.76
Credit	0.02	0.99	0.81
FtlZr	0.85*	0.11	0.00
N = 251 F(10, 240) = 22.93 P > F=0.00 R2=0.49			

* Significant at 1% level, ** significant at 5% level, *** significant at 10% level.

Along with technology, output in the study area is determined by land size, education level of the household head, access to extension service, and family size. On the other hand, household characteristics such as marital status, religion, and age of the household head and institutional factors such as access to road and credit facilities have no significant impact on productivity in the study area.

CONCLUSIONS AND RECOMMENDATIONS

Conclusions

Population growth, land fragmentation, and associated over-utilization of land have been serious causes of low productivity, food self insufficiency, and malnutrition in developing countries in general and Ethiopia. Using agricultural technology such as fertilizer and improved seeds has been advocated to cure the soil's loss of natural fertility and associated low productivity. Apart from these consensuses, the degree of technology adoption varies spatially as well as temporally. Some of the possible explanations for the variation are capacity constraints (lack of credit access and high technology price), low educational attainment of the farm households.

The low rate of technology adoption, adopters' and no adopters' productivity difference is very significant and positive. In contrast, the variability of productivity (the standard deviation of output) is very large (about 53) within the technology adopters, which implies that the uniformity of the adoption is still a problem that might be emanated from farmers' low education level as well as constrained access to extension service.

Recommendation

Since technology adopters are more productive than their counterparts, the concerned stakeholders such as local and federal government, NGOs, and research institutions shall encourage technology adoption of local farm households to bridge the gap. Significant variation in terms of productivity (output per hectare) has been witnessed in the area. Therefore, the government should work (through the Development agents) to bring farmers on the same page regarding their technology adoption in the sector.

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