American Journal of Theoretical and Applied Statistics
2023; 12(6): 187-194
http://www.sciencepublishinggroup.com/j/ajtas
doi: 10.11648/j.ajtas.20231206.15
ISSN: 2326-8999 (Print); ISSN: 2326-9006 (Online)

Determinants of Climate Smart Agriculture Technology Practices in Ghana: Application of Multinomial Logistic Regression

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To cite this article:

Ibrahim Hashim, Abukari Alhassan, Richard Puurbalanta, Edward Akurugu, Yahaya Iddrisu et al. (2023). Determinants of Climate Smart Agriculture Technology Practices in Ghana: Application of Multinomial Logistic Regression. *American Journal of Theoretical and Applied Statistics*, *12*(6), 187-194. https://doi.org/10.11648/j.ajtas.20231206.15

Received: November 19, 2023; **Accepted**: December 9, 2023; **Published**: December 22, 2023

Abstract: The study primarily examined the determinants of Climate Smart Agriculture technology practices on maize production. Data on socio-demographic and farming characteristics were obtained from the Climate Change, Agriculture and Food Security Partnership for Up Scaling the project's targeted communities (Bompari, Dazuuri and Toto) in the Lawra municipality of the Upper West Region of Ghana. A total of 300 peasant farmers completed the questionnaire. Results from the model building confirmed models 1 and 2 to have strong explanatory power. Notwithstanding that, further evaluation with the adoption of Likelihood Ratio and log-likelihood favoured model 1 Furthermore, the post estimation results (Average Marginal Effects) from model 1 revealed that farming experience and household head status have no significant impact on predicting Climate Smart Agriculture technology practices. The results also confirmed that farmers who have practiced Climate Smart Agriculture technology for 6 to 10 years were found to be accompanied by a low probability (15.47%) of using improved variety/treated seeds as compared to those farmers who have practiced the technology for a period of 1–5 years. Also, tied ridges as Climate Smart Agriculture technology practiced by farmers resulted in a high probability of 11.44% for high yields relative to low yields. We recommend the need for further study to investigate the underlying reasons, if any, based on the non-significant relationship established at the 5% level between the determinants of mineral chemical fertiliser and monoculture respectively.

Keywords: Climate Change, Climate Smart Agriculture, Multinomial Logistic Regression, Predictions

1. Introduction

The agricultural sector is essential in the fight against extreme poverty and hunger, supporting the lives of approximately 1.5 billion people living in smallholder rural households around the world [1]. In many economies, the sector is also recognized to be the overarching driver of economic growth [2, 3].

Despite the crucial role of the sector, agriculture is highly prone to climate change and variability, resulting in a global decrease in agricultural productivity [4, 5], with small-scale farmers suffering disproportionately as a result of poverty, a high reliance on natural resources, and a lack of ability to adopt new livelihood strategies [6]. In addition, according to a study by [7], the industry is plagued by a lack of high-yielding technologies, droughts caused by climate change, floods, and the effects of climate change.

Climate change and extreme weather events amplify food insecurity issues while also posing new challenges to the continent's long-term development [8, 9]. In addition, due to its heavy reliance on rain-fed agriculture and the preponderance of large agriculture, Sub-Sahara Africa (SSA) is particularly vulnerable to climate change and major weather shocks [10, 11]. For example, in the 2015/2016 crop seasons, El Niño droughts wreaked havoc on maize yields, resulting in significant food security issues in the region [12, 9].

In Ghana, just like in any other emerging economy, the impact of climate change has resulted in a decrease and uncertain production, exacerbating food insecurity and poverty. The effects of these climatic shifts will be felt much more strongly by peasant farmers, whose farming practices are weather-dependent and vulnerable to climate change [5, 13]. To ensure resilience, adoption of climate smart practices among peasant farmers is necessary.

Despite the importance of climate smart practices in strengthening resilience, increasing production, reducing greenhouse gas emissions, and mitigating environmental degradation, peasant farmers around the world have been slow to embrace them [14, 15]. This is due to several defects and issues that have yet to be resolved [16]. Most of the research has focused on the impact of climate change on agriculture and adaptation strategies, but only a few studies have investigated the factors that necessitate the adoption of adaptation approaches [5, 17].

According to the Ghana Statistical Service, the Upper West region is one of the lowest among the ten regions of Ghana, ranked 10th in poverty, exposing the region to susceptibilities including climate change and variability [18]. However, over the years, improved technologies, including climate smart practices, have been extensively studied among peasant farmers in other jurisdictions using Multinomial Logistic Regression (MLR) [19, 20], but sequel to that of the Lawra municipality of the Upper West region remains not investigated among these peasant farmers towards the adaptation of these unfavourable climatic conditions. In view of this, the study was instituted to examine the determinants of Climate Smart Agriculture (CSA) technology practices on peasant farmers in the Lawra municipality.

2. Material and Methods

Primary data was used in the study with the aid of a structured questionnaire to solicit information from peasant farmers within the Climate Change, Agriculture and Food Security Partnership for Up Scaling (CCAFS P4S) project's targeted communities (Bompari, Dazuuri and Toto) of the Lawra municipality. In order to ascertain the determinants of CSA technology practices, data on socio-demographic and farming characteristics were also collected for this study. The variables used in the study were measured on both continuous and discrete scales.

In determining the sample size for the study, [21] criteria were used to obtain the initial sample size of 341 peasant farmers. However, an equal proportional allocation was adopted based on the populations of each community. In view of this, a total of 341 peasant farmers was considered as the final sample size. Out of the 341 peasant farmers, 300 valid responses were retrieved, representing a response rate of 88%.

2.1. Determination of Sample Size

The issue of sample size is considered important in any study. This is because meaningful generalisations can be deduced from the population by determining the appropriate sample size which is reflective of the population under study. In view of this, considering a confidence level of 95% and a 5% margin of error, then according to [21], the sample size for this study was determined using the minimum sample size formula in equation (1) as:

$$n = \frac{N}{1 + N\ell^2}, \tag{1}$$

where n = the required sample size, N = the population size and ℓ = tolerable error (which in this study was fixed at 0.05). The total population for the three communities is 2,300, hence the required sample size can be determined as:

$$n = \frac{2300}{1 + 2300(0.05)^2},$$

$$n = 340.704 \approx 341$$

In order to ascertain the samples to be taken from each stratum/community, the proportional allocation of sample size is found appropriate as stated in equation (2) as:

$$n_k = \frac{N_h}{N} \times n, \tag{2}$$

where n_h = sample size of stratum h (that is the sample size for each community), N = total size of population, n = total sample size and N_h = population size of stratum h (population size of each community). Table 1 shows the sample distributions of the various communities.

Table 1. *Sample Size Distribution of Study Communities.*

Community	Total Population	Sample Size
Bompari	800	118.61≈ 119
Dazuuri	900	133.43 ≈ 133
Toto	600	88.95 ≈ 89
Total	2300	341

2.2. Multinomial Logistic Regression Model (MLR)

The MLR model is basically premised on the assumption that the dependent variable (CSA technology practices) in this study has more than two categories (improved variety/treated seeds, mineral chemical fertiliser, monoculture, crop rotation and tied ridges), where these categories are of no natural ordering based on several independent variables (gender, years of CSA technology practice, status of yield (high or low) in bags, farming experience and status of household head (migrant or indigene)). Under MLR, the model can be obtained by assuming that the outcomes that are $J = 1, 2, 3, \ldots, n$ being observed in the outcome variable (y) and predictor variables (X_i), then the estimated coefficients from the logit model can be given as:

$$\ln\left(\frac{\pi_i}{\pi_J}\right) = \psi_i + \phi^{(i)} X_i,\ i = 1,2,3,...,J-1. \tag{3}$$

The logit model from equation (3) through setting $\phi^{(1)} = 0$, then a measure of changes relative to $\phi^{(1)} = 1$ can be obtained from the coefficients $\left(\phi^{(2)}, \phi^{(3)}, ..., \phi^{(n)}\right)$. Also, the predicted probabilities can be ascertained from the following equations:

$$P(y=1) = \frac{1}{1+\exp\left(\phi^{(1)}X_1\right)+\exp\left(\phi^{(2)}X_2\right)+\cdots+\exp\left(\phi^{(n)}X_n\right)}. \tag{4}$$

$$P(y=n) = \frac{\exp\left(\phi^{(n)}X_n\right)}{1+\exp\left(\phi^{(1)}X_1\right)+\exp\left(\phi^{(2)}X_2\right)+\cdots+\exp\left(\phi^{(n)}X_n\right)}. \tag{5}$$

The relative probability of the categories of CSA technology practices (mineral chemical fertiliser, monoculture, crop rotation and tied ridges) that is in this case $y = 2,3,...,n$ to the reference category of CSA technology practice (improved variety/treated seeds) that is, in this case, $y = 1$ can be derived based on the following equations:

$$\frac{P(y=2)}{P(y=1)} = \frac{\exp\left(\phi^{(2)}X_2\right)\left\{1+\exp\left(\phi^{(1)}X_1\right)+\exp\left(\phi^{(2)}X_2\right)+\cdots+\exp\left(\phi^{(n)}X_n\right)\right\}}{1+\exp\left(\phi^{(1)}X_1\right)+\exp\left(\phi^{(2)}X_2\right)+\cdots+\exp\left(\phi^{(n)}X_n\right)} = \exp\left(\phi^{(2)}X_2\right) \tag{6}$$

$$\frac{P(y=n)}{P(y=1)} = \frac{\exp\left(\phi^{(n)}X_n\right)\left\{1+\exp\left(\phi^{(1)}X_1\right)+\exp\left(\phi^{(2)}X_2\right)+\cdots+\exp\left(\phi^{(n)}X_n\right)\right\}}{1+\exp\left(\phi^{(1)}X_1\right)+\exp\left(\phi^{(2)}X_2\right)+\cdots+\exp\left(\phi^{(n)}X_n\right)} = \exp\left(\phi^{(n)}X_n\right) \tag{7}$$

Considering that X_i and $\phi_k^{(n)}$ to be accompanied with the respective vectors $(x_1, x_2, \cdots, x_k)$ and $\left(\phi_1^{(n)}, \phi_2^{(n)}, \cdots, \phi_k^{(n)}\right)'$, a one-unit change in x_i, then the ratio concerning the risk, which is the risk of the outcome to the reference category (improved variety/treated seeds) can be obtained from;

$$\frac{\exp\left(\phi_1^{(n)}x_1\right)+\exp\left(\phi_2^{(n)}x_2\right)+\cdots+\exp\left(\phi_i^{(n)}x_{i+1}\right)+\exp\left(\phi_k^{(n)}x_k\right)}{\exp\left(\phi_1^{(n)}x_1\right)+\exp\left(\phi_2^{(n)}x_2\right)+\cdots+\exp\left(\phi_i^{(n)}x_i\right)+\exp\left(\phi_k^{(n)}x_k\right)} = \exp\left(\phi_i^{(n)}\right). \tag{8}$$

The study adopted Average Marginal Effects (AME) to obtain the actual magnitude of changes in probabilities instead of the estimates of the MLR model which tend to give the direction of the explanatory variables on the outcome variables which sometimes becomes difficult to interpret model coefficients. In this study, the AME can be achieved by considering that if there exist n factor levels of variable L;

$$h(x,\theta) = f(x,\theta \mid L = n) - f(x,\theta \mid L = improved\ \mathrm{var}iety\ /\ treated\ seeds). \tag{9}$$

2.3. Assumption of Multinomial Logistic Regression

The assumption underlying the MLR model depends on the Independence of Irrelevant Alternatives (IIA). This assumption postulates that the inclusion or exclusion of categories of the dependent variable does not in any way affect the relative risks associated with the regressors in the remaining categories. However, this assumption does not hold in all instances [22]. When this assumption is violated, the IIA is relaxed by using the Hausman test via the Seemingly Unrelated Estimation. This test allows for an assessment of equal common coefficients of the dependent variable across corresponding models for the null hypothesis. According to [23], the steps involved in testing the hypothesis of IIA for the Hausman type are:

1) Estimate the full model with the inclusion of all J outcomes for which these estimates are found in $\hat{\phi}_{Full}$
2) Estimate the constrained (restricted) model of which one or more outcomes categories are eliminated and let these estimates be found in $\hat{\phi}_{\mathrm{Re}duced}$.

3) Define $\hat{\phi}^*_{Full}$ as a subset of $\hat{\phi}_{Full}$ after the elimination of coefficients not found to be estimated in the constrained (restricted) model.

Following the above steps, the Hausman test linking the IIA is provided as:

$$H_{IIA} = \left(\hat{\phi}_{\mathrm{Re}duced} - \hat{\phi}^*_{Full}\right)' \left[\hat{V}\left(\hat{\phi}_{\mathrm{Re}duced}\right) - \hat{V}\left(\hat{\phi}^*_{Full}\right)\right]^{-1} \left(\hat{\phi}_{\mathrm{Re}duced} - \hat{\phi}^*_{Full}\right). \tag{10}$$

The test is asymptotically distributed as χ^2 with degrees of freedom found to equal the rows in $\hat{\phi}_{\mathrm{Re}duced}$ if the IIA is true. It is well established that failure to reject the null hypothesis $\left(H_{IIA}\right)$ at any significant level is a confirmation that the assumption of IIA holds [24] and that the MLR can be employed in modelling the CSA technology practices.

3. Results and Discussion

The study basically made use of CSPro version 7.5 for the data entry while STATA 16.1 was used to analyse the required data. The study targeted a total of 341 peasant farmers from the three communities in the Lawra municipality. However, 300 peasant farmers completed the questionnaire, representing approximately an 88% response rate.

Table 2 presents a description of the socio-demographic and farming characteristics of respondents in the study. Out of the three hundred (300) households interviewed, 185 (61.7%) were males, while 115 (33.3%) were females. Most of the respondents were indigenes, numbering 231 (77.6%), while 69(22.4%) migrated from other parts of the region for the purpose of farming or settlement. CSA is an important part of today’s farming practices. In the modelling, farmers used 86(30.39%) improved variety/treated seeds, 72 (25.44%) mineral chemical fertilizer, 51 (18.02%) monoculture, 39 (13.78%) crop rotation and 35 (12.37%) tied ridges. The result from Table 2 indicated that most of the household 151 (53.95%) practiced CSA technology and have gained working experience between 1 and 5 years while 106 (37.86%) practiced CSA technology with working experience between 6 and 10 years. Few farmers of about 23 (8.21%) practiced CSA technology for eleven (11) years and more. Table 2 also revealed that the majority (75.78%) of the peasant farmers on average had high yields while the remaining 24.22% on average had low yields for the five farming seasons (2016 to 2020).

Table 2. *Descriptive Statistics of Socio-Demographic and Farming Variables.*

Variables	Frequency (%)	Variables	Frequency (%)
Gender		CSA Technology Practice	
Female	115 (38.33)	Improved variety/treated seed	86 (30.39)
Male	185 (61.67)	Mineral chemical fertiliser	72 (25.44)
Status of Household Head		Monoculture	51 (18.02)
Migrant	69 (22.74)	Crop Rotation	39 (13.78)
Indigene	231 (77.26)	Tied Ridges	35 (12.73)
Years of CSA Technology Practice		Status of Yield (in 100kg bags)	
1-5 years	151 (53.93)	Low yield	54 (24.22)
6-10 years	106 (37.86)	High yield	169 (75.78)
11 and above	23 (8.21)		

In order to decide on the model to use in making predictions on CSA technology practices, the study adopted the model building strategies of which all the candidate models have one of the categories (improved variety/treated seeds) omitted in model 1. This was followed by an omission of mineral chemical fertiliser, monoculture, crop rotation and tied ridges for models 2 to 5 respectively. From the output in Table 3, except for model 1 and model 2, all the other models were not significant at the 5% significant level. This means that models 1 and 2 have strong explanatory power as compared to the other models [23]. However, further evaluation of these two models (model 1 and model 2) finds a high likelihood ratio χ^2 (36.99) and the least log-likelihood (-302.0844) to favour model 1 and hence to be utilised in assessing the assumption of IIA [23].

Table 3. *Hausman Specification Test with and without Constraints on CSA Technology Practices.*

	Constrained Models				
	Model 1	Model 2	Model 3	Model 4	Model 5
N	209	153	171	185	183
d.f	24	18	18	18	18
p-value	0.0438*	0.0228*	0.0795	0.0951	0.1565
LR χ^2	36.9900**	31.8700	26.9700	26.2100	23.9600
LL	-302.0844**	-183.1736	-207.9992	-232.9672	-230.1018

Footnote: Models 2-5 are the constraint models, N=Number of observations, d.f=degree of freedom, LR=Likelihood Ratio and LL=Log Likelihood, p-value < 0.05, ** means the least LR and LL.

The tradition of any model is that it must satisfy the necessary basic assumptions. In this study, the MLR as used in modelling the data employed the assumption of IIA. This assumption posits that considering any two alternatives, the probabilities of its ratios should be independent of other alternatives available. Notwithstanding, this assumption does not hold in all cases [22]. A classical illustration is present in a study by [22] in a transportation model with four possible alternatives (riding a train to work, taking a bus to work, driving the Ford to work, and driving the Chevrollet). The study indicated that "drives Ford to work" is a closer replacement to "drives the Chevrolet" as compared to "ride the train" (at least for most people). The impulse from the view of McFadden can be conveyed to mean that not considering or excluding "drives the Ford" from the transportation model is expected to affect the relative risks of the remaining alternatives, hence deviate from the assumption of IIA. Based on this, Seemingly Unrelated Estimation is devised in this study to relax the assumption of IIA [24]. The test seeks to determine whether the coefficients associated with CSA technology practices are the same across the various models.

The results from Table 4 find the coefficients associated with each of the dependent variables (Model 2 to Model 5) to be the same, with p-values not exceeding the 5% level of significance. Also, the simultaneous tests of the coefficients of the dependent variables fail to reject the null hypothesis of equal coefficients across the various models. This means that the assumption of IIA holds under the chosen model (model 1), which is in line with a study by [24].

Table 4. *Test of IIA Assumption via Seemingly Unrelated Estimation.*

Model + Intercept	d.f	χ^2	p-value
Mineral Chemical Fertiliser	21	3.48	1.0000
Monoculture	21	3.29	1.0000
Crop Rotation	21	5.70	0.9996
Tied Ridges	21	9.20	0.9875
Accumulation	42	47.31	0.2647

Table 5 presents the AME from MLR on the CSA technology practiced by peasant farmers in the Lawra municipal of the Upper West region. In all, gender, years of CSA technology practiced, status of yield, farming experience and household head status were used in predicting the choice of CSA technology practices by farmers of the Lawra municipal. STATA 16.1 was used to estimate the parameters of the MLR model. However, these parameter estimates were further subjected to post estimation in STATA 16.1 to obtain the AME (that is, the average changes associated with the choice of CSA technology practices for a unit change in a specific independent variable).

It is worth noting from Table 3 that the LR Chi-square statistic of 36.9900 with a degree of freedom of 24 is significant (*p-value* <0.0438) at the 5% level, which signifies that the model has strong explanatory power. Also, the Pseudo R-squares for McFadden, Cragg & Uhler and Maximum Likelihood are around 0.0580, 0.1700 and 0.1620 indicating that the explanatory variables accounted for 5.8%, 17% and 16.2% of the variation in CSA technologies practiced by farmers respectively [24]. The standards of the Pseudo R-squares reveal that there is a weaker relationship between the outcome variable (CSA technologies practiced by farmers) and the explanatory variables (gender, years of CSA technology practice, status of yield, farming experience and household head status) in the model. For the interpretation of the estimates in connection with the AME, a positive value means that the predictor contributes positively to the choice of CSA technology practiced by the peasant farmer, and a negative value shows that the predictor variable contributes negatively to the choice of CSA technology practiced by the peasant farmer.

From Table 3, being a male has a high probability but a non-significant effect on the following CSA technology practices (that is, improved varieties/treated seeds, monoculture and tied ridges) as compared to females in the Lawra municipality. This is because men stand the chance of attending meetings with institutions that know about the CSA technology practices. For instance, the study revealed that male farmers have a higher probability of using improved variety/treated seeds by 8.49%, monoculture by 2.12% and tied ridges by 4.98% respectively relative to female farmers. The outcome also confirms the position of [25] that males are more likely to adopt CSA technology practices than their female counterparts. Also, male farmers have a lower probability of 0.06% and 15.53% of using mineral chemical fertilizers and crop rotation respectively. However, such a decrease in the average marginal effect of gender under crop rotation was found to be significant (*p-value=0.01*).

The results show that farmers who have practiced CSA technology ranging from 6 to 10 years were found to be accompanied by a low probability of 15.47% of using improved variety/treated seeds as compared to those farmers who have practiced CSA technology for 1 to 5 years, but such a decrease in probability was significant at the 5% level. This means that farmers with 1 to 5 years of experience stand a better chance of using improved varieties/treated seeds than those with 6 to 10 years of farming experience as well as those with 11 or more years of farming experience accompanied by a decrease in the probability of 5.28%. Also, the results revealed that years of CSA technology practiced by peasant farmers for 6 to 10 years had a low probability of 0.76% for using mineral chemical fertilizer relative to the base outcome (1 to 5 years of CSA technology practice). However, 6 to 10 years of practicing CSA technology was found to have high probabilities of 0.71%, 6.92% and 8.60% of using monoculture, crop rotation and tied ridges respectively relative to the reference outcome (1 to 5 years of CSA technology practice).

Meanwhile, these probabilities were not significant at the 5% level. The result further revealed that peasant farmers who have CSA technology practice experience of 11 or more years were found to be associated with low probabilities of 5.58%, 6.85% and 5.54% for improved varieties/treated seeds, mineral chemical fertiliser and tied ridges respectively as compared to that of 1 to 5 years of experience of CSA technology practice. Higher probabilities were recorded for CSA technology practice of 11 or more years towards the use of monoculture and crop rotation by 15.08% and 2.89% respectively as compared to the reference level (1 to 5 years of CSA technology practice). However, these observed probabilities were not significant at the 5% level of significance.

The study further indicated that peasant farmers with high yield status were associated with a decrease in probabilities of use of improved varieties/treated seeds (5.95%), mineral chemical fertiliser (4.94%), and monoculture (11.34%) respectively as compared to those with low yield. On the other hand, crop rotation and tied ridges recorded an increase in probabilities of 0.91% and 11.44 respectively for high yield as compared to low yield, meaning that crop rotation stands the chance of increasing yield by 0.91% and tied ridges by 11.44% as compared to a decrease in yield respectively. However, none of these probabilities was observed to be significant at the 5% level apart from tied ridges.

Farming experience refers to the number of years a household spends on crop cultivation. From this perspective, it can be anticipated that the more years a farmer is involved in the practice of farming, the better the experience gathered in the activities of farming, all things being equal. The study revealed that an additional year of farming experience increases the use of improved varieties/treated seeds by 0.23%, monoculture by 0.34% and tied ridges by 0.07%. This outcome is in line with a study by [26, 27] positing higher chances of adopting an improved maize variety for those with longer years of farming experience than those with fewer. Also, a study by [28] is consistent with this current study, where a significant positive relationship between the length of farming experience and the adoption of farming technologies was established. On the other hand, a unit increase in farming experience is found to decrease the use of mineral chemical fertiliser by 0.39% as well as crop rotation by 0.25%. This finding on crop rotation established is in line with a study by [29] which found years of farming to be negatively associated with crop rotation practice. Also, the decreases recorded in mineral chemical fertilizer and crop rotation could be subjected to the cost associated with fertilizers and the issue of land litigation, which barely makes it impossible for the aged who have stayed long in farming to practice such technologies. Meanwhile, none of these was significant at the 5% level.

From Table 5, households who are natives or indigenes of the study communities recorded low probabilities with regards to the use of improved varieties/treated seeds (5.91%), mineral chemical fertiliser (0.01%) and monoculture (2.09%) as compared to migrants respectively. This decrease in such CSA technology practices could be attributed to a lack of CSA knowledge in the communities. Furthermore, indigenes had a higher probability of using CSA technology practices for crop rotation (5.67%) and tied ridges (2.33%) when compared to migrants.

Table 5. *Average Marginal Effects from MLR on CSA Technology Practices.*

	Improved Variety/Treated Seeds	*Mineral Chemical Fertiliser*	*Mono culture*	*Crop Rotation*	*Tied Ridges*
	dy/dx (p-value)	*dy/dx (p-value)*	*dy/dx (p-value)*	*dy/dx (p-value)*	*dy/dx (p-value)*
Gender					
Female (*)					
Male	0.0849 (0.21)	-0.0006 (0.99)	0.0212 (0.71)	-0.1553 (0.01*)	0.0498 (0.29)
Years of CSA Practice					
1-5 years (*)					
6-10 years	0.1547 (0.02*)	-0.0076 (0.91)	0.0071 (0.89)	0.0692 (0.17)	0.0860 (0.10)
11+ years	0.0558 (0.63)	-0.0685 (0.51)	0.1508 (0.16)	0.0289 (0.72)	-0.0554 (0.25)
Status of Yield					
Low yield (*)					
High yield	-0.0595 (0.45)	-0.0494 (0.48)	-0.1134 (0.10)	0.0091 (0.84)	0.1144 (0.00*)
Farming Experience	0.0023 (0.35)	-0.0039 (0.13)	0.0034 (0.07)	-0.0025 (0.25)	0.0007 (0.67)
Status of HH					
Migrant (*)					
Indigene	0.0591 (0.49)	-0.0001 (0.99)	-0.0209 (0.77)	0.0567 (0.22)	0.0233 (0.65)

Footnote: Number of Observations=209, LR χ^2 (24) =36.9900, Prob> χ^2 =0.0438, McFadden's R^2 = 0.0580, Cragg &Uhler R^2 =0.1700, Log Likelihood=-302.0844, Maximum Likelihood R^2 =0.1620 and * means p-value < 0.05.

4. Conclusions

The study adopted the MLR to model the determinants of CSA technology practiced by peasant farmers within the CCAFS P4S project's targeted communities (Bompari, Dazuuri and Toto) of the Lawra municipality. In modelling the determinants of CSA technology practices, model building strategies were devised, from which it turned out that models 1 and 2 have strong explanatory power. However, further evaluation through the LR and log-likelihood tends to support model 1 (that is, the model with improved variety omitted). Also, model 1 passed the assumptions of the IIA and hence was found appropriate to model the determinants of CSA technology practices.

Based on the findings of this study, male peasant farmers are less likely to use crop rotation as compared to females. Also, on the length of CSA technology practiced by peasant farmers, those with a duration of 6 to 10 years and 11 years and over are less likely to use improved variety/treated seeds relative to those with 1 to 5 years respectively. In addition, using tied ridges as a CSA technology practice was more common among farmers of high yield status as compared to those of low yield status. In another vein, tied ridges as a technology practiced by farmers stands the chance of resulting in high yields relative to low yields.

Moreover, the determinants (farming experience and status of household head) in the MLR model do not in any way impact significantly on the prediction of the various CSA technology practices considering maize production. Besides this, none of the determinants utilised under the MLR model are associated significantly with both mineral chemical fertiliser and monoculture relative to the base (reference) outcomes.

Conflicts of Interest

The authors declare no conflicts of interest.

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