Heliyon 6 (2020) e03543

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Research article

Modelling adoption intensity of improved soybean production technologies in Ghana - a Generalized Poisson approach

Abass Mahama [a], Joseph A. Awuni [a], Franklin N. Mabe [a], Shaibu Baanni Azumah [b,*]

[a] Department of Agricultural and Resource Economics, University for Development Studies, P. O. Box TL 1350, Tamale, Ghana
[b] Solidaridad Network – West Africa, East Legon, Accra PMB KD 11, Kanda, Accra, Ghana

ARTICLE INFO

Keywords:
Count data models
Ghana
Generalized Poisson
Production technologies
Soybeans
Agricultural economics
Agricultural policy
Agricultural technology
Agricultural water management
Organic farming
Economics
Agriculture

ABSTRACT

Soybean is an important cash crop especially for farmers in the north of Ghana. However, cultivation of the commodity is dominated by smallholders equipped with traditional tools, coupled with low or no adoption of improved soybean production technologies. Using primary data collected from 300 soybean farmers across northern Ghana, the study employed count data modelling to estimate the determinants of adoption intensity of sustainable soybean production technologies. The study accounted for potential estimation errors due to under-dispersion and over-dispersion, by using a model based on the generalized Poisson distribution. On the average, a farmer adopted 50% of the identified sustainable soybean production technologies. Age, education, extension visits, mass media through radio, and the perception of adoption of soybean production technologies being risky are significant with positive influence on the adoption intensity of sustainable soybean production technologies. The study therefore recommends among others, that various extension programmes should intensify education on the benefits of adopting sustainable soybean production practices. There is the need to set up many technology demonstration farms to give farmers hands-on training during field days.

1. Introduction

The agricultural sector has remained pivotal and continue to contribute to the growth in most developing economies especially across sub-Saharan Africa. The growth and economic development of most developing countries is centered on agriculture which plays a pivotal role in the transformation of the lives of a large majority of people that depends on it (Todaro and Smith, 2011). Achieving agricultural sustainability requires that a wide range of approaches that meet the needs and priorities of farmers are looked at and implemented at different levels. Agricultural output growth is considered one of the surest ways of effectively addressing poverty in the developing part of the world. However, the agriculture sector in Ghana is faced with a major challenge of low productivity especially for staple crops such soybeans, maize and rice. In fact, statistics from the Ministry of Food and Agriculture (MoFA) (2017a, b) reveals that the average soybean yield stands at 1.3Mt/ha as against potential yields of 3.0Mt/ha, meaning that soybean yields in Ghana are still far below the achievable potential. This under performance is attributed to lower capacity to adopt and use improved technologies by soybean farmers (Ministry of Food and Agriculture, 2017a, b).

Crop production pattern in Ghana vary markedly in accordance with the agro climatic conditions. Several leguminous grain crops are widely cultivated in the northern part of Ghana. Legume base crops are the second abundant crop both in production and consumption next to cereals and are a major source of dietary protein, fiber, carbohydrates and essential minerals (Mohammed et al., 2016). Soybean is considered as one of the valuable legume crops in the world and can grow successfully on soils low in nitrogen and has the capacity to fix a valuable source of atmospheric nitrogen into the soil including its lower susceptibility to pests and diseases (Ugwu and Ugwu, 2010).

Soybean is an important cash crop in northern Ghana and its cultivation is dominated by small scale farmers equipped with traditional tools coupled with low adoption of improved soybean production practices. A number of institutions including the Savannah Agriculture Research Institute (SARI) and the International Institute of Tropical Agriculture (IITA) have been involved in research on improved soybean production technologies in Northern Ghana for closed to a decade. Since 2015, MoFA and some non-governmental organizations such as the International Fertilizer Development Centre (IFDC) have led in the implementation of improved soybean production technologies (i.e. inoculants, Triple Superphosphate (TSP), certified seeds and pests and disease

* Corresponding author.
E-mail address: raszumah1983@gmail.com (S.B. Azumah).

https://doi.org/10.1016/j.heliyon.2020.e03543
Received 22 June 2019; Received in revised form 22 October 2019; Accepted 2 March 2020

control measures) using various extension approaches aimed at stimulating adoption of improved soybean production technologies. In this study, we modelled the factors that influence the intensity of adoption of soybean production technologies in northern region of Ghana.

Certified seeds are seeds that are sourced from known and reliable institutions such as research organisations, private seed producers/traders and agro-input dealers after passing inspection and testing. Certified seeds are high quality seeds that are not broken, diseased, wrinkled and shrunken (Bogdanović et al., 2015). Inoculants are bacteria that form a symbiotic relationship with the soybean roots to stimulate nodules formation that enhances nitrogen production and biological fixation throughout the entire growing season (Thilakarathna et al., 2019). TSP is a phosphorus-based fertilizer that contains zero nitrogen. TSP is very soluble in water, making it readily available for uptake by plants. It is suitable for leguminous crops by supplementing the biological fixation of nitrogen by leguminous crops (Noor-Us-Sabah et al., 2016). Pest and disease control measures is part of a group of good agricultural technologies used to enhance the growth, plant health and yield of crops. Depending on the type of crop and biological characteristics (e.g. spring or winter crops) different control measures are used.

Many adoption studies have employed various count data models in determining intensity of adoption of technologies. Popular among the count data models used include standard Poisson, zero inflated Poisson, gamma count and endogenous switch Poisson models. For instance, Awuni et al. (2018) used zero inflated Poisson to measure intensity of adoption of rice production technologies; Azumah et al. (2017) and Mensah-Bonsu et al. (2017) used Poisson to explain adoption intensity of climate change coping strategies and land and water management practices respectively. Abdul-Rahman (2017) used Poisson with endogenous treatment to explain intensity of adoption of maize production technologies. Nkegbe and Shankar (2014) also employed gamma count models to measure the intensity of adoption of soil and water conservation practices.

As widely accepted in literature, the starting point for count data analysis is the Poisson regression. Many of the afore mentioned adoption studies may account for equi-dispersion or overdispersion. However, most real-life data is often characterized by under-dispersion, over-dispersion and excess zeros therefore the equality of the conditional mean and variance of the distribution would have been rejected (Erdman et al., 2008). This assumption of equi-dispersion is usually not reflective of most count data. The most likely occurrence in count data is over-dispersion that is, where the variance is greater than the mean. In other cases where the variance is less than the mean, the data is said to be under-dispersed.

According to Harris et al. (2012), dealing with under-dispersed data will require that, the best models are used to avoid cases where the standard errors are over estimated and inferences misleading. Few models have been developed to deal with the incidence of under-dispersed data (Yang et al., 2007). For instance, Nkegbe and Shankar (2014) used gamma count model to account for under-dispersion by explaining the intensity of adoption of soil and water management practices. In this study, we also account for under-dispersion by using a model based on the generalized Poisson distribution which is also appropriate for dealing with under-dispersion in measuring intensity of adoption of soybean production technologies in northern region.

2. Materials and methods

2.1. Study location

The study was conducted in Chereponi District of Northern Region of Ghana. The District lies between latitudes $10^0 10^1$ and 10^0 20^1 eastwards and longitude $10^0 10^1$N and 10^0 20^1 northwards. The District shares boundary with four districts in Northern Region of Ghana, to the west is Gushegu District, Bunkpurugu and Yunyoo districts to the North, Saboba and Yendi districts to the South –West. It has a total land area of 1,374.7 Sq. km.

Chereponi District is part of the savannah ecological zone of Northern Ghana. The climatic condition of the District is characterized by wet and dry seasons. The wet season spans from May to October and the peak of the wet season is from August to September with some occasional rainfall in the month of October. The district records an annual rainfall that range from 1000mm to 4000mm (Ghana Statistical Service vd(GSS), 2014). From November to April, the district is characterized by total dryness with minimal or no cropping activities except some few irrigation farming in isolated areas. Generally, the temperature is high throughout the year and ranges between 21 °C and 41 °C. The district records the highest of 35 °C and the lowest temperature levels of 21 °C.

The vegetation of the district is generally the guinea savannah type dominated by mostly grass growing alongside some drought resistant trees and shrub species. The commonest tree species of economic value to the people of the district are Parkia, Baobab and Shea trees. The vegetation is mostly very green in the rainy season and very dry and brownish in the dry season (harmattan period).

Agriculture is the major economic activity of the people of Chereponi District. An estimated 40 percent of the total land area is used for agricultural purposes with a greater portion of the land left uncultivated (Ghana Statistical Service (GSS), 2014). It is estimated by Ghana Statistical Service (GSS), 2014 that nine out of ten households (90%) in the rural areas are agricultural households. In the urban localities, six out of ten (60%) of households are into agriculture. This shows clearly that agricultural activities are dominated by rural households. Farming in the district is largely done on subsistence basis with many small farm holdings done across the entire district with an average per capita land size of about 0.8ha. However, some farmers are engaged in commercial farming cultivating large areas of soybeans, maize, yam and rice. The district is known for its production of soybeans and other leguminous, cereals as well as root and tuber crops (Ghana Statistical Service (GSS), 2014).

Available soybean yield data from MoFA shows that the Chereponi district recorded average yield figures of 1.76Mt/Ha in 2017 with a total production figure of 7,086MT; 1.00MT/Ha in 2016 with a total production yield of 3, 264MT; and 1.65MT/Ha in 2015 with a total production of 1,381MT. Also, a total of 4,026 ha of land was put under soybean production in 2017; 3,264 ha in 2016 and 837 ha in 2015. It is observed that the total production in terms of yield and area put under cultivation has increased steadily due to support from some past existing projects, non-governmental organisations, and institutional buyers.

2.2. Sampling and data collection

With limited or no data on the population of soybean farmers in the district, the decision of an appropriate sample technique is tough. A multistage sampling technique was used. The study area was divided into five zones, namely; North, West, South-West, East and Central using cluster sampling method. A simple random sampling procedure was used to sample two communities from each of the five zones which are known for soybean production and have benefited from soybean project intervention (either in the past or present). Thus, ten communities were sampled as follows: Jakpa, Banjani, Famisa, Kpaboku, Namariku, Sangbana, Tombu, Tusunga, Akromabila No. 1 and Ando-Kajura.

A list of soybean farmers was obtained from MoFA and opinion leaders in the communities and a simple random sampling technique was employed in selecting 300 soybean farmers. These respondents included beneficiaries and non-beneficiaries. The research data was obtained from primary sources. The primary data was collected using semi-structured questionnaires made up of closed and open-ended questions in a face to face administration of the questionnaire to soybean farmers in the selected communities for the study.

The data collection exercise was conducted in close collaboration with the Chereponi District Agriculture Development Unit during the 2018 cropping season. The unit assisted with production data such as

district soybean yield, community level yield, existing technologies and transfer mechanisms and adoption behaviour of farmers in communities that are of interest to this study.

2.3. Data analysis – model specification

Most real-life data are often characterized by under-dispersion, over-dispersion and excess zeros therefore the equality of the conditional mean and variance of the distribution could be rejected in most count data modelling (Erdman et al., 2008; Greene, 2002). Most variables that comprise of count data are usually modelled or analyzed with basic count data models such as the Poisson regression model (Harris et al., 2012). The underlying assumption of the Poisson regression model is that, variance is equal to the mean (equi-dispersion). This assumption of equi-dispersion is usually not reflective of most count data. The most likely occurrence in count data is over-dispersion that is, where the variance is greater than the mean. In other cases where the variance is less than the mean, the data is said to be under-dispersed.

According to Harris et al. (2012), dealing with under-dispersed data will required that, the best models are used to avoid cases where the standard errors are overestimated and inferences misleading. Few models have been developed to deal with the incidence of under-dispersed data (Yang et al., 2007). Normally for under-dispersed data, a model that is based on the generalized Poisson distribution may be appropriate.

Suppose Y_i is a count response variable, and follows a generalized Poisson distribution, the probability mass function (PMF) of Y_i, i = 1, 2,…, n according to Famoye et al. (2004), Famoye (1993), Wang and Famoye (1997), is specified as:

$$f(y_i) = \Pr(Y_i = y_i) = \left(\frac{\lambda_i}{1+\alpha\lambda_i}\right)^{y_i} \frac{(1+\alpha y_i)^{y_i-1}}{y_i!} \exp\left[\frac{-\lambda_i(1+\alpha y_i)}{1+\alpha\lambda_i}\right], y_i = 0, 1, 2, \ldots. \quad (1)$$

The mean and variance of Y_i are mathematically specified as:

$$E(Y_i|x_i) = \lambda_i, Var(Y_i|x_i) = \lambda_i(1+\alpha\lambda_i)^2 \quad (2)$$

The generalized Poisson regression model is by far an extension or generalization of Poisson regression model. Where $\alpha = 0$, the probability mass function in reduces to the standard Poisson regression model. In practice, this assumption is often not reflective of real-life data because the conditional variance could either be lesser or greater than the conditional mean. However, if there is inequality of the variance and mean, the estimates in Poisson regression model are still consistent but are inefficient, leading to over estimation or invalidation of standard errors and wrong inference (Famoye et al., 2004).

When $\alpha > 0$, it is assumed the variance is greater than the mean and which case the Generalized Poisson regression (GPR) model represents count data with over-dispersion. Also, when $\alpha < 0$, the variance is assumed to be less than the mean and therefore, the generalized Poisson regression model represents count data with under-dispersion. The dispersion parameter (α) is called the dispersion parameter can be estimated along with the regression parameters in the generalized Poisson regression model. The maximum likelihood method is used to calculate the estimates of α and β in the generalized Poisson regression model.

Several non-parametric test can be used to measure the goodness-of-fit of Generalized Poisson Regression model based on the deviance or Pearson test statistic (Famoye, 1993). The test based on the deviance or Pearson statistic is approximated by the distributional effect of the chi-square when μ_i's are large. Usually, computing the deviance or Pearson test statistic with the Stata command can be complex. Therefore, the log-likelihood value is often used to measure the goodness-of-fit of the Generalized Poisson regression model. In comparing the Standard Poisson and the Generalized Poisson regression models, the model with large log-likelihood value is often considered the best (Rashwan and Kamel, 2011).

The log likelihood (L) for the GPR model is specified as:

$$lnL(\beta,\alpha) = \sum_{i=1}^{n}\left[y_i ln\left(\frac{\lambda_i}{1+a\lambda_i}\right) + (y_i-1)ln(1+\alpha y_i) - lny_i! - \frac{\lambda_i(1+\alpha y_i)}{1+\alpha\lambda_i}\right] \quad (3)$$

A test of hypothesis of adequacy of the GPR model over the Standard Poisson model is given by:

$$H_0 : \alpha = 0 \text{ against } H_a : \alpha \neq 0 \quad (4)$$

The test of H_0 is an indication of significance of the dispersion parameter. Therefore, when H_0 is rejected, the appropriate model to use is the generalized Poisson Regression model. The test could be conducted by using the asymptotically normal Wald 't', which is defined as the ratio of the estimate of α to its standard error. Alternatively, the likelihood ratio test statistic could be used to test for the null hypothesis. This is approximately chi-square distributed and have one degree of freedom when the null hypothesis is true.

According to Bozdogan (2000), one other way of choosing the best count data model is by considering the value of the Akaike Information Criterion (AIC). Mathematically the AIC is presented as follows:

$$AIC = -2\ln L(\tilde{\theta}) + 2k \quad (5)$$

where the L(θ) is defined as the log likelihood value, and k denotes the number of parameters considered for estimation. Usually, the model with smaller AIC value is considered the best model (Fabozzi et al., 2014).

3. Results and discussions

3.1. Summary statistics of variables

Summary statistics of the 13 independent variables used in the study are presented in Table 1. About 50% of respondents had benefited from some form of soybean production project in the past either from government or NGOs operating in the area. The average age of soybean farmers in the study area was found to be 34.8 years. This means that, majority of farmers in the study area are largely youthful and are in the bracket of economically active age group. Ministry of Food and Agriculture (2013) estimated the average age of farmers in Ghana to be 55 years. This implies that the present finding of relative lower average age among farmers in the study area is good for agricultural development in northern Ghana considering that agricultural activities involves the use of labour because mechanisation and intensification mechanisms are slow.

The average years spent schooling was low at 1.66 years. This implies that a large section of soybean farmers had extremely low levels of education. Averagely, farmers in the study area have a substantial experience in soybean production (15 years). This implies that with the huge experience attained by farmers, it is expected that adoption of improved technologies could either be high or low since farmers would have tried similar technologies in the past and would have seen the impact of these technologies on their yields. Income entails revenue generated from the sale of soybean. The average income earned per hectare from soybean production was estimated at GH¢752.17 (about US$ 140 at the time of the study). In absolute values, farmers were offered relatively low prices per every 100kg of soybean as compared to what is offered on the international market. At the time of this study, farmers received an amount of $14 (GH¢75) per 100kg of soybean as against an amount of $37 (GH¢ 196) per 100kg of soybean sold on the international market.

The average distance covered by soybean farmers from their farm to input market was 6.38km. This meant, farmers travel relatively short

Table 1. Definition and summary statistics of variables.

Definition and definition	A priori expectation	Mean	Std. Dev.
Household specific factors			
Age (in years)	+	34.84	9.79
Education (in years of formal schooling)	+	1.66	3.73
Soybean project beneficiary (1 = beneficiary, 0 = otherwise)	+	0.5	0.5
Farm specific factors			
Number of years in soybean farming (years)	+	15.27	9.92
Previous year's income from soybean production (in GH¢)	+	752.17	402.88
Distance from farm to input dealer (kilometers)	+	6.38	2.93
Cropping system (1 if respondent does mono-cropping, 0 if otherwise)	+/-	0.58	0.49
Institutional specific factors			
Extension (number of contact times with extension agent)	+	2.77	1.97
Credit (1 if farmer had access to credit, 0 if otherwise)	+	0.41	0.49
Mass media method (1 if respondent is exposed, 0 if not)	+/-	0.133	0.34
Demonstration method (1 if respondent is exposed, 0 if not)		0.79	0.4
Household extension method (1 if respondent is exposed, 0 if not)	+/-	0.26	0.44
Technological specific factors			
Risk (1 = technologies are risky, 0 = otherwise)	+/-	0.79	0.64

Source: Computed from field data, 2019.

distances to acquire inputs from dealers and this could influence the adoption of improved soybean productions technologies positively. Extension is an important and critical source through which many farmers acquire information, either indirect contact with colleague farmers who have experience transferring agricultural information to other farmers, or directly, through contact with extension agents (Azumah et al., 2018). On average farmers have received 2.77 number of extension visits from agricultural extension agents in the last season. About 41% of farmers had access to farm credit for farm production purposes. Accessing farm credit is largely influenced by the intervention of NGOs and Village Savings and Loans Associations operating in the study area. Low involvement of commercial financial institutions was attributed to the risky nature of farming, low yields, low profit margins, and relatively small farm sizes cultivated by farmers' couple with the lack of collateral security to present for credit facilities.

A wide range of mechanisms have been used to expose or introduce improved technologies to farmers. In this study, three technology transfer mechanisms namely; Mass media (most through radio), technology demonstrations and household extension methods were identified as major sources through which farmers accessed information on soybean production technologies. About 13% of farmers accessed information on improved soybean technologies through the mass media via radio. Also, about 79% of farmers were exposed to improved soybean technologies by participating in technology demonstrations field days. Meanwhile, 26% of the farmers accessed information on improved soybean technologies via household extension method. The results from Table 1 also reveals that about 79% of farmers think that soybean production technologies are risky to adopt since they may not improve yields.

Extant literature review and expert opinions from research scientists from SARI, as well as extension agents from MoFA, revealed key improved soybean production technologies that are currently disseminated for improving the yields of soybean farmers in Northern Ghana. The study looked at four key technologies promoted by SARI, MoFA, IITA and IFDC, which include inoculation, the use of triple super phosphate (TSP), the use of certified soya seeds, and pest and disease control measures.

The average soybean yield in Ghana stands at 1.3MT/Ha (Ministry of Food and Agriculture, 2017a, b). It is estimated by the Feed the Future USAID RFA- FTF Ghana ATT project (2016) that when farmers adopt only certified seed technology, a yield of 1.16MT/Ha is realized. However, with the adoption of a combination of inoculant and certified seed, farmers are able to realize a yield of 1.54MT/Ha. Also, adoption of certified seed and TSP in combination, gives farmers a yield of 1.94MT/Ha. Additionally, adoption of a combination of certified seed, inoculant, pest and disease control measures, and TSP produce 2.0MT/Ha. Their findings conclude by reporting an average soybean yield increase of 76% with the adoption of the combination of inoculant, TSP, certified seed, and pest and disease control measures, which translates to an increase of 67.7% in average gross margin.

3.2. Factors determining intensity of adoption of soybean production technologies

The study identified four key soybean production technologies that are important to achieving sustainable higher yield. Targeted farmers were required to indicate the soybean production practices they adopted and have continuously used for the past three year. The dependent variable was then modelled around the number of technologies adopted by farmers. The intensity of adoption of soybean production practices is presented in Table 2.

From Table 2, the results show that 10.33% of farmers did not adopt any of the soybean production technologies and therefore recorded a zero count, whereas 19.67% of farmers adopted three technologies. Also, about 13.33% of farmers adopted two soybean production technologies while 37% (majority) of farmers adopted only one soybean production technology. However, all the four soybean production technologies were adopted by about 19.67% of the sampled farmers. The mean adoption intensity was about 2, with a variance of about 1.8.

The various soybean production technologies adopted by farmers is shown in Table 3. The results show that majority (86.67%) of farmers adopted certified seeds, while 32.33% of farmers adopted inoculants. Also, Triple Super Phosphate was adopted by 41.67% of farmers with 40.67% of the farmers also adopting pest and disease control measures that improve production.

In Table 4, the results of the factors that influence the adoption intensity of soybean production technologies are presented. Model diagnostic tests were performed to determine the appropriate functional model to use. The parametric estimates across the four models are quite uniform (see Table 4). A few diagnostic tests performed revealed the existence of few zero counts (under dispersion). A goodness of fit test using the log-likelihood value was used to compare the count data models, i.e. Generalized Poisson (GP), Standard Poisson

Table 2. Intensity of adoption of soybean production technologies (SPTs).

Number of technologies adopted	Freq.	Percent
0	31	10.33
1	111	37.00
2	40	13.33
3	59	19.67
4	59	19.67
Mean adoption	*2.01*	
Variance	*1.77*	

Source: Computed from field data, 2019

Table 3. Soybean production technologies.

Soybean production technology	Freq. (No. of farmers who adopted)	Percent
Inoculants	97	32.33
Triple Super Phosphate (TSP)	125	41.67
Certified seeds	260	86.67
Pest and disease control	122	40.67

N = 300.
Source: Computed from field data, 2019

(SP), Zero Inflated Poisson (ZIP) and Negative Binomial Regression (NBR) model.

The log-likelihood values indicate the GP model to have the largest value, implying that the generalized Poisson model fit the data significantly well. The test of hypothesis of adequacy of the generalized Poisson over the standard Poisson shows that the dispersion parameter is less than zero (-0.30), suggesting evidence of significant under dispersion of the data. Therefore, the null hypothesis of equi-dispersion is rejected. Also, a test of Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) revealed the generalized Poisson model had marginally lower values than the other count data models, providing significant justification for the choice of the generalized Poisson model over the other count data models to estimate the intensity of adoption of soybean production technologies. The proceeding discussion of the results in Table 4 is therefore based on estimates of the generalized Poisson regression model.

About thirteen variables were estimated with the generalized Poisson regression model, 10 variables are statistically significant in explaining the intensity of adoption of soybean production technologies. Age of respondents, education, number of extension contacts, mass media (radio) and risk associated with technologies are statistically significant and positively influence the number of soybean technologies adopted farmers in northern Ghana. Also, farmers experience in soybean production, cropping system used by farmers, distance from farm to input dealer shop, exposure to household extension method and access to production credit are significant but bear inverse relationship with the number of soybean technologies adopted.

The results from Table 4 imply that as a farmer's age increases, it is assumed that they become more responsible for themselves and their immediate family members. As a result, they tend to have a strong desire to adopt a combination of technologies that can enhance their yields to improve their incomes to be able to take care of their families. This finding is in tandem with the a priori expectation of positive relationship and corroborates with Fitsum (2016) and Mustapha et al. (2012). However, the result diverges from Awuni et al. (2018) and Pokhrel et al. (2018) who reported an insignificant effect of age on intensity of adoption of improved rice technologies and irrigation technologies respectively. Nkegbe and Shankar (2014) also found a negative and insignificant relationship between age and intensity of adoption of soil and water conservation practices. The plausible explanation to these divergences could be as a result of differences in technologies measured.

Table 4. Factors that influence the adoption intensity of SPTs.

Model	Generalized Poisson		Standard Poisson		Zero Inflated Poisson		Negative Binomial	
Variable	Coef.	Std. Err	Coef.	Std. Err	Coef.	Std. Err	Coef.	Std. Err
Soybean project beneficiary	0.050	0.064	0.079	0.087	0.079	0.088	0.079	0.087
Age	0.037**	0.015	0.032**	0.019	0.032*	0.020	0.032*	0.019
Education	0.023**	0.008	0.015*	0.011	0.015	0.011	0.015	0.011
Farming experience	-0.029**	0.015	-0.025	0.019	-0.025	0.019	-0.025	0.019
Previous year's income	8.020	0.000	8.900	0.000	8.85e-0	0.000	8.85e-06	0.000
Distance to input market	-0.12***	0.011	-0.13***	0.016	-0.134***	0.016	-0.134***	0.016
Cropping system	-0.185**	0.066	-0.174**	0.088	-0.174**	0.089	-0.174**	0.088
Demonstration method	0.140	0.091	0.115	0.125	0.114	0.126	0.115	0.125
Household method	-0.262**	0.084	-0.286**	0.113	-0.286**	0.114	-0.286**	0.113
Extension visits	0.030**	0.016	0.035**	0.021	0.034*	0.021	0.035*	0.021
Access to credit	-0.112**	0.066	-0.153**	0.092	-0.153*	0.093	-0.153*	0.092
Mass media (radio)	0.200**	0.096	0.279**	0.124	0.279**	0.124	0.279 **	0.124
Risky	0.113**	0.044	0.088	0.056	0.088	0.056	0.088	0.056
Constant	0.367	0.349	0.578	0.454	0.577	0.458	0.578	0.454
alpha							1.93e-10	
LR Chi^2 (13)	161.39		118.73		114.56		118.72	
Prob > Chi^2	0.0000		0.0000		0.0000		0.0000	
Pseudo R^2	0.1611		0.1182		NA		0.1182	
Log likelihood	-420.125		-442.907		-442.908		-442.908	
AIC	870.25		913.81		919.81		913.81	
BIC	925.80		965.66		982.78		965.67	
Dispersion	-0.30		NA		NA		NA	
Likelihood-ratio test of delta=0: chi^2(1) = 45.56 Prob>=chi^2 = 0.0000								

Note: *, ** and *** indicate significance at 10%, 5% and 1% levels respectively.
Source: Computed from field data, 2019

Some technologies require some experience in their use while others may require some amount of physical strength in their application.

Education explained as the number of years spent in formal schooling is also significant and positively impacts on adoption intensity. This suggest that as farmers spend more years in school, their understanding of the benefits of applying sustainable techniques in production improves. Awuni et al. (2018) made a diverging finding where education had an insignificant but a positive relationship with intensity of adoption of improved rice production technologies by rice farmers in northern Ghana. However, the findings of Dhraief et al. (2018), and Charles et al. (2017) support our a priori expectation of a positive relationship of age with intensity of adoption of soybean production technologies.

Also, farmers contact with extension agents during soybean production had a positive impact on the intensity of adoption, a result that highlights the important role extension services play in disseminating improved agricultural technologies. The finding is consistent with that of Awuni et al. (2018) who reported extension contacts to have a positive and significant impact on intensity of adoption, and that of Nkegbe and Shankar (2014), also in northern Ghana, who reported a positive effect of extension contacts on intensity of adoption of soil and water conservation practices. In a similar study, Danso-Abbeam et al. (2017) also reported a significant and positive effect of extension contacts on the adoption of improved maize variety in northern Ghana.

Contrary to findings of Awuni et al. (2018), mass media through radio had a significant and positive effect on the number of technologies adopted by farmers in the study area. This means that transfer of technologies via mass media can reach and impact more farmers in adopting soybean production technologies. The wider audience reached using radio cannot be underestimated. Transferring technologies via this platform has been found by many researchers to be very effective in influencing adoption of many agricultural technologies (Aker, 2011). For instance, Azumah et al. (2018) observed that the use of radio was perceived to be effective among other media platforms in terms of its influence on adoption of improved technologies among rice farmers in upper east and northern regions of Ghana.

Farmers experience in soybean production was anticipated to have a positive effect on intensity of adoption of soybean production technologies. Experienced farmers are thought to have accumulated technical know-how over time and therefore are positioned better to adopt technologies. A good count of empirical studies has found a positive effect of farming experience on adoption of agricultural technologies (Awuni et al., 2018; Pedzisa et al., 2015; Mazvimavi and Twomlow, 2009). Experience in farming (in this study) was found to have a significant but inverse relationship with intensity of adoption, corroborating with Kunzekweguta et al. (2017). This finding highlights the fact that many experienced farmers feel rather comfortable and secured with conventional technologies which they have practiced over time.

Similarly, distance covered from farm to input market is significant and negatively related to adoption intensity of soybean production technologies in the study area. This means that if distance to input dealer shop increases by one kilometer, the intensity of adoption of soybean production technologies decreases by 12%. This is consistent with a prior expectation of negative relationship with adoption intensity. This is also consistent with the finding of Berihun et al. (2014) and Tefera et al. (2016). This therefore suggest that any efforts aimed at increasing adoption intensity of technologies must ensure easy access to these technologies by bringing input dealers closer to farmers.

As reported by Awuni et al. (2018), household extension method enables farmers to have close contact with extension agents by clarifying techniques that are not well understood. However, the high ratio of extension agent to farmer in Ghana as reported by Ghana Statistical Service (GSS), 2014 presents a great challenge in terms of the capacity of the agent to visit individual households to influence change. Household extension method is negative and a significant determinant of intensity of soybean production technologies adoption in the study area. This means that the household extension method contributed less in terms of the number of technologies adopted by soybean farmers. This finding is in tandem with Awuni et al. (2018), who reported household extension method had negative impact the intensity of adoption of improved rice production technologies in northern Ghana.

Access to credit is considered as one of the most important steps in dealing with the constraints associated with adoption of agricultural technologies (Doss, 2003). However, results from Table 4 show a negative effect of credit on intensity of adoption of improved soy production technologies. This implies that as farmers' access to credit increase, their desire to venture into other non-farm profit making enterprises also increase, limiting their investments in soybean production. The reason is also ascribed to the risky nature of farm enterprises in Northern Ghana which is prone to unpredicted rainfall and temperature patterns. Traditionally also, soybean is not a staple food crop and therefore the utilization of the crop is often low in the study area. Farmers will therefore either invest more of acquired credit in the production of staple crops that improve their food security status or other non-farm activities that will stabilise their incomes. This observation is consistent with Motin et al. (2014) and Hamidi and Sabbaghi (2016) who reported diversion of farm credit to non-farm activities by farmers in the Upper West region of Ghana. The negative effect of credit diverges from that of Mensah-Bonsu et al. (2017) and Ullah et al. (2018) who reported significant and positive impact of credit on intensity of adoption of land conservation practices in Ghana and improved peach cultivars in Pakistan respectively. This divergence can be attributed to the differences in consumption pattern for both crops (i.e. soybean and maize). While maize is a staple crop in Ghana and widely utilised both at domestic and industrial levels, the soybean crop is mainly utilised by industries.

4. Conclusions and policy recommendations

This study was conducted to determine the factors that account for adoption intensity of soybean production technologies among farmers in northern Ghana. The study accounted for potential estimation errors due to under-dispersion and over-dispersion by using a model based on the generalized Poisson distribution. The study concludes that age of respondents, education, number of extension contacts, mass media (radio) and risk associated with technologies are statistically significant and positively influence the number of soybean production technologies adopted by farmers in northern Ghana. Also, farmers' experience in soybean production, cropping system used by farmers, distance from farm to input dealer shop, exposure to household extension method, and access to production credit are significant but bear inverse relationship with the number of soybean production technologies adopted. As a matter of policy, it is recommended among others that, various agricultural extension programmes in Ghana should intensify education on the benefits of adopting improved soybean production technologies. There is the need to set up many technology demonstration farms to give farmers hands-on training during field days in order to boost the adoption of improved production techniques.

Declarations

Author contribution statement

Abass Mahama, Shaibu Baanni Azumah, Conceived and designed the experiments; Analyzed and interpreted the data; Wrote the paper.

Franklin N. Mabe, Joseph A. Awuni: Conceived and designed the experiments; Wrote the paper.

Funding statement

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Competing interest statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

Acknowledgements

We acknowledge the support of the Chereponi District Agriculture Development Unit for helping in the data collection processes. We all acknowledge the work of all the anonymous reviewers for the constructive feedback.

References

Abdul-Rahman, M., 2017. Contract Farming and Adoption of Improved Technologies in maize Production in the Northern Region of Ghana. MPhil Thesis, Faculty of Agribusiness and Communication Sciences. University for Development Studies.

Aker, J.C., 2011. Dial "A" for agriculture: using information and communication technologies for agricultural extension in developing countries. Agri. Econ. 42, 631–647.

Awuni, J.A., Azumah, S.B., Donkoh, S.A., 2018. Drivers of adoption intensity of improved agricultural technologies among rice farmers: evidence from northern Ghana. Rev. Agric. Appl. Econ. 21 (2), 48–57.

Azumah, S.B., Donkoh, S.A., Awuni, J.A., 2018. The perceived effectiveness of agricultural technology transfer methods: evidence from rice farmers in northern Ghana. Cogent Food. Agric. 4, 1–11.

Azumah, S.B., Donkoh, S.A., Ansah, I.G.K., 2017. Contract farming and the adoption of climate change coping and adaptation strategies in the northern region of Ghana. Environ. Dev. Sustain. 1–21. Springer.

Berihun, K.H., Bihon, K.A., Kibrom, A.W., 2014. Adoption and impact of agricultural technologies on farm income: evidence from Southern Tigary, Northern Ethiopia. Int. J. Food Agric. Econ. 2 (4), 91–106.

Bogdanović, S., Mladenov, V., Balesevic, T.S., 2015. The importance of using certified seed. Selekcija i semenarstvo 21, 63–67.

Bozdogan, H., 2000. Akaike's information criterion and recent developments in informational complexity. J. Math. Psychol. 44, 62–91.

Charles, N.T., Simon, N., Patrick, K., 2017. Factors affecting adoption of tissue culture bananas in the semi-arid areas of Lower Eastern region of Kenya. Int. J. Recent Res. Life Sci. (IJRRLS) 4 (3).

Danso-Abbeam, G., Bosiako, J.A., Ehiakpor, D.S., Mabe, F.M., 2017. Adoption of improved maize variety among farm households in the northern region of Ghana. Cogent Econ. Finance 5 (1), 1416896.

Dhraief, M.Z., Bedhiaf-Romdhania, S., Dhehibib, B., Oueslati-Zlaouia, M., Jebali, O., Ben-Youssef, S., 2018. Factors affecting the adoption of innovative technologies by livestock farmers in arid area of Tunisia. FARA Res. Rep. 3 (5), 22.

Doss, C.R., 2003. Understanding Farm-Level Technology Adoption: Lessons Learned from CIMMYT's Micro Surveys in Eastern Africa. Economics working paper 03 – 07.

Erdman, D., Jackson, L., Sinko, A., 2008. Zero-inflated Poisson and zero-inflated negative binomial models using the COUNTREG procedure. SAS Institute Inc.. Cary, NC. Paper 322.

Fabozzi, F.J., Focardi, S.M., Rachev, S.T., Arshanapalli, B.G., 2014. AIC and BIC. The basics of financial econometrics: tools, concepts, and asset management applications. Model Selection Criterion John Wiley Sons.

Famoye, F., Wulu, J.T., Singh, K.P., 2004. On the generalized Poisson regression model with an application to accident data. J. Data Sci. 2, 287–295.

Famoye, F., 1993. Restricted generalized Poisson regression model. Communications in Statistics. Theory Methods 22, 1335–1354.

Fitsum, M., 2016. Analysis of the factors affecting adoption of soybean production technology in Pawe district, Metekele zone of benshangul Gumuz regional state, Ethiopia. World Sci. News 53 (3), 122–137.

Ghana Statistical Service (GSS), 2014. National Accounts Statistics. Final 2012 Gross Domestic Product & Revised 2013 Gross Domestic Product. Ghana, Accra. www.statsghana.gov.gh.

Greene, W.H., 2002. Econometric Analysis, fifth ed. New York University.

Hamidi, M., Sabbaghi, M.A., 2016. Investigating the factors influencing the diversion of the use of agricultural facilities by villagers in Shush County. Int. J. Humanit. Cult. Stud. (IJHCS) 1–15. ISSN 2356–5926.

Harris, T., Yang, Z., Hardin, J.W., 2012. Modeling underdispersed count data with generalized Poisson regression. STATA J. 12 (4), 736–747.

Kunzekweguta, M., Rich, K.M., Lyne, M.C., 2017. Factors affecting adoption and intensity of conservation agriculture techniques applied by smallholders in Masvingo district, Zimbabwe. Agrekon 56 (4), 330–346.

Mazvimavi, K., Twomlow, S., 2009. Socioeconomic and institutional factors influencing adoption of conservation farming by vulnerable households in Zimbabwe. Agric. Syst. 101 (1–2), 20–29.

Mensah-Bonsu, A., Sarpong, D.B., Al-Hassan, R., Asuming-Brempong, S., Egyir, I.S., Kuwornu, J.K., Osei-Asare, Y.B., 2017. Intensity of and factors affecting land and water management practices among smallholder maize farmers in Ghana. Afr. J. Agric. Resour. Econ. 12 (2), 142–157.

Ministry of Food and agriculture, MoFA, 2013. Agriculture in Ghana: Facts and Figures (2012). Statistics, Research and Information Directorate (SRID). Accra, Ghana, pp. 1–45.

Ministry of Food and Agriculture, 2017a. Planting for Food and Jobs. Strategic Plan for Implementation (2017-2020). Crop Services Directorate. Accra, Ghana.

Ministry of Food and Agriculture, MoFA, 2017b. Agriculture in Ghana. Facts and Figures 2016. Statistics, Research and Information Directorate (SRID) of MoFA. Accra, Ghana.

Mohammed, S.A.R., Al-hassan, S., Amegashie, D.P.K., 2016. Technical efficiency of soybean farmers in the northern region of Ghana. ADRRI J. Agric. Food Sci. 2 (11), 20–38.

Motin, B., Moses, D., Gordon, T.S., 2014. Analysis of the sources of farm investment credit in the Upper West region of Ghana. Int. J. Curr. Res. Acad. Rev. 2 (5), 1–15.

Mustapha, S.B., Makinta, A.A., Zongoma, B.A., Iwan, A.S., 2012. "Socio-Economic factors affecting adoption of soya bean production technologies in Takum local government area of Taraba state, Nigeria". Asian J. Agric. Rural Dev. 2 (2), 271–276.

Nkegbe, P., Shankar, B., 2014. Adoption intensity of soil and water conservation practices by smallholders: evidence from Northern Ghana. Bio base Appl. Econ. 3 (2), 159.

Noor-Us-Sabah, Sarwar, G., Tahir, M.A., Muhammad, S., 2016. Comparative efficiency of high (triple super phosphate) and low (rock phosphate) grade P nutrition source enriched with organic amendment in maize crop. Pakistan J. Bot. 48 (6), 2243–2248.

Pedzisa, T., Rugube, L., Winter-Nelson, A., Baylis, K., Mazvimavi, K., 2015. Abandonment of conservation agriculture by smallholder farmers in Zimbabwe. J. Sustain. Dev. 8 (1), 69–82.

Pokhrel, B.K., Paudel, K.P., Segarra, E., 2018. Factors affecting the choice, intensity, and allocation of irrigation technologies by U.S. Cotton farmers. Water 10 (6), 706.

Rashwan, N.A., Kamel, M.M., 2011. Using generalized Poisson log linear regression models in analyzing two-way contingency tables. Appl. Math. Sci. 5, 213–222.

Tefera, T., Tesfay, G., Elias, E., Diro, M., Koomen, I., 2016. Drivers for Adoption of Agricultural Technologies and Practices in Ethiopia. CASCAPE Project Report No. NS_DfA_2016_1, Addis Ababa/Wageninge.

Todaro, M.P., Smith, S.C., 2011. Economic Development, 10th ed. Addison-Wesley, Pearson.

Thilakarathna, M.S., Chapagain, T., Ghimire, B., Pudasaini, R., Tamang, B.B., Gurung, K., Choi, K., Rai, L., Magar, S., BK, B., Gaire, S., Raizada, M.N., 2019. Evaluating the effectiveness of rhizobium inoculants and micronutrients as technologies for Nepalese common bean smallholder farmers in the real-world context of highly variable hillside environments and indigenous farming practices. Agriculture 9 (20), 1–17.

Ugwu, D.S., Ugwu, H.C., 2010. Soybean production, processing and marketing in Nigeria. J. Appl. Sci. Dev. 1 (1), 45–61.

Ullah, A., Khan, D., Zheng, S., Ali, U., 2018. Factors influencing the adoption of improved cultivars: a case of peach farmers in Pakistan. Ciência Rural. 48 (11).

USAID RFA- FTF Ghana ATT project, 2016. Overview and Strategy of Feed the Future Ghana's Agriculture Technology Transfer Project. Promoting the Commercial and Sustainable Supply of Early Generation Seed of Food Crops. February 25-26 2016, Addis Ababa – Ethiopia.

Wang, W., Famoye, F., 1997. Modeling household fertility decisions with generalized Poisson regression. J. Popul. Econ. 10, 273–283.

Yang, Z., Hardin, J.W., Addy, C.L., Vuong, Q.H., 2007. Testing approaches for overdispersion in Poisson regression versus the generalized Poisson model. Biom. J. 49, 565–584.