Potential uptake determinants of climate-smart push-pull technology in drier agro-ecological zones of eastern Africa

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Invited paper presented at the 4th International Conference of the African Association of Agricultural Economists, September 22-25, 2013, Hammamet, Tunisia

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Abstract

The adaptation of push-pull technology to the drier ecological zones is of critical importance for its sustainability in view of the effects of global climate change. While intensified dissemination of the climate-smart technology would ensure its maximum adoption, knowledge of its potential adoption is necessary before dissemination resources are commitment. Potential adoption of a technology is however based on a wide range of farm, farmer, institutional and socioeconomic characteristics. This study was interested on these determinants of potential adoption of the climate-smart push-pull *ex ante*. The study adopted the multinomial logit technique to evaluate potential adoption determinants, and the findings were consistent with expectations based on theoretical hypothesis with gender, striga rating, push-pull awareness, input market access and country dummy variables being the significant predictors of the potential adoption. These findings are critical if effective targeting of the dissemination messages is to be accomplished.

Key words: climate-smart push-pull, willingness to adopt, Multinomial logit

Introduction

Cereal crops are crucially important to food security in Africa, providing the daily calories and cash income for most households in the rural areas. In the last two decades, African region has been experiencing a decline in the per capita food production, with cereal explaining most of the observed variance in total food production (FAO, 2006). This instability in cereal production has continuously affected food self sufficiency in the region thus exposing the communities to food shortages and famines. Many constraints have been ascribed to the acute food shortages with the stemborers, striga weed and land degradation notably taking the lead (Khan and Pickett, 2004). Although farmers have made attempts to contain the negative effects of the two pests, the control measures they have taken have been futile. Thus, the productivity of cereal crops in Africa has continued to dwindle subjecting most rural households to abject poverty.

Responding to some of these challenges, research organization both national and international has come up with various control strategies to manage these constraints. Among them is push-pull technology which was developed and promoted by the International Centre of Insect Physiology and Ecology (*icipe*). The conventional push-pull technology utilizes plant to plant interaction to repel the stemborers moths as well as to put the striga weed under control (Khan et al., 2004, Midega et al., 2010). The technology has been one of the most successful methods and with an advantage of controlling both the stemborers and striga weed simultaneously, while improving soil fertility status. Despite the imminent advantages of this conventional push-pull technology, its sustainability has been affected by the global effects of climate change which has limited its expansion to drier areas where striga weed is quickly spreading and adapting. To counter this, *icipe* further adapted the conventional push-pull technology to suit the adverse effects of weather change by selecting drought tolerant companion crops. In this new control fit termed as climate-smart push-pull technology, the cereal crop (maize or sorghum) is intercropped with the green leaf desmodium (*D.intortum*) which is more tolerant to drought as compared to the silver leaf desmodium (*D. uncinatum*) commonly used in the conventional push-pull technology. This cereal desmodium intercrop is then surrounded by three rows of brachiaria cv mulato (*Brachiaria spp.*) grass in place of Napier grass. Likewise, the brachiaria cv mulato II grass is not only tolerant to drought as compared to the Napier grass but also resistant to the stunting disease which has continuously affected the Napier grass, and yet no effective control measure has been identified for it.

Maximum adoption of this new technology is embedded upon successful information dissemination to the target recipients. However, it is important to allocate dissemination resources to a technology that has a high adoption potential in order to ensure positive returns to investment. However, the uneven distribution and variations in characteristics of potential adopters is likely to affect the overall adoption process (Keelan et al., 2009). Understanding these factors and being able to predict who will benefit from adoption is important for technology-promoters (Rubas, 2004). While many studies have examined factors associated with the adoption of a specific technology, both *ex ante* and *ex post*, the conflicting results of such varied studies make further generalizations impossible. Therefore, technology specific studies are necessary in order to avoid misspecification which could otherwise be associated with such generalizations. This study was interested in evaluating the determinants of farmers' willingness to adopt climate-smart push-pull technology in selected regions of eastern Africa. The study is part of the on-going process of up-scaling the climate-smart push-pull technology to the low rainfall agro-ecological zones and the findings presented herein are extracted from an extensive *ex ante* baseline and gender analysis study conducted prior to the implementation of the project.

Methodology

Sites description and sampling

The study was conducted between March and May 2012 in selected sites in Kenya, Tanzania and Ethiopia. The choice of the sites was motivated by the need to up-scale the climate-smart push-pull to marginal areas where stemborers and striga weed are quickly adapting as a result of the existing global climate change. The study employed a multistage sampling method where the country, region and districts were purposively sampled based on the severity of the striga and stemborer and the key priority areas guided by the country research teams. The key respondents were randomly sampled from a sampling frame generated by village elders and development agents in the selected sites.

Data collection

A household survey using structured questionnaires on personal interviews with the selected respondents was conducted. In general, the questionnaire was structured to collect information on farmers' socio-economic characteristics (e.g. age, gender education, family size etc), farm characteristics (farm size, tenure systems), farmers' perception of striga infestation, stemborer infestation and household social capital among others. Specifically, farmers' were asked if they had any information on the climate-smart push-pull technology for stemborer and striga weed control. For those farmers who were not aware of the technology, the enumerators took time to explain about the technology and used photos and posters to demonstrate how it worked and expected benefits. Upon thorough demonstration, the farmers were asked if they were willing to try the technology on their farms. A farmer is said to be willing to adopt the technology when after observations from a demonstration or an explanation of how the technology works, he/she expresses the interest to use the technique. In our case, farmers were given four possible choices to this answer, 1 = Yes, I am willing to adopt, 2 = No, I will not adopt, 3 = Yes, I will adopt if I get more information and 4 = I don't know. Since the number of respondents in category 3 and 4 were few, the two codes were collapsed into 1 and recoded as "uncertain" during the data entry. In that case, we had three possible choices; 1 = Yes, 2 = No, 3 = Uncertain.

Data analysis

Evaluating the determinants of potential adoption

The anticipated beliefs and expected net benefits define the farmers' perception and attitudes towards new technologies and thus, farmers would seek best value that they can be derived from participating or intentions to participate in a particular technology (Napier et al., 1986; Napier and Napier, 1991; Läpple and Kelley, 2010). In our case, the intention by the farmers to take up the new climate-smart push-pull technology or not was evaluated using three possible choices; 1 = Yes, 2 = No and 3 = Uncertain. Allowing these multiple choices reflects the dynamics of decision making with respect to the adoption which would otherwise mis-state the probability of adoption (Zepeda, 1990). The choices however depend on several social economic and demographic characteristics of the farmer which are of interest if an increase in the uptake of the technology in question is to be achieved (Läpple and Kelley, 2010). Depending on the farmers' responses, several econometric models can be applied to evaluate the link. For example, the intentions of farmers to take up a new technology can be measured using a limited dependent variable such as logit and probit model, where such dependent responses are 1 = Yes, where the respondent is willing to adopt, and 2 = No if otherwise. However, the dependent variable used in such models locks out farmer who are still in the process of making decision. For example, in our case, some farmers were uncertain and were only willing to adopt if they received more information about the technology, meaning they are still in the process of making the decision. Since the response was thus characterized by a polychotomous choice among the three mutually exclusive alternatives, and these were not practically ordered, a Multinomial Logit model was chosen to express the probability of a farmer making one of the three possible choices. The multinomial logit specifications provide insights into the manner in which changes in farm and farmer characteristics push the individuals in and out of different categories (Useche et al., 2005). The model is predicted on the utility that the farmer would derive by choosing one of the three possible choices. According to Nerlove and Press (1973), the multinomial logit model is presented as follows;

$$\Pr ob(Y_i = j) = \frac{e^{\beta_j' x_i}}{\sum_k^j e^{\beta_j' x_i}} \tag{1}$$

Where Y_i is the observed outcome for the i^{th} individual with a vector of x_i attributes, *Pr* (.) is the probability *j* is one of the j^{th} choices and β are the parameters to be estimated (Greene, 2000). For the purposes of data analysis, farmers responses were re-coded as 0 = No, 1 = Uncertain and 2 = Yes. We further estimated the coefficients and marginal effects of variables associated with each choice. Marginal effects of the continuous variables are estimated at their mean values while those of the dummy variables are estimated as;

$$\Pr\left[Y_i = 1 \mid \overline{X}_*, d = 1\right] - \Pr\left[Y_i = 1 \mid \overline{X}_*, d = 0\right] \tag{2}$$

where *d* is represents the dummy variable (Greene, 2000).

Results

The descriptive summaries presented in Table 2 shows that 80% of the households interviewed in the whole sample were male-headed. The percentage of male-headed households in Tanzania and Ethiopia were 87.5% and 92.6% respectively. In Kenya however, the percentage of male-headed household was lower (67.4%), while female-headed households were 32.6%. The mean age for the household heads in the whole sample was 49.5 years. There were slightly more elderly farmers in Kenya (mean age 52.5 years), followed by Tanzania (49.2 years) and lastly Ethiopia (46 years). In the overall sample, 24.3% of the household heads had no education, 56.9% had attained primary level education, and 14.9% secondary level education and 4% post secondary level. The illiteracy level was highest in Ethiopia where 56.7% of the household heads having no formal education. The average household size for the sample was about 6 persons with Tanzania leading with an average 7.3 family members.

Land sizes were smallest in Ethiopia with an average of 3.14 acres, followed by Kenya (3.52 acres) while Tanzania recorded the largest parcels of land (10.4 acres). The average land size recorded for the sample was 5.23 acres. Over 80% of the respondents kept livestock, with an average farming experience of 24 years. The number of Tropical Livestock Units (TLUs) owned was highest in Tanzania (6.53), followed by Kenya (2.51), and Ethiopia had the least (2.3). The sample average was 3.52. Over 90% of the sample respondents reported having access to both input and output markets and the average distance to the market was 4.14 kilometres. Credit was accessed by approximately 80% of the sampled respondents, while 77.8% belonged to organized farmer groups.

Table 3 presents a summary of how respondents perceived the striga and stemborer constraints in their farms. Perception on the severity was captured using a likert scale rating where 1 = No problem, 2 = Minor problem, 3 = Moderate problem, 4 = Serious problem and 5 = Very serious problem. Cumulatively, over 90% felt that at least striga was a problem in their farm only that the severity varied from farm to farm. The percentages derived from this analysis indicate that 36.2% and 26.8% of the respondents felt that the striga was a 'serious problem' and a 'very serious problem' respectively. The severity of stemborer was however rated as moderate as opposed to the striga weed. Only 11.8% of the respondents perceived stemborer infestation to be a very serious problem. Overall, 73.7% responded that maize was the cereal crop mostly affected by striga, and these percentages varied from 91.2% in Kenya, 71.1% in Tanzania and 48.3% in Ethiopia.

Farmers' awareness of the climate-smart push-pull technology was still very low. Only 36.3% of the respondents in the overall sample were aware of the technology as a control measure for stemborers and striga weed. The awareness was highest in Kenya (54.3%), followed by Tanzania where about a third (31.7%) of the respondents were also aware of the technology, while only 18.2% of the respondents in Ethiopia were aware of the technology. After getting the information about the climate-smart push-pull, 87.8% of the respondents in the overall sample were willing to adopt push-pull, 3% were not willing to adopt and 9.2% were uncertain.

Table 4 presents the multinomial logit coefficients, marginal effects, corresponding standard errors and *P*-values on determinants of willingness to take up push-pull. The model was significant at 1% (p = 0.000). Since the frequency for farmers who were willing to adopt captured as 2 = Yes was higher compared to the other two options, it was used as the base category for reference purposes. Thus, the coefficients and marginal effects were interpreted based on their comparison to the base category. A positive coefficient means that as the explanatory variable increases, a farmer is more likely to choose alternative *j* than the base category "Yes" and the opposite is true.

Gender of the household head (*HHgender*), farmers' rating of striga severity (*strgsever*), awareness of push-pull (*PPThear*), access to input market (*inpmrkacc*) and the country dummy for Kenya (*kenya*) were the significant predictors of farmers' willingness to adopt the climate-smart push-pull, all of which displayed an inverse relationship. The coefficient for these variables were; -0.984 and -0.784 for 'No' and 'Uncertain' options respectively for gender variable, -0.333 for the 'No' option but insignificant for the 'Uncertain option' for perception on striga severity variable, -0.814 and -0.759 for 'No' and 'Uncertain' options respectively for push-pull awareness variable, -0.300 and -4.714 for 'No' and 'Uncertain' options respectively for input market access variable, and -0.571 for the 'No" option and insignificant for 'Uncertain' option for the country dummy variable. The marginal effects were estimated for the three options (Yes, No, Uncertain) and were significant for *HHgender, strgsever, PPThear,* and *inpmakacc* under the ‘Yes’ option (MEs = 0.060, 0.010, 0.042, and 0.738 respectively); *strgsever* and *kenya* were significant under the ‘No’ option (MEs = -0.006, and -0.025 respectively; while *PPThear* and *inpmrkacc* were significant under the ‘Uncertain option’ (MEs = -0.029 and -0.686 respectively).

Discussions

The farmer socioeconomic attributes

Most of the farmers in the selected sites were essentially smallholder farmers with minimal land for cereal crops and livestock production. The farmers were of diverse socio-economic background which is likely to influence their decision to adopt new technologies depending on how they perceived the benefits (Napier et al., 2000; Roberts et al., 2004; Prokopy et al., 2008). For example, the gender disparities of the household heads would be manifested in the inability by female-headed households to adopt new technologies due to lack of access to basic resources (Adesina et al., 2000). This is so particularly for Kenya where the highest percentage of female-headed households (32.6%) was encountered. Proper targeting of dissemination is necessary to ensure equal access to information and other facilities that are likely to encourage adoption, and for which female farmers may be disadvantaged of.

The observed age however portrays a middle aged farming community and one that is positively linked to willingness to technology adoption. Adoption studies have shown age of the farmers to either be positively significant, negatively significant or insignificant in influencing the adoption decision. In some cases, old farmers are viewed as having a shorter time horizon for making decision to adopt, while young and middle aged categories have a long decision making horizon, and therefore are likely to take up new technologies. However, elderly farmers may also be viewed as more experienced and wealthier than the young farmers and therefore stand a better chance of adopting. All these varied effect of age may be attributable to the characteristics of the technology in question.

The observed differences in education levels of the household heads require that proper targeting of dissemination strategies in considered. For example, the illiteracy level in Ethiopia was quit high with 56.7% of the household heads having no formal education. Such farmers are likely to resist adoption if the messages are relayed in a complex language and/or pathways that are incompatible with their preferences and knowledge base (Murage et al., 2011). This means that the dissemination experts should use specific dissemination methods that are suitable for various education categories. Education is also linked to early adoption of technologies and farmers with some levels of education are expected to have the ability to understand and evaluate the information on new technologies (Feder et al., 1985).

Potential determinants of willingness to adopt climate-smart push-pull

The negative coefficient for gender variable under the 'No' and 'Uncertain' option implies that compared to the male-headed household, the female-headed household were likely not to adopt, or would wait a little longer before making the decision to adopt (uncertain). The positive and significant marginal effect for the 'Yes' option implies that being in a male-headed household increased the willingness to adopt by 6% (ME = 0.060) as opposed to being in a female-headed household. The unwillingness of female farmers to adopt a new technology may be attributed to the nature of the technology, in which, such a technology could be male dominated and /or is likely to benefit the male farmers only (Malton 1994; Adesina, 1996; Adesina et al., 2000). However, in our case, push-pull technology is a technology that is bound to benefit both male and female, especially if cereal productivity is improved and additional benefits that goes to livestock production. In that case, the negative sign of gender in the current study could be attributed to the wealth differentials between the male-headed and the female headed households. As noted earlier, female-headed household are often constrained of basic resources necessary for uptake of new technologies. In view, such families are more likely to be undecided unlike the male-headed households who not only have access to basic resources, but they also own and control these resources. Although push-pull is relatively compatible with the resource poor farmers, its initial investment may prevent female farmers from committing to adoption if they are not assured of resource access.

The inverse relationship between the variable representing farmers perception of striga severity shows that a unit change of the perception from being not a problem to a minor, serious or very serious problem decreases the probability of choosing to ‘No’ option compared to the base category. This implies that farmers are less likely not to adopt push-pull if they perceive striga infestation as a serious problem on their farms. This is supported by the marginal effects which shows a probable 1% increase (ME = 0.010) in willingness to adopt, if farmers perceived striga infestation to be a major problem. Though subjective, farmers’ perception has been shown to have a direct influence in their decision to adopt, and therefore should be included in the adoption models (Adesina and Baidu-Forson, 1995; D’Antoni et al., 2012). Some of these past studies evaluated how farmers’ perception of the technology attributes affect farmers’ decision to take up the technology with varied results. In our case, we investigated how farmers’ perception on the extent of the problem/constraint (Striga and stemborer infestation) in question does affect their decision to take up the new technology or not. Our results show that, if farmers perceive the problem as severe, then they are more likely to take up the new technology than if they perceived it as less severe.

Although the awareness of push-pull technology in the selected sites was still low, our results show that being aware of the technology increases the chances of adoption by 4.2% (ME = 0.042 for *PPThear* variable). It further reduced the possibility of being uncertain by 2.9% (ME = -0.029). Awareness is a critical first stage in technology adoption and diffusion process. It has been modeled as an endogenous variable to adoption and a potential policy variable that can be used to influence the probability of adoption (Morgenstern, 1996; Daberkow and McBride, 2003). Our results are consistent with those of Daberkow and McBride (2003) who observed that awareness significantly influenced the decision to adopt precision farming by farmers in the United States. This implies a need for intensified dissemination of the technology in order to increase the exposure levels which in turn maximizes adoption.

Inability to access markets for inputs would mean that farmers resist adoption of new technology. This is portrayed by the inverse relationship between the input market access variable whose coefficient was negative. The prevailing marginal effects indicates that having access to input markets increased the willingness to adopt climate-smart push-pull by 73.8% (ME = 0.783), and reduced the probability of being uncertain by 68.6% (ME = -0.686). Farmers who had access to input market were more likely to adopt the technology compared to those who did not have such access. This scenario would be expected given that availability of inputs in particular the desmodium seed in this case is critical if push-pull were to be taken up by the recipients. This observation is critical given that in the past, inability to access desmodium seeds in the market coupled with the perceived high prices was shown to limit expansion of the conventional push-pull (Fischler, 2010).

Finally, the coefficient and marginal effects for the country dummy variables indicate that compared to Tanzania which was the reference variable, respondents in Kenya were less likely not to adopt. The marginal effects show that being in Kenya reduced the likelihood of not adopting by 2.5% (ME = -0.025) as opposed to being in Tanzania. Many factors could be attributed to this scenario. First and foremost, the awareness of push-pull was much higher in Kenya than in Tanzania and Ethiopia, having been introduced in the former earlier. Thus, farmers in Kenya are at an advanced stage of decision making, having received the information earlier, and therefore more likely to make quick decisions to adopt while in the case of Tanzania, farmers are still waiting to acquire more information about the technology before making the decision to adopt. This is common since farmers are said to be risk averse, and would only make decisions if they gather information up to a certain threshold that reduces their risk aversion. This further implies that provision of quality information is vital if farmers are expected to promptly adopt the technology. Past studies have shown that information plays a key role in determining adoption more than does the socio-economic characteristics of the farmers (Mauceri et al., 2005; Langyintuo and Mungoma, 2008, Murage et al., 2012). Other factors attributable to the inverse relationship of the country dummy could be the diversities in cultural, political, climatic and economic characteristics in the countries.

Conclusion and implications

The climate-smart push-pull offers a valid option for farmers in the drier agro-ecological zones to control stemborer and striga weeds and therefore improve cereal productivity. Its impact is hinged upon maximum adoption, which is a function of several socio-economic and farm characteristics of the farmer. This study evaluated the farmers' willingness to adopt and its potential impact *ex ante*. In general the findings of the econometric model were consistent with expectations based on theoretical expectations and findings from previous studies in adoption literature. These findings are critical for the researchers and the extension agents prior to planning the dissemination. In order to achieve maximum adoption, effective targeting of the population as well as packaging of information and the messages is necessary to suit the socioeconomic setup of the farmers. Generalized information dissemination without prior consideration of the observed relationships is likely to lead to non-adoption.

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Table 1: Description of model variables

Variable label	Description	Variable type	Variable measurement
HHgender	Gender of the household head	Dummy	0 = Female, 1 = Male
HHage	Age of the household head	Continuous	Years
No_educ	If household head had no education	Dummy	0 = No, 1 = Yes
prim_educ	If household head had primary level education	Dummy	0 = No, 1 = Yes
pprim_educ	If household head had post primary level education (Dropped as a reference variable)	Dummy	0 = No, 1 = Yes
hh_size	Household size	Continuous	Number of persons
landsz	Land size (acres)	Continuous	Acres
TLU	Tropical livestock units	Continuous	Units
strgsever	Rating of striga severity	Categorical	0 = No problem, 1 = Minor problem, 2 = Moderate problem, 3 = Serious problem, 4 = Very serious problem
stemsever	Rating of stemborer severity	Categorical	0 = No problem, 1 = Minor problem, 2 = Moderate problem, 3 = Serious problem, 4 = Very serious problem
PPThear	Push-pull awareness	Dummy	0 = No, 1 = Yes
grpmemb	Group membership	Dummy	0 = No, 1 = Yes
inpmrkacc	Input market access	Dummy	0 = No, 1 = Yes
kenya	Country dummy for Kenya	Dummy	0 = No, 1 = Yes
tanzania	Country dummy for Tanzania	Dummy	0 = No, 1 = Yes
ethiopia	Country dummy for Ethiopia (Dropped as a reference variable)	Dummy	0 = No, 1 = Yes

Table 2: Summary statistics of the selected sample

	Kenya		Tanzania		Ethiopia		Overall sample		Statistics	
	Freq	Mean/percent	Freq	Mean/percent	Freq	Mean/percent	Freq	Mean/percent	F-value	Chi^2
Gender of household (%)										
Female	117	32.6	30	12.5	22	7.4	169	18.8		76.28***
Male	242	67.4	210	87.5	276	92.6	728	81.2		
Education level (%)										
None	27	7.6	28	11.7	157	56.7	212	24.3		295.35***
Primary level	207	58.0	188	78.3	102	36.8	497	56.9		
Secondary level	97	27.2	21	8.8	12	4.3	130	14.9		
Post secondary	26	7.3	3	1.3	6	2.2	35	4.0		
Age of the household head (years)	337	52.94 (0.71)	236	48.84(0.84)	297	44.93(0.79)	870	49.09(0.46)	29.08***	
Household size	360	5.55(0.11)	240	7.32(0.19)	298	5.82(0.13)	898	6.11(0.08)	41.84***	
Total land size (acres)	360	3.52(0.31)	240	10.40(0.71)	298	3.14(0.14)	898	5.23(0.25)	90.65***	
Farming experience (years)	359	21.81(0.70)	235	24.47(0.92)	294	27.17(0.71)	888	24.29(0.45)	13.52***	
If livestock are kept (%)										
Yes	326	91.1	215	89.6	257	86.2	798	89.1		3.97
No	32	8.9	25	10.4	41	13.8	98	10.9		
Tropical livestock units (units)	360	2.51(0.13)	240	6.53(0.67)	298	2.30(0.11)	898	3.52(0.20)	45.58***	
Access to input market (%)										
Yes	311	86.4	228	95.0	283	95.0	822	91.5		
No	49	13.6	12	5.0	15	5.0	76	8.5		20.56***
Access to output market (%)										
Yes	347	96.4	228	95.0	285	95.6	860	95.8		.704
No	13	3.6	12	5.0	13	4.4	38	4.2		
Access to credit (%)										
Yes	257	71.4	205	85.4	259	86.9	721	80.3		30.27***
No	103	28.6	35	14.6	39	13.1	177	19.7		
Membership to organized groups (%)										
Yes	342	96.3	153	63.8	197	67.0	692	77.8		118.05***
No	13	3.7	87	36.3	97	33.0	197	22.2		
Distance to market (km)	348	3.38(0.19)	199	6.30(0.4)	284	3.55(0.18)	831	4.14(0.14)	38.80***	

Figures in parenthesis are standard errors associated with the means.
*** Significant at 1%, ** 5% and *10%

Table 3: Perception on striga and stemborer infestation

	Kenya		Tanzania		Ethiopia		Overall sample		Chi^2
	N	%	N	%	N	%	N	%	
Farmers' rating of striga severity									
Very serious problem	104	30.2	65	30.7	37	17.5	206	26.8	29. 7***
Serious problem	115	33.4	76	35.8	87	41.0	278	36.2	
Moderate problem	80	23.3	32	15.1	51	24.1	163	21.2	
Minor problem	25	7.3	24	11.3	32	15.1	81	10.5	
No problem	20	5.8	15	7.1	5	2.4	40	5.2	
Farmers' rating of stemborer severity									
Very serious problem	54	15.0	22	9.2	30	10.1	106	11.8	50.9***
Serious problem	81	22.2	85	35.4	63	21.1	229	25.5	
Moderate problem	70	19.4	70	29.2	67	22.5	207	23.1	
Minor problem	80	22.2	45	18.8	59	19.8	184	20.5	
Not a problem	75	20.8	18	7.5	79	26.5	172	19.2	
Crop mainly affected by striga									
Maize	309	91.2	150	71.1	102	48.3	561	73.7	131.8***
Sorghum	19	5.6	38	18	58	27.5	115	15.1	
Finger millet	2	0.6	1	0.5	3	1.4	6	0.8	
Pearl millet	3	0.9	1	0.5	2		6	0.8	
Maize and sorghum	6	1.8	21	10	46	21.8	73	9.6	
Farmers' awareness of climate-smart push-pull									
Yes	195	54.30	76	31.70	54	18.20	325	36.30	94.35***
No	164	45.70	164	68.30	242	81.80	570	63.70	
Willingness to adopt push-pull									
Uncertain	52	14.40	10	4.20	21	7.00	83	9.20	25.25***
No	5	1.40	9	3.80	13	4.40	27	3.00	
Yes	303	84.30	221	92.10	264	88.60	788	87.80	

*** Significant at 1%, ** 5% and *10%

Table 4: MNL coefficients and marginal effects on willingness to accept climate-smart push-pull

	MNL coefficients				MNL marginal effects					
	No		Uncertain		Yes		No		Uncertain	
	Coef.	Std. Err.	Coef.	Std. Err.	dy/dx	Std. Err.	dy/dx	Std. Err.	dy/dx	Std. Err.
HHgender	-0.984**	0.556	-0.784**	0.391	0.060**	0.031	-0.023	0.018	-0.037	0.024
HHage	-0.004	0.018	0.006	0.013	0.000	0.001	0.000	0.000	0.000	0.001
No_educ	0.477	0.762	0.028	0.540	-0.010	0.028	0.009	0.017	0.001	0.021
prim_educ	0.069	0.693	-0.635	0.410	0.024	0.022	0.002	0.012	-0.026	0.017
hh_size	0.120	0.089	0.013	0.076	-0.003	0.003	0.002	0.002	0.000	0.003
TOTlandsz	-0.021	0.037	-0.023	0.047	0.001	0.002	0.000	0.001	-0.001	0.002
TLU	0.026	0.027	-0.012	0.041	0.000	0.002	0.000	0.000	0.000	0.002
strgsever	-0.333**	0.154	-0.119	0.127	0.010**	0.006	-0.006**	0.003	-0.004	0.005
stemsever	0.239	0.184	-0.118	0.132	0.000	0.006	0.004	0.003	-0.005	0.005
PPThear	-0.814*	0.479	-0.759**	0.363	0.042***	0.017	-0.014	0.009	-0.029**	0.014
grpmemb	0.335	0.480	-0.075	0.485	-0.003	0.021	0.006	0.008	-0.003	0.019
inpmrkacc	-3.000***	0.647	-4.714***	0.404	0.738***	0.059	-0.051	0.033	-0.686***	0.063
kenya	-1.571**	0.830	-0.142	0.523	0.030	0.024	-0.025**	0.013	-0.004	0.020
tanzania	-0.292	0.622	-0.774	0.622	0.030	0.021	-0.004	0.010	-0.026	0.018
_cons	0.937	1.667	4.119***	1.317						

N = 860, LR $chi^2(28) = 273.66$, *Prob >* $chi^2 = 0.000$, *Pseudo* $R^2 = 0.363$, *Log likelihood = -239.92*

*** Significant at 1%, ** 5% and *10%