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Adoption of Improved Mungbean Production Technologies in Selected East African Countries

Frank Mmbando [1,*], Emmanuel Mbeyagala [2], Papias Binagwa [1], Rael Karimi [3], Hellen Opie [2], Justus Ochieng [4], Tarcisius Mutuoki [3] and Ramakrishnan Madhavan Nair [5]

1 Selian Centre, Tanzania Agricultural Research Institute (TARI), P.O. Box 6024 Arusha, Tanzania; hongera1984@gmail.com
2 National Agricultural Research Organization-National Semi Arid Resources Research Institute (NARO-NaSARRI), P.O. Box 56 Soroti, Uganda; kmbeyagala@gmail.com (E.M.); hellenop@gmail.com (H.O.)
3 Kenya Agricultural and Livestock Research Organization (KALRO)—Katumani, Machakos, Nairob 00100, Kenya; rkarimi213@gmail.com (R.K.); kiambimutuoki@gmail.com (T.M.)
4 World Vegetable Center, P.O. Box 10 Duluti, Arusha, Tanzania; Justus.ochieng@worldveg.org
5 World Vegetable Center, South Asia, ICRISAT Campus, Patancheru, Hyderabad 502324, India; ramakrishnan.nair@worldveg.org
* Correspondence: fmmbando@gmail.com; Tel.: +255-76-716-0951

Abstract: This study analyzes the factors that influence the probability and extent of the adoption of mungbean production technologies in Tanzania, Kenya and Uganda, using multivariate probit and Poisson regression models. The results show that the probability and extent of the adoption of mungbean production technologies are influenced by gender of the household, household size, farm size, livestock size, household assets, access to extension services and access to credit. The study suggests that policy interventions that aimed at targeting women farmers, increasing household asset and information dissemination, such as field demonstrations and training programs, are crucial in enhancing technology adoption among smallholder farmers.

Keywords: adoption; mungbean; production technologies; multivariate probit; poisson regression; East Africa

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1. Introduction

Agriculture is the most important economic sector and is the main source of livelihood for about 70 percent of the population in Tanzania, Kenya and Uganda. Mungbean (*Vigna radiata* (L). Wilczek) is one of the major pulses in East Africa, alongside soybeans, chickpeas and common beans. Mungbean is grown on about 302,292 ha and 148,885 ha in Kenya and Tanzania, respectively [1,2]. Mungbean is rich in proteins (23–25%) and micronutrients (iron and zinc), thus complementing the mainly starch-based diets among underprivileged communities in East Africa. The crop has a short maturity, is drought tolerant, and able to improve soil fertility through nitrogen fixation due to a symbiotic rhizobia relationship. In the arid and semi-arid areas of East Africa, mungbean is widely grown by smallholder farmers for both food and income [3].

Despite the potential importance of mungbean, the productivity has been low as a result of both social and physical environments in which the crop is grown. In East Africa, the average on-farm yield of mungbean is estimated at 0.5 t/ha as against the potential yield of 1.5 t/ha, meaning that is still far below the achievable potential. Low productivity is attributed to biotic and abiotic stresses, poor cultivation techniques and limited access to improved varieties [3]. The adoption of improved mungbean production technologies is one important strategy to tackle these challenges. Accordingly, these technologies may include the use of improved varieties, the use of chemical fertilizers, crop rotation, row planting, conservation tillage and integrated pest management (IPM). The adoption of these production technologies increases productivity among smallholder farmers. Therefore, improving technology adoption among smallholder farmers is essential for improving household food security and agricultural sustainability in East Africa. Regardless of the benefits, the adoption of improved crop production technologies is still low in rural areas of developing countries [4], despite a considerable effort to promote various technologies. Moreover, few empirical studies have been carried out on the adoption of multiple production technologies in East Africa. While the decision to adopt is usually a binary one (i.e., adopt or not adopt), the intensity of adoption goes on to look at the extent to which the various technologies are adopted. Given that poverty is more widespread in rural areas, new empirical results on the factors affecting the probability and intensity of adoption of improved crop production technologies are crucial to making policy interventions more effective in improving crop productivity and living standards of the rural population.

The study contributes to the growing literature on technology adoption in the following ways: first, the study jointly analyzes multiple technology adoption decisions such as improved varieties, crop rotation, chemical fertilizer, integrated pest management (IPM), conservation tillage and row planting. The study not only provides empirical evidence about the factors influencing the probability of technology adoption but also analyzes the extent of adoption. Such knowledge is important to formulate specific policies to facilitate the adoption of improved technologies.

2. Materials and Methods

2.1. Data and Sampling Procedure

The empirical analysis uses household level data gathered in 2019 in Tanzania, Kenya and Uganda. The surveys were conducted in the respective countries by national agricultural research institutes (NARIs). Data were collected using electronic data collection tools: Open Data Kit (ODK) and Kobo Toolbox. In total, 797 farm households were surveyed from 3 countries, 15 districts, and 30 villages. A multistage sampling procedure was used to select districts, villages and farm households in each country. In the first stage, five districts were selected in each country based on mungbean production. In the second stage, 10 villages (two from each district) were selected in each country based on mungbean production potential. Finally, a random sample of 250–288 farm households in each country (25–30 households from each village) was drawn from farm households that produced mungbean in the most recent production season and surveyed using the semi-structured survey instrument. The respondents were the household head or household principal male or female members who directly took part in the decisions and managed the farm. Table 1 presents a summary of the number of districts, villages and households in each country.

Table 1. Study countries, sample districts, villages and households.

Kenya			Tanzania			Uganda		
County	**Villages**	**Households**	**District**	**Villages**	**Households**	**Districts**	**Villages**	**Households**
Makueni	2	51	Masasi	2	51	Adjuman	2	52
Kitui	2	50	Bariadi	2	53	Alebtong	2	50
Tharaka-Nthi	2	50	Misungwi	2	51	Katakwi	2	58
Embu	2	50	Igunga	2	52	Otuke	2	57
Machakos	2	51	Moshi rural	2	50	Soroti	2	71
Total	10	252		10	257		10	288

2.2. Econometric Models Employed for Analysis

This study used a multivariate probit model (MVP) to assess the factors influencing the probability of adopting mungbean production technologies and a count data model (Poisson model) for estimating the intensity of adoption.

The MVP can be modelled from the random utility framework [5]. A farmer i will adopt a technology in plot p if and only if U_b that represents the benefit of adopting the technology is greater than U_a (the benefit derived from existing technology). However, B_a denotes a farmer's decision to adopt improved varieties (1), crop rotation (2), chemical fertilizer (3), integrated pest management (IPM) (4), conservation tillage (5) and row planting (6). Thus, a farmer will adopt technology on plot p if $Y^*_{ipa} = U^*_b - U_a > 0$.

The net benefit (Y^*_{ipa}) from adoption of the a^{th} technology is a latent variable determined by observed plot-level, institutional and household characteristics (Y'_{ip}) and the error term (ε_{ip}):

$$Y^*_{ipa} = X'_{ip}\beta_a + \varepsilon_{ip},\ (a = 1,\ 2,\ 3,\ 4,\ 5,\ 6) \tag{1}$$

where Y^*_{ipa} is a latent variable associated with the benefits of technology a and farmer i in plot p.

Using the indicator function, the unobserved preferences in Equation (1) can be translated into a binary outcome as follows:

$$Y_{ipa} = \begin{cases} 1 & if\ Y^*_{ipa} > 0, \\ 0 & otherwise \end{cases} \quad (a = 1,2,3,4,5,6) \tag{2}$$

In the multivariate model, where the adoption of several technologies is possible, the error terms jointly follow a multivariate normal (MVN) distribution, with zero conditional mean and variance normalized to unity, where $\varepsilon_{ip} \sim MVN(0,\Omega)$ and the covariance matrix Ω is given by:

$$\begin{bmatrix} 1 & p12 & p13 & p14 & p15 & p16 \\ p21 & 1 & p23 & p24 & p25 & p26 \\ p31 & p32 & 1 & p34 & p35 & p36 \\ p41 & p42 & p43 & 1 & p45 & p46 \\ p51 & p52 & p53 & p54 & 1 & p56 \\ p61 & p62 & p63 & p64 & p65 & 1 \end{bmatrix} \tag{3}$$

where p (rho) represents the pair-wise correlation coefficients of the error terms to be estimated in the model.

2.3. Estimation of Count Data Models

The MVP model, as defined above, solely takes into consideration the probability of adopting the mungbean production technologies. However, it does not take into account that farmers can adopt more than one technology, thus not taking into consideration the intensity of adoption. This study used a count data model (Poisson model) to assess the determinants of the intensity of the adoption of mungbean production technologies. The count of the number of mungbean production technologies adopted by each farming household defines the dependent variable of the model (y); it is thus a discrete nonnegative integer-valued count variable.

Following [5], if Y is a Poisson random variable, then its probability density function can be represented as:

$$f(y_i|x_i) = P(Y_i = y_i) = \frac{e^{-\lambda_i}\lambda_i^{y_i}}{y_i!}\ ,\ y_i = 0,1,2,3\ldots \tag{4}$$

where y_i is the number of improved mungbean production technologies adopted by a farmer and x_i are variables that affect the adoption of improved mungbean production technologies.

The mean parameter λ_i represents the expected number of events and is expressed as: where β is a vector of unknown parameters to be estimated.

If we assume the independence of the observations, the log-likelihood function associated with the estimation can be expressed as:

$$lnL(\beta) = \sum_{i=1}^{n}[y_i x_i'\beta - \exp(x_i'\beta) - lny_i!] \tag{5}$$

The marginal effects in the Poisson model are given by:

$$\frac{\partial E(y_i|x_i)}{\partial x_i} = \lambda_i \beta \tag{6}$$

This marginal effect, as in other count data models, is interpreted as the unit change in the intensity of adoption variable resulting from a change in the explanatory variable [6].

However, properties of the Poisson regression model have a major shortcoming of assuming equality between the mean and variance of the count-dependent variable (y_i), known as the equi-dispersion condition [5,6]. That is $E(y_i) = var(y_i) = \lambda$. However, in most empirical studies, the count-dependent variable has been observed to exhibit over-dispersion, implying the variance is greater than the conditional mean, due to the great number of zero observations of the dependent variable. As a result, most empirical applications have employed a negative binomial model, which is suitable for modelling over-dispersion [7].

In the negative binomial model, the variance function is presented as:

$$var(y_i) = \lambda_i + \alpha \lambda_i^2 \tag{7}$$

where α is the dispersion parameter to be estimated.

The Poisson regression is a special case of the negative binomial with $\alpha = 0$. Under the assumption that the specification of the mean is the same as that in the Poisson regression model, the log-likelihood function associated with the negative binomial formulation is expressed as:

$$\text{In}L(\alpha, \beta) = \sum_{j=1}^{n} \{ \sum_{j=0}^{y_i^{-1}} In(\, j + \alpha^{-1}\,) - In(y_i) - \left(y_i + \alpha^{-1}\right) In\left[+\alpha \exp\left(X_i^1 \beta\right)\right] + y_i \text{In}\alpha + y_i X_i^1 \beta \,\} \tag{8}$$

If the dispersion parameter α is known and the variance function is correctly specified, then the maximum-likelihood estimator for the NBM is robust to distributional misspecification [6]. On the other hand, if α is unknown, the quasi-generalized pseudo maximum likelihood estimation can be made using a consistent estimator, $\hat{\alpha}$ [5].

2.4. Description of the Variables

2.4.1. Dependent Variables

The dependent variables in the MVP model include six dummy variables corresponding to use of improved mungbean varieties, maize–mungbean crop rotation, chemical fertilizer, integrated pest management (IPM), conservation tillage and row planting (Table 2). The use of improved mungbean varieties and row planting are important in improving productivity and income for the rural population [8]. Crop rotation, the use of chemical fertilizer and conservation tillage contributes to increased yields through improved soil nutrition. IPM integrates different pest management practices to minimize pesticide use and ensure favorable economic and ecological consequences [9]. The dependent variable in the Poisson model was the number of improved mungbean production technologies adopted in the sample of households. Farmers were asked which mungbean production technologies they adopted during 2017/18 cropping season. The responses formed the basis for the construction of the dependent variable.

2.4.2. Independent Variables

The independent variables hypothesized to influence the adoption of mungbean production technologies were mainly based on economic theory and past empirical work on the adoption of agricultural technologies [4,10–13] among others. The variables were organized into three broad categories: household demographic characteristics, wealth variables and institutional and access-related variables (Table 2).

Table 2. Definition of variables used in the analysis.

Variable	Description
Dependent variables	
Improved varieties	Use of improved varieties (1 = yes; 0 = no)
Crop rotations	Maize-legume crop rotations (1 = yes; 0 = no)
Chemical fertilizer	Use of chemical fertilizer (1 = yes; 0= no)
IPM	Use of IPM (1 = yes; 0 = no)
Conservation tillage	Conservation tillage (1 = yes; 0 = no)
Row planting	Row planting in mungbean (1 = yes; 0 = no)
Number of technologies	Number of technologies adopted (counts)
Independent variables	
Household demographic characteristics	
Age	Age of the household head (years)
Gender	Dummy = 1 if household head is male
Education	Years of education of household head
Household size	Total number of household members
Wealth variables	
Farm size	Total farm size (acre)
Off-farm income	Dummy = 1 if household earns off-farm income
Livestock	Livestock size (TLU)
Asset index	Household asset index (PC score)
Institutional and access related variables	
Extension	Number of contacts with extension agents
Credit	Dummy = 1 if has access to credit
Group	Dummy = 1 if membership to farmer group/organization
Distance	Distance to the nearest input market (km) where farmers can buy inputs such as seeds, fertilizers, etc.
Country dummies	
HH in Uganda	Household is located in Uganda (1 = yes)—reference
HH in Kenya	Household is located in Kenya (1 = yes)
HH in Tanzania	Household is located in Tanzania (1 = yes)

Household demographic characteristics: Household characteristics was controlled by including the age, gender, and years of education of the household head and household size. These are relevant variables that may influence adoption decisions in countries where there are market imperfections and institutional failures. The age of the household head was incorporated because it is believed that, with age, farmers accumulate personal capital and show a greater likelihood of investing in innovations. However, it may also be that younger farmers are more flexible, interested in trying new things and hence more likely to adopt new technologies than older farmers [11]. Male farmers are expected to be more likely to adopt and intensify the use of new technologies because women have limited access to resources such as land, capital and extension [14]. Educated farmers are typically to be better able to process information and search for appropriate technologies to alleviate their production constraints. Education gives farmers the ability to perceive, interpret and respond to new information much faster than their less educated counterparts [15]. A large family often has many working members, and this is expected to have a positive impact on the adoption of new technologies such as labor-demanding technologies.

Wealth variables: The wealth of the households was proxy through farm size, off-farm income sources, livestock size (TLU) (Tropical Livestock Units (TLU) estimated using FAO conversion factors) and assets index (the asset index was constructed using principal component analysis (PCA), which covers a range of variables on the ownership of major farm assets. The key assets included are plough, ox cart, push cart, oxen, knapsack sprayer, spade, axe, water pump, wheelbarrow, bicycle, motorbike, mobile phone and power tiller) of major farm equipment. Farmers with larger farms are more likely to adopt improved technologies than those with small farms because farmers with large farms can afford to devote part of their land to try out the new technology [10]. Households that have an alternative source of income may be better able to adopt new technology because of improved liquidity, and because off-farm income may widen the information horizons of the farmer about new technologies [4]. However, alternative sources of employment may also compete for time and effort with agricultural activities, reducing investment in technologies and the availability of labor. Therefore, the effect of an alternative source of employment variable on adoption is hypothesized to be ambiguous.

Institutional and access-related variables: The institutional and access-related variables included in the model were extension service, credit access, membership to a farmer group and distance to market. Farmers' contact with extension agents is expected to have a positive effect on adoption. According to the innovation–diffusion theory, such contacts, by exposing farmers to information, can be expected to stimulate adoption [16]. Credit access gives farmers the ability to invest in new technologies [17]. Membership of a farmers' group or cooperative is included to capture the effect of social capital. A farmers' group facilitates the exchange of information and the opportunity to learn from one another [16]. It also enables farmers to access inputs on schedule and overcome credit constraints and shocks. It can reduce transaction costs and increase farmers' bargaining power, helping farmers earn higher income. This in turn can affect technology adoption. Market access impacts transaction costs for a farm household in accessing information and technologies, and hence is assumed to play an important role in technology adoption [18]. Distance to the nearest input market where farmers can buy inputs such as seeds, fertilizers, etc. was used as a proxy for market access. Access to markets may influence the net benefits from the adoption of new technologies [4]. The hypothesis here is that the farther away a household is from an input market, the lower the likelihood that it will adopt new technology.

Location characteristics: The unobserved location-specific effects were controlled using country dummy variables. These variables were included in the model to capture differences in the household technology adoption that might have arisen due to infrastructure, remoteness, production potential and resource endowment across countries. The dummy for Uganda was made as a reference and was left out of the model to avoid the dummy variable trap.

3. Results

3.1. Descriptive Statistics

Descriptive statistics for dependent and independent variables are presented in Table 3. The analysis of the results shows that the widely adopted technologies in the pooled data were crop rotation (69%), the use of improved varieties (39%) and row planting (38%). Crop rotation appears common in Kenya (92%) compared with Uganda (66%) and Tanzania (50%). The use of improved mungbean varieties is high in Kenya at 73%, compared to Tanzania (31%) and Uganda (15%). Similarly, row sowing is practiced by most farmers in Kenya (99%) compared with Tanzania (45%) and Uganda (only 3%). The use of mineral fertilizer was uncommon among farmers in the study area. The average proportion of households using chemical fertilizer was quite low in Uganda (3%) and Tanzania (7%) compared with Kenya (32%). Generally, IPM was practiced by very few farmers in Kenya (2%) and Tanzania (4%), compared to Uganda (12%). The mean number of technologies adopted in Kenya, Tanzania and Uganda were 3.1, 1.6 and 1.0, respectively.

The average age of the household head was 48 years in the pooled data; it ranged from 43 to 55 years across the study countries. About 81% of the sample households were female-headed households; it ranged from 75% in Kenya to 84% in Uganda. The average educational attainment of household heads was 7 years. The average household size was 7. Households in Kenya had a smaller farm size (6 acres) compared to Tanzania (9 acres) and Uganda (7 acres). Few of the sampled farm households in Tanzania (2%) and Uganda (9%) had off-farm income sources compared with Kenya (18%). The asset index was higher in Uganda as compared with Tanzania and Kenya, while the livestock size (TLU) ranged from 2.7 in Tanzania to 1.4 in Uganda. The average number of contacts with extension agents during the 2017/18 crop season was high in Kenya (3.5) compared to 0.9 in Tanzania and 0.3 in Uganda. Farmers who had access to credit ranged from 11% in Tanzania to 5% in Uganda. The average distance to the nearest input market ranged from 4.5 km in Kenya to 6.4 km in Uganda. About 94% of farmers in Kenya belonged to farmer groups/organizations, compared with 67% in Uganda and 60% in Tanzania.

Table 3. Descriptive statistics of the variables used in the analysis.

Variable	Mean			
	Pooled Data	**Tanzania**	**Kenya**	**Uganda**
Dependent variables				
Improved varieties	0.39	0.31	0.73	0.15
Crop rotation	0.69	0.50	0.92	0.66
Chemical fertilizer	0.14	0.07	0.32	0.03
IPM	0.07	0.04	0.02	0.12
Conservation tillage	0.12	0.21	0.12	0.03
Row planting	0.38	0.45	0.99	0.03
Number of technologies	1.9	1.6 (1.02)	3.1	1.0 (0.79)
Household demographic characteristics				
Age	47.87 (14.02)	47.18 (12.91)	54.60 (13.58)	42.61 (12.95)
Gender	0.81 (0.39)	0.83 (0.38)	0.75 (0.43)	0.84 (0.37)
Education	6.96 (4.09)	6.11 (2.66)	8.12 (4.21)	6.69 (4.76)
Household size	6.68 (3.59)	6.51 (3.84)	5.42 (2.23)	8.11 (3.048)
Wealth variables				
Farm size	7.16 (8.57)	8.97 (12.07)	5.95 (5.23)	6.97 (7.94)
Off-farm income	0.10 (0.29)	0.02 (0.14)	0.18 (0.38)	0.09 (0.29)
Livestock	2.20 (3.22)	2.73 (3.61)	2.57 (4.29)	1.44 (0.91)
Asset index	0.40 (1.33)	0.29 (0.52)	0.22 (0.29)	0.68 (2.12)
Institutional and access related variables				
Extension	1.49 (3.99)	0.90 (1.62)	3.52 (6.40)	0.26 (0.77)
Credit	0.08 (0.27)	0.11 (0.31)	0.08 (0.27)	0.05 (0.22)
Group	0.73 (0.44)	0.60 (0.50)	0.94 (0.24)	0.67 (0.47)
Distance	5.61 (6.15)	5.78 (7.31)	4.55 (5.55)	6.40 (5.34)
Location characteristics				
HH in Uganda	0.36 (0.48)			
HH in Kenya	0.32 (0.47)			
HH in Tanzania	0.32 (0.47)			

Source: authors' calculations using the survey data. Notes: numbers in parentheses are the standard deviation.

3.2. Number of Mungbean Production Technologies Adopted by Farmers

The number of mungbean production technologies adopted by the sampled households are presented in Table 4. The results show that about 26.7% and 0.811.7% of the sampled households in Uganda and Tanzania, respectively, did not adopt any of the technologies and thus have a zero count. Only 7% and 1% of the sample households (in Tanzania and Kenya, respectively) adopted five of the technologies, with no household adopting all six. In Kenya, about 49.6% (majority) adopted three technologies and the average number of technologies adopted among the sample households was 3.1. In Tanzania, about 41.6% of the sampled households adopted one technology and the average number of technologies adopted among the sample households was 1.6. In Uganda, 48.3% of the sampled households adopted one technology and the average number of technologies adopted was one, suggesting that averagely, each farmer adopted at least one technology.

Table 4. Distribution of counts of mungbean production technologies adopted.

Technology Counts	Number of Adopters			Percentage of Adopters		
	Tanzania	Kenya	Uganda	Tanzania	Kenya	Uganda
0	30	0	77	11.7	0.0	26.7
1	107	5	139	41.6	2.0	48.3
2	73	53	63	28.4	21.0	21.9
3	36	125	8	14.0	49.6	2.8
4	8	55	1	3.1	21.8	0.3
5	3	14	0	1.2	5.6	0.0
Total	257	252	288	100.0	100.0	100.0
Mean	1.6	3.1	1.0			
Standard deviation	1.02	0.85	0.79			

Source: authors' calculations using the survey data.

3.3. Regression Results

3.3.1. MVP Model Results

The maximum likelihood estimates of the MVP model of the adoption of improved mungbean production technologies are presented in Table 5. The MVP model were run in four separate regressions—one for the pooled data and one each for the countries: Tanzania, Kenya and Uganda. The model fits the data reasonably well: the Wald test of the hypothesis that all regression coefficients in each equation, which are jointly equal to zero is rejected. The results in the pooled model showed that male-headed households are more likely to use improved seeds and conservation tillage. This implies that the probability that they would adopt improved seeds and conservation tillage is higher among male-headed households than their female counterparts. For the country models, male-headed households are more likely to use chemical fertilizer and row planting in Tanzania, and improved seed in Uganda. The results suggest that older farmers are significantly less likely to use chemical fertilizer in the pooled model and in Tanzania. Older farmers are also less likely to use row planting in Tanzania, improved seed and IPM in Kenya and use of conservation tillage in Uganda (Table 5). The results show that the size of the household members has the positive effect on the adoption of improved seeds, crop rotation and IPM in the pooled data. It also has the positive effect on the adoption of improved seed, conservation tillage and row planting in Tanzania, and crop rotation and IPM in Uganda.

Farm size leads to a higher probability of adopting crop rotation in the pooled data and in Tanzania and makes the adoption of conservation tillage less likely in Kenya. Livestock had a negative significant influence on the adoption of conservation tillage in Kenya and Uganda. On the other hand, it significantly increases the probability of the adoption of row planting in Uganda. The asset index positively influences the adoption of improved seeds in the pooled data, Tanzania, Kenya and Uganda. Similarly, the asset index had a positive significant impact on the adoption of conservation tillage in Uganda.

Farmers' contact with extension agents during mungbean production had a positive impact on the adoption of conservation tillage in the pooled data, Tanzania and Uganda, and IPM in Uganda. This highlights the important role extension services play in disseminating improved agricultural technologies. On the other hand, access to credit increases the probability of adopting chemical fertilizer in the pooled data and in Tanzania, Kenya and Uganda. Similarly, access to credit increases the probability of adopting row planting in the pooled data, IPM in Kenya, and conservation tillage in Uganda and Tanzania. Farmers who are organized in groups are more likely to adopt improved seeds and IPM in the pooled data. The results further show that farmers who are organized in groups are more likely to adopt crop rotation and IPM in Tanzania and Uganda, improved seeds in Kenya and Uganda, and chemical fertilizer in Kenya. The distance to an input market is negative and statistically significant in the pooled data and all the three countries. Households located closer to an input market are more likely to use improved seed and chemical fertilizer in the pooled data, Tanzania, Kenya and Uganda. Similarly, households located closer to input markets are more likely to adopt conservation tillage and row planting in the pooled data and in Tanzania.

Table 5. Estimates of the MVP model.

Variables	Pooled Data (1)						Tanzania (2)					
	Improved Seeds	Fertilizer	Crop Rotation	IPM	Conservation Tillage	Row Planting	Improved Seeds	Fertilizer	Crop Rotation	IPM	Conservation Tillage	Row Planting
Age	−0.003	−0.006 **	−0.001	0.005	−0.003	0.000	−0.001	−0.023 **	0.007	0.021	−0.002	−0.013 *
	(0.004)	(0.002)	(0.004)	(0.006)	(0.005)	(0.006)	(0.007)	(0.012)	(0.007)	(0.017)	(0.008)	(0.007)
Gender	0.238 *	−0.100	0.056	−0.125	0.250 *	−0.266	0.130	0.765 ***	0.084	−0.245	−0.221	0.431 *
	(0.132)	(0.139)	(0.137)	(0.183)	(0.155)	(0.179)	(0.229)	(0.297)	(0.225)	(0.471)	(0.235)	(0.227)
Education	−0.005	0.001	−0.006	−0.023	0.011	0.034 **	−0.026	0.002	−0.030	0.006	0.022	0.048
	(0.013)	(0.016)	(0.013)	(0.022)	(0.016)	(0.015)	(0.034)	(0.052)	(0.034)	(0.076)	(0.037)	(0.035)
Household size	0.041 *	0.014	0.038 **	0.057 *	−0.007	0.020	0.056 *	0.048	0.015	−0.065	0.057 *	0.047 *
	(0.022)	(0.022)	(0.020)	(0.033)	(0.026)	(0.028)	(0.031)	(0.050)	(0.029)	(0.097)	(0.033)	(0.028)
Farm size	−0.001	0.001	0.012 **	−0.002	0.008	0.005	−0.005	0.004	0.013 *	−0.001	−0.004	0.005
	(0.006)	(0.006)	(0.006)	(0.009)	(0.007)	(0.007)	(0.007)	(0.011)	(0.008)	(0.026)	(0.009)	(0.007)
Off-farm income	0.158	−0.150	0.082	0.201	−0.099	0.012	0.594	−0.441	0.371	−0.563	−0.512	−0.118
	(0.183)	(0.194)	(0.197)	(0.264)	(0.229)	(0.295)	(0.581)	(1.693)	(0.438)	(0.614)	(0.538)	(0.615)
TLU	0.006	0.010	0.021	−0.051	0.013	−0.011	−0.021	−0.012	0.005	0.022	0.196	0.027
	(0.017)	(0.015)	(0.019)	(0.046)	(0.016)	(0.026)	(0.029)	(0.054)	(0.023)	(0.057)	(0.182)	(0.023)
Asset index	0.099 **	−0.140	−0.068	−0.446	0.011	−0.034	0.094 **	−0.506	0.247	−2.886	−0.327	−0.238
	(0.044)	(0.118)	(0.044)	(0.284)	(0.051)	(0.070)	(0.045)	(0.482)	(0.180)	(2.880)	(0.249)	(0.179)
Extension	−0.008	0.009	0.051	0.001	0.030 **	0.002	−0.043	−0.076	0.041	−0.493	−0.007	0.026
	(0.014)	(0.013)	(0.033)	(0.038)	(0.014)	(0.032)	(0.055)	(0.107)	(0.051)	(0.693)	(0.060)	(0.052)
Credit	−0.073	0.635 ***	0.114	0.054	−0.190	0.544 *	−0.273	0.608 **	0.344	0.865	0.755 **	−0.350
	(0.194)	(0.219)	(0.186)	(0.273)	(0.241)	(0.292)	(0.308)	(0.304)	(0.286)	(0.803)	(0.402)	(0.518)
Group	0.267 **	0.044	0.041	0.372 **	−0.160	0.108	−0.078	0.286	0.463 **	1.097 **	−0.244	−0.219
	(0.122)	(0.137)	(0.115)	(0.175)	(0.151)	(0.163)	(0.178)	(0.291)	(0.176)	(0.571)	(0.191)	(0.175)
Distance	−0.018 **	−0.033 ***	−0.005	−0.025	−0.015 *	−0.016 *	−0.026 **	−0.045 ***	−0.024	−0.018	0.000	−0.047 ***
	(0.009)	(0.009)	(0.008)	(0.018)	(0.009)	(0.010)	(0.013)	(0.013)	(0.024)	(0.044)	(0.012)	(0.013)
HH in Kenya	1.158 ***	1.431 ***	−1.280 ***	−1.178 ***	0.557 **	4.042 ***	-	-	-	-	-	-
	(0.151)	(0.195)	(0.175)	(0.270)	(0.208)	(0.294)						
HH in Tanzania	1.667 ***	0.226	−0.731 ***	−0.414 ***	0.863 ***	0.821 ***	-	-	-	-	-	-
	(0.161)	(0.151)	(0.183)	(0.178)	(0.173)	(0.180)						
Constant	1.560 ***	−0.254	1.480	−0.698	−1.507 ***	−2.073 ***	0.277	−2.265 ***	−0.391	−1.470	−0.160	0.718
	(0.342)	(0.370)	(0.353)	(0.426)	(0.361)	(0.412)	(0.558)	(0.884)	(0.545)	(1.399)	(0.609)	(0.547)
Observations	772						257					
Log likelihood	−1659.9667						−234.802					
Wald χ * (84, 72) *	738.55 ***						119.25 **					
Variables	**Kenya (3)**						**Uganda (4)**					
	Improved Seeds	**Fertilizer**	**Crop Rotation**	**IPM**	**Conservation Tillage**	**Row Planting**	**Improved Seeds**	**Fertilizer**	**Crop Rotation**	**IPM**	**Conservation Tillage**	**Row Planting**
Age	−0.014 *	−0.008	−0.016	−0.046 *	−0.003	−0.038	0.005	−0.001	−0.003	−0.003	−0.032 *	0.001
	(0.008)	(0.007)	(0.012)	(0.026)	(0.008)	(0.084)	(0.008)	(0.013)	(0.006)	(0.009)	(0.018)	(0.015)
Gender	−0.371	−0.010	0.040	5.869	−0.170	−6.839	0.477 *	4.509	−0.114	−0.089	−0.739	−0.321
	(0.235)	(0.212)	(0.331)	(9.349)	(0.269)	(8.270)	(0.252)	(4.924)	(0.231)	(0.304)	(0.500)	(0.520)
Education	−0.035	0.020	−0.040	−0.074	0.013	0.095	0.022	−0.027	0.008	−0.028	0.041	0.036
	(0.024)	(0.023)	(0.035)	(0.080)	(0.030)	(0.229)	(0.019)	(0.052)	(0.018)	(0.031)	(0.028)	(0.025)
Household size	0.026	−0.057	−0.070	−0.029	−0.012	0.064	−0.051	−0.009	0.090 **	0.203 ***	−0.124	−0.045
	(0.051)	(0.051)	(0.067)	(0.145)	(0.065)	(0.279)	(0.043)	(0.088)	(0.034)	(0.060)	(0.083)	(0.085)
Farm size	0.023	−0.021	−0.008	−0.014	−0.037 *	0.156	0.014	−0.068	−0.010	−0.007	0.025	0.027
	(0.019)	(0.020)	(0.025)	(0.053)	(0.020)	(0.153)	(0.014)	(0.055)	(0.012)	(0.018)	(0.016)	(0.018)
Off-farm income	0.400	−0.070	−0.301	−0.447	−0.202	5.485	1.007 **	−4.486	−0.047	0.880 **	0.005	−0.400
	(0.253)	(0.234)	(0.346)	(0.572)	(0.312)	(6.325)	(0.504)	(7.664)	(0.291)	(0.355)	(0.576)	(0.704)
TLU	0.011	−0.007	0.111	−0.212	−0.059 **	2.229	0.175	0.003	0.116	−0.192	−0.442 **	0.444 **
	(0.026)	(0.023)	(0.085)	(0.272)	(0.024)	(2.112)	(0.108)	(0.203)	(0.098)	(0.126)	(0.177)	(0.201)
Asset index	0.983 **	0.188	0.598	0.164	−0.224	−0.764	0.120 **	−0.101	0.031	−0.726	0.098 *	−0.041
	(0.458)	(0.293)	(0.779)	(1.563)	(0.492)	(4.263)	(0.061)	(0.285)	(0.067)	(0.652)	(0.054)	(0.127)
Extension	−0.012	0.006	0.076	−0.169	0.027	0.321	0.042	0.196	0.067	0.343 **	0.376 **	−3.922
	(0.016)	(0.015)	(0.057)	(0.186)	(0.017)	(0.467)	(0.126)	(0.151)	(0.116)	(0.135)	(0.189)	(5.204)
Credit	−0.087	0.728 **	4.217	1.339 *	−0.586	4.912	−0.126	1.109 **	0.656	0.224	1.152 **	−4.124
	(0.343)	(0.320)	(7.626)	(0.832)	(0.540)	(9.415)	(0.452)	(0.457)	(0.436)	(0.478)	(0.536)	(5.657)
Group	0.093 ***	0.495 ***	0.095	4.311	0.257	−3.262	0.655 ***	0.697	0.406 **	0.571 **	0.084	0.096
	(0.040)	(0.147)	(0.487)	(8.289)	(0.555)	(5.414)	(0.203)	(0.460)	(0.180)	(0.270)	(0.393)	(0.421)
Distance	−0.014 ***	−0.030 *	0.012	−0.120	0.018	1.767	−0.049 **	−0.075 ***	−0.027	−0.024	0.035	−0.034
	(0.007)	(0.016)	(0.027)	(0.163)	(0.019)	(1.722)	(0.021)	(0.025)	(0.026)	(0.036)	(0.025)	(0.055)
HH in Kenya	-	-	-	-	-	-	-	-	-	-	-	-
HH in Tanzania	-	-	-	-	-	-	-	-	-	-	-	-
Constant	1.815 **	−0.515	2.391	−0.808	−1.608 *	0.610	−0.412	−6.051	0.955 **	0.340	−1.191	−3.011 ***
	(0.717)	(0.713)	(1.005)	(0.971)	(0.862)	(0.971)	(0.542)	(7.925)	(0.471)	(0.663)	(1.002)	(1.063)
Observations	252						288					
Log likelihood	−254.537						−143.1760					
Wald χ * (84, 72) *	63.47 **						123.86 **					

Source: authors' calculations using the survey data. Note: robust standard errors are in parentheses. *** = significant at 1% level; ** = significant at 5% level; * = significant at 10% level.

The country dummies in the pooled model indicate that households located in Uganda are significantly less likely to adopt improved seed, conservation tillage and row planting than those in Kenya and Tanzania. However, households in Uganda are more likely to adopt crop rotation and IPM. Likewise, households located in Kenya are more likely to adopt chemical fertilizer than those in Tanzania and Uganda. This finding can be attributed to the variation in the levels of use of technologies among households in the three countries in addition to variations in biophysical and institutional factors.

3.3.2. Poisson Result

The results of the Poisson and negative binomial models are presented in Table 6. Four separate regressions were run—one for the pooled data and one each for the countries:

Tanzania, Kenya and Uganda. The results indicate a reasonable degree of uniformity regarding the sign of the parameter estimates and the statistical significance for both the Poisson and the negative binomial specifications. The estimated dispersion parameter (α) from the negative binomial regression model is negative and insignificant, which indicates the absence of over-dispersion; hence, the Poisson regression model is appropriate. Additionally, the Poisson model has smaller values of Akaike information criterion (AIC) and Bayesian information criterion (BIC) estimates compared to the negative binomial model and these showed that the Poisson model is more appropriate for the estimation (Table 6). The LR chi-square values were also significant at 1% and 5%, suggesting that the explanatory variables included in the model jointly explained mungbean farmers' adoption decisions on improved production technologies. This study only discusses the results of the Poisson model due to its significant statistical test.

Results from the Poisson model show that gender of the household head has a positive and statistically significant effect on the pooled data and in Tanzania. This result implies that male-headed households in the pooled data and in Tanzania increases the intensity of the adoption of mungbean production technologies by 18% and 43%, respectively. Education explained as the number of years spent in formal schooling was also significant and positively impacts the adoption intensity in the pooled data and in Tanzania. This implies that a one-year increase in education increases the intensity of the adoption of mungbean production technologies in the pooled data and in Tanzania by 0.3% and 6.4%, respectively. Household size was identified to have a positive and significant association with the number of technologies adopted by the mungbean farmers in Uganda, but insignificant impacts in the pooled data, Kenya and Tanzania. This implies that households with more members in Uganda have about 9% higher intensity of adopting improved technologies in mungbean production.

A number of wealth variables have statistically significant effects on the adoption intensity decisions of households. The results show that owning more farmland is correlated with the intensity of the adoption of mungbean production technologies in the pooled data and in Kenya. This indicates that, as cultivated farmland increases by one unit in the pooled data and in Kenya, the number of improved mungbean technologies adopted increases by 0.3% and 0.6%, respectively. Livestock size was found to have a positive and significant association with the intensity of the adoption of improved mungbean production technologies in the pooled data, Uganda and Kenya. Households with a high number of livestock in the pooled data, Uganda and Kenya increased the intensity of the adoption of mungbean production technologies by 0.5%, 6% and 0.7%, respectively. Th asset index showed a positive and significant impact on the number of improved technologies adopted by mungbean farmers in the pooled data and in all the three countries, i.e., Tanzania, Kenya and Uganda.

Farmers' contact with extension agents in the pooled data, Tanzania, Kenya and Uganda increases the intensity of the adoption of mungbean production technologies by 1.5%, 1.7%, 1.8% and 12%, respectively. Additionally, access to credit in the pooled data, Tanzania and Uganda increases the intensity of the adoption of mungbean production technologies by 19%, 51% and 50%, respectively.

Location variables in the pooled model have a positive effect on intensity of the adoption of mungbean production technologies. Being located in Kenya and Tanzania could increase the number of mungbean production technologies adopted than those in Uganda. This is attributed to the variation in biophysical and institutional factors in the study countries.

Table 6. Marginal effects for the Poisson and negative binomial regression models.

Variables	Standard Poisson				Negative Binomial Regression			
	Pooled Data (1)	Tanzania (2)	Kenya (3)	Uganda (4)	Pooled Data (1)	Tanzania (2)	Kenya (3)	Uganda (4)
Age	0.001 (0.001)	0.003 (0.008)	−0.010 (0.010)	0.001 (0.005)	0.00 0(0.004)	0.003 (0.008)	−0.010 (0.010)	0.001 (0.005)
Gender	0.180 ** (0.133)	0.434 ** (0.266)	0.001 (0.316)	−0.141 (0.201)	0.180 ** (0.138)	0.434 ** (0.266)	0.001 (0.316)	−0.141 (0.201)
Education	0.003 ** (0.001)	0.064 ** (0.037)	−0.011 (0.034)	0.009 (0.014)	0.003 ** (0.001)	0.064 ** (0.037)	−0.011 (0.034)	0.009 (0.014)
Household size	0.022 (0.022)	0.040 (0.032)	−0.024 (0.074)	0.088 *** (0.030)	0.022 (0.022)	0.040 (0.032)	−0.024 (0.074)	0.088 *** (0.030)
Farm size	0.003 ** (0.001)	−0.007 (0.008)	0.006 *** (0.026)	0.008 (0.010)	0.001 (0.006)	−0.007 (0.008)	0.006 ** (0.026)	0.008 (0.010)
Off-farm	0.011 (0.165)	0.358 (0.714)	0.037 (0.345)	−0.280 (0.209)	0.011 (0.165)	0.358 (0.714)	0.037 (0.345)	−0.280 (0.209)
TLU	0.005 ** (0.002)	−0.010 (0.010)	0.007 *** (0.01)	0.062 ** (0.024)	0.002 (0.005)	−0.010 (0.010)	0.007 * (0.010)	0.062 *** (0.024)
Asset index	0.000 ** (0.000)	0.000 * (0.000)	0.000 * (0.000)	0.000 * (0.000)	0.000 ** (0.000)	0.000 * (0.000)	0.000 * (0.000)	0.000 * (0.000)
Extension	0.015 ** (0.005)	0.017 ** (0.058)	0.018 ** (0.020)	0.123 ** (0.077)	0.015 ** (0.005)	0.017 ** (0.058)	0.018 ** (0.020)	0.123 ** (0.077)
Credit	0.190 ** (0.057)	0.509 ** (0.292)	0.251 (0.501)	0.504 * (0.351)	0.057 (0.190)	−0.509 ** (0.292)	0.251 (0.501)	0.504 ** (0.351)
Group	0.182 (0.131)	0.085 (0.195)	0.216 (0.567)	−0.208 (0.148)	0.182 (0.131)	−0.085 (0.195)	0.216 (0.567)	−0.208 (0.148)
Distance	−0.001 (0.004)	−0.008 (0.013)	0.017 (0.024)	0.006 (0.013)	−0.002 (0.008)	−0.008 (0.013)	0.017 (0.024)	0.006 (0.013)
HH in Kenya	2.677 *** (0.258)	-	-	-	2.677 (0.258)	-	-	-
HH in Tanzania	1.107 *** (0.174)	-	-	-	1.107 *** (0.174)	-	-	-
Constant	0.545 *** (0.138)	1.146 *** (0.267)	1.482 *** (0.254)	0.821 *** (0.275)	0.545 *** (0.138)	1.146 *** (0.267)	1.482 *** (0.254)	0.821 *** (0.275)
Observation	772	257	252	288	772	257	252	288
Alpha	-	-	-	-	0.0005	0.0005	0.0003	0.0001
LR χ * (14, 12)	359.07	23.10	25.19	36.63	358.14	21.81	24.69	31.87
Prob > χ *	0.0000	0.0269	0.01675	0.0003	0.0000	0.0394	0.01512	0.0014
Pseudo R *	0.1262	0.1253	0.0591	0.1446	NA	NA	NA	NA
Log likelihood	−1243.2598	−445.574	−393.649	−392.18817	−1243.2598	−441.2209	−399.2206	−382.9174
AIC	2516.520	912.4419	813.297	795.8348	2518.525	917.178	828.4413	810.376
BIC	2586.254	963.286	859.180	850.7792	2589.259	881.3827	857.995	

Source: authors' calculations using the survey data; Notes: standard errors are in parentheses. *** = significant at 1% level; ** = significant at 5% level; * = significant at 10% level.

4. Discussion

The results of the MVP model suggest that older farmers are significantly less likely to use chemical fertilizer in pooled data, chemical fertilizer and row planting in Tanzania, improved seed and IPM in Kenya, and the use of conservation tillage in Uganda (Table 4). This may be due to the fact that young farmers are better able to provide the labor needed by productivity-enhancing technologies and thus are less risk averse. Male-headed households are more likely to use improved seeds and conservation tillage in pooled data, chemical fertilizer and row planting in Tanzania, and improved seed in Uganda. This result is consistent with findings by Diallo et al. [19] in Mali who found that male-headed households have a higher probability of adopting row planting. The size of the household members is used as a proxy for labor availability for farm activities. The result shows that the size of the household members has the positive effect on the adoption of improved seed, crop rotation and IPM in the pooled data. Household size also has the positive impact on the adoption of improved seed, conservation tillage and row planting in Tanzania, and crop rotation and IPM in Uganda. A similar result was found by Diallo et al. [19] in Mali. In addition, farmers who have off-farm income were more likely to adopt improved seed and IPM in Uganda.

Consistent with the findings of Kassie et al. [4] on technology adoption, farm size leads to a higher probability of adopting crop rotation in the pooled data and in Tanzania, and makes the adoption of conservation tillage less likely in Kenya. Livestock had a negative significant influence on the adoption of conservation tillage in Kenya and Uganda. On the other hand, it significantly increases the probability of the adoption of row planting in Uganda. A study reported by Kassie et al. [4] found the same impact of livestock on technology adoption. The asset index positively influences the adoption of improved seeds in the pooled data, Tanzania, Kenya and Uganda. The asset index also has a positive impact on adoption of conservation tillage in Uganda.

The results show the key roles played by rural institutions and transaction costs in technology adoption. Access to extension services increased the adoption of conservation tillage in the pooled data and in Uganda. Similarly, it is also increased the adoption of IPM in Uganda. This result is consistent with findings by Asfaw et al. [20] in Niger, which suggest that farmers' contact with extension agents is expected to have a positive effect on the adoption of technologies. The access to credit variable was important in explaining the adoption of chemical fertilizer and row planting in the pooled data, chemical fertilizer and conservation tillage in Tanzania, chemical fertilizer and IPM in Kenya, and chemical fertilizer and conservation tillage in Uganda. Since row planting is carried out using human labor, it implies that the demand for labor would increase and this would mean that more capital is required. Farmers who are organized in groups are more likely to adopt improved seeds and IPM in the pooled data, crop rotation and IPM in Tanzania, improved seeds and chemical fertilizer in Kenya, and improved seed, crop rotation and IPM in Uganda. Farmer groups as networks of sharing knowledge can improve the flow of information about new technology. The results further show that access to an input market influences farmers' adoption decisions. Households located closer to an input market are more likely to use improved seed, chemical fertilizer, conservation tillage and row planting in the pooled data; improved seed, chemical fertilizer and row planting in Tanzania, and improved seed and chemical fertilizer in Kenya and Uganda. This could be linked to the fact that access to markets may influence the net benefits from the adoption of new technologies. The distance from the market can reduce the expected profitability of a new technology, since obtaining professional support and advice about the new technology becomes difficult, and access to complementary inputs becomes limited and costly [4]. This result is consistent with findings by Asfaw et al. [20] in Niger.

Location variables have a positive effect on the probability of the adoption of mungbean production technologies. This finding can be attributed to the variation in the levels of use of improved technologies among households in the three countries in addition to variations in biophysical and institutional factors.

The results from the Poisson model show that gender and education had a positive and significant impact on the number of technologies adopted in the pooled data and in Tanzania. Male-headed households were more likely to adopt and intensify the use of improved mungbean production technologies because women have limited access to resources such as land, capital and extension services [14]. Consistent with a previous study on technology adoption [4], household size was identified to have a positive and significant association with the number of technologies adopted by the mungbean farmers in Uganda, but insignificant impacts in the pooled data, Kenya and Tanzania. Households with more members in Uganda have about 9% higher intensity of adopting improved technologies in mungbean production. A large household size signifies access to working members, which have a positive impact on the adoption of new technologies such as labor-demanding technologies.

Farm size had a positive and significant influence on the number of improved production technologies adopted by mungbean farmers in the pooled data and in Kenya. This confirms the expectation that owning more farmland is correlated with the intensity of adoption. Kassie et al. [18] found a similar result in their study in Uganda. Livestock size was found to have a positive and significant association with the number of improved technologies adopted by the mungbean farmers in the pooled data, Uganda and Kenya. This implies that households with high numbers of livestock in the pooled data, Uganda and Kenya increased the intensity of the adoption of mungbean production technologies by 0.5%, 6% and 0.7%, respectively. This result is consistent with findings by Kassie et al. [21] who reported the positive effect of livestock on the intensity of adoption of agricultural practices among smallholder farmers in Kenya, Malawi and Tanzania.

Household wealth, proxy by asset index showed a positive and significant impact on the number of improved technologies adopted by mungbean farmers in all the three countries. There was a positive association between adoption and asset index, probably because wealthier households are better able to bear possible risks associated with the adoption of technologies and may be more able to finance the purchase of technologies.

Farmers' contact with extension agents had a positive impact on the number of technologies adopted by farmers in the pooled data, Tanzania, Kenya and Uganda. This suggests that contact with extension agents facilitates technology transfer and promotes adoption at lower cost [18]. This result is consistent with that of Kassie et al. [4], who reported the positive effect of contact with extension staff on the adoption of sustainable agricultural practices among smallholder farmers in Tanzania. Access to credit is considered as one of the most important steps in dealing with the constraints associated with the adoption of agricultural technologies. Access to credit was positively associated with the number of improved mungbean production technologies adopted by farmers in the pooled data, Tanzania and Uganda. This result is consistent with that of Mariano et al. [17], who reported the positive effect of credit access on the intensity of the adoption of best management practices among rice farmers in the Philippines.

Location variables have a positive effect on the intensity of the adoption of mungbean production technologies. This finding can be attributed to the variation in the levels of use of improved technologies among households in the three countries in addition to variations in biophysical and institutional factors. Nkegbe and Shankar [22] also employed count data models and found evidence of regional effects in the adoption intensity of soil and water conservation practices among smallholder farmers in Ghana.

5. Conclusions

Using household-level data collected from smallholder farmers in Tanzania, Kenya and Uganda, the study analyzed the factors that influence the probability and intensity of the adoption of mungbean production technologies, using multivariate probit and Poisson regression models. The results showed that household characteristics such as gender and household size significantly influence the probability and intensity of the adoption of mungbean production technologies, with female-headed households being less likely to adopt, possibly because of limited access to resources such as land. Policy interventions that increased the targeting of women for technology adoption could increase the adoption and impact of improved technologies among smallholder farmers.

Wealth indicator variables such as farm size, livestock size and asset index positively influence adoption, implying that wealthier households are better able to bear possible risks associated with the adoption of improved technologies, and may be more able to finance the purchase of technologies. This suggests that appropriate policy interventions focusing on maintaining or increasing household assets are crucial in enhancing smallholders' adoption of improved technologies.

The significant role of institutional and access-related variables such as access to extension services, farmer groups and credit access in adoption suggests the need for the policy interventions that focus on strengthening agricultural extension, farmer groups and credit service providers to assist farmers in accessing information, credit, inputs and markets outlets. However, an increased emphasis on information dissemination, field demonstration and training programs to disseminate new technologies are required to enhance technology adoption among smallholder farmers.

The presence of location effects in the probability and intensity of adoption decision implies that different strategies should be employed for different locations if policy makers aim at promoting the adoption of improved mungbean production technologies.

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