Determinants of adoption of cover cropping technology: an application of multivariate logistic analysis in Imo State, Nigeria

Edna C. Matthews-Njoku

Department of Agricultural Extension, Federal University of Technology, P.M.B. 1526, Owerri, Imo State, Nigeria

Received August 7, 2008

Abstract

This study analysed the determinants of adoption of cover cropping soil conservation technology in Imo State, Nigeria. Data were collected with questionnaire from 126 randomly selected farmers composed of 72 adopters and 54 non-adopters of cover cropping technology and analyzed using multivariate logistic regression model. Results showed that education level, age, farmsize, extension contact, credit access, membership of farmers' association, farm income and farming experience were significant determinants of adoption of cover cropping soil conservation technology. More liberal credit policy, increased farmland allocation and increasing the extension contacts between farmers and extension personnel are critical for policy designed to increase farm output through adoption of cover cropping soil conservation technology. [Life Science Journal. 2009; 6(1): 90 – 93] (ISSN: 1097 – 8135).

Keywords: determinants; adoption; cover cropping; logistic; soil conservations

1 Introduction

In many areas of tropical rain forest zone of Nigeria, soil erosion has washed away between 25% and 75% of the top soil with consequent fertility depletions, resulting in a situation where yield in most farms in the zone were below 10% – 20% of the potential level (Okezie and Amaefule, 2006; Babalola, 2000).

Imo State of Nigeria falls within the tropical rainforest zone. It is characterized by heavy and long rainy season with attendant heavy gully erosion, increasing person to land ratio and reduction in fallow years. The state has witnessed serious soil degradation problems. The soils are fragile and characterized by high exchangeable sodium, high PH, high salt concentration dominated by sodium carbonates and bicarbonates, low infiltration rate, low organic matter, deficiency of nitrogen and zinc, etc (Ofoh, 2001; Udoh *et al*, 2002).

In view of the mounting pressure on the soil resource, the conservation of these degradend soils assume paramount importance. Several technological options, such as cover cropping have been recommended to farmers by the Research Institutes and Agricultural Development Projects in Nigeria to conserve these soils (Matthews-Njoku, 2005; IITA, 2003). This soil conservation practices serves as means of halting degradation and restoring fertility and productivity where it has been reduced (FAO, 2001). The pace of conserving degraded soils using cover cropping technology appear quite slow and the analytical studies to identify the main factors affecting the adoption of the conservation technology are very few and far between. The effects of policy alternatives on its adoption have never been assessed. For rational analysis, a method is required to identify and assess the relative effectiveness of the important factors influencing the adoption of cover cropping technology, thereby providing a framework for assessing the impact of policy alternatives on the adoption behaviour of the farmers. The present study is an attempt in this direction.

2 Materials and Methods

Study Area: This study was conducted in Imo State

*Corresponding author. Email: edmac 11@yahoo.com

of Nigeria. The State consists of three agricultural zones namely; Owerri, Okigwe and Orlu, and has 27 Local Government Areas (LGAs). Three LGAs were purposively selected from each agricultural zone for the study, on the basis of adopters and non-adopters of cover cropping soil conservation technology as indicated by Imo ADP records. From each selected LGA, two Communities were randomly selected giving a total of 18 communities. The sampling frame was the list of crops farmers that adopted and those that did not adopt the cover cropping technology in the selected communities prepared by extension agents and key informants like the officials of registered food crops farmers associations. From this sampling frame, four farmers that adopted and three farmers that did not adopt the cover cropping technology were randomly selected from each community, giving a sample size of 126 farmers, composed of 72 adopters and 54 non-adopters of cover cropping soil conservation technology.

Data were collected with structured and validated questionnaire in the 2007 cropping year, on variables such education, age, farm size, extension contact, credit access, social organization membership, sex, farming experience, farm income, and adoption of cover cropping technology.

Data were analyzed using descriptive statistics such as mean and multivariate logistic regression techniques adopted by Sharma (1997), Ohajianya (2004) and Ohajianya et al (2007).

Analytical Model

The adoption behavioural model with dichotomous (binary) dependent variable is frequently used as a conceptual framework to examine the factors associated with the adoption of technology (Malla, 1982; Shakya and Flinn, 1985; Green and Ngongola, 1993). Although Ordinary Least Squares (OLS) estimates can be computed for binary model, the error terms are likely to be heteroscedastic leading to inefficient parameter estimates. An alternative method employed in this study, is to use probability models. If linear model is used, the predicted values may fall outside the 0 and 1 interval, thereby violating the basic tenets of probability. The use of profit and logit models, which give maximum likelihood estimates, overcome most of the problems associated with linear probability models and provide parameter estimators which are asymptotically consistent, efficient and guassian so that the analogue of the regression t-test can be applied.

Soil conservation decision making can be described as a mental process which the farmers follow from the knowledge of technology, to form an attitude towards soil conservation and finally deciding to adopt or reject the cover cropping technology. The process, commonly called the innovation decision process, has been extensively applied to investigate the adoption of agricultural technologies (Raintree, 1983; Rogers 2003; Evans, 2000). Following diffusion theory, the innovation-decision process is expected to be influenced by the farmer's socio-economic, communication and psychological characteristics at all the stages.

The dependent variable used in the logit model is a binary variable regarding the adoption of cover cropping technology. The variable is assigned the value of one if the farmer has adopted the cover cropping technology, and a value of zero otherwise. Joshi and Parshad (1989), Parshad (1992) and Sharma (1997) have reviewed the range of personal, socio-economic and biophysical factors associated with the adoption of soil conservation and land reclamation technologies.

In this study, the explanatory variables influencing the adoption of cover cropping technology are represented by education, age, farmsize, extension contact, credit access, farmers' association membership, , farm income, farming experience and sex of the farmer.

Before specifying the model, the independent variables were checked to see if they are correlated. The examination of correlation matrix showed that multicollinearity is not a problem between the variables used in the models.

The adoption behavioural model used to estimate the adoption of cover cropping technology is specified as follows:

$$Yi = f(Zi)n \text{ and}$$

$$Zi = ao + \sum_{j=1}^{n} \beta j \; Xji$$

$Zi = aa + a1\,X1i + a2\,X2i + a3X3i + a4X4i + a5X5i + a6X6i + a7X7i + a8X8i + aaX9i + ei$, where Yi is the observed response of the ith farmer (ie, the binary variable, Yi = 1 for an adopter, Yi = 0 for a non-adopter).

Zi is an underlying and unobserved stimulus index for the ith farmer (when Zi exceeds some threshold level (Zth), the farmer is observed to be an adopter, otherwise he is a non-adopter when Zi falls below the threshold value). X1 is the educational level in years, X2 is the age in years, X3 is farm size in ha, X4 is extension contact in number of visits per year X5 is credit access (dummy variables, 1 for credit access, zero otherwise), X6 is farmers association membership (dummy variable, 1 for membership, zero otherwise), X7 is farm income in Naira, X8 is farming experience in years, and X9 is the sex of the farmer (dummy variable, 1 for male, zero for female) F is the functional relationship between field observation (Yi) and the stimulus index (Zi) which determines the probability of technology adoption, ei is stochastic error term,

I = 1, 2, … m, are observations on variables for the adoption model, m being the sample size, j = 1, 2, …, n, where n, is the total number of explanatory variables, 90 is constant and ai are the unknown parameters.

The logit model based on cumulative logistic probability function was used in this study because both probit and logit models are quite similar but computing the logit model is easier to use than the other types. The logit model is specified as;

$$P_i = F(Z_i) = F(Z_i) = F\left(a + \sum_{J=1}^{n} \beta_i X_{ji}\right) = \frac{1}{1 + e^{-z_i}}$$

$$= \frac{1}{1 + e^{-(a + \sum_{J=1}^{n} \beta_i X_{ji})}}$$

Where e represents the base of natural logarithms, Pi is the probability that an individual will make a certain choice, given knowledge of Xj. The logit model assumes that the underlying stimulus index (ZJ) is a random variable which predicts the probability of soil conservation.

$$P_i = \frac{\exp Z_j}{1 + \exp z_j}$$

Therefore, for an individual farmer;

$$Z_J = \text{Ln} \frac{P_i}{1 - p_i} = a + \sum_{J=1}^{n} \beta_i X_{ji}$$

which is a logit model (Pindyck and Rubinfield, 1981).

The relative effect of each explanatory variable Xi on the probability of adoption of technology is measured by differentiating with respect to

XJ, ie, $\partial P_i / \partial X_{ji}$ and using quotient rule:

$$\frac{\partial P_i}{\partial X_{ji}} = \frac{\beta_i \exp z_j}{(1+\exp z_j)2}$$

where Pi is the probability of occurrence of the dependent varable, and Xji is the vector of explanatory variables.

In aggregate, the predicted changes in the probability of adopting soil conservation technology can be used to estimate the change in the number of farmers adopting cover cropping. Therefore, given a policy change, comparison of the estimated number of adopters before and after the policy change provides a measure of its impact.

The logit model with individual observations uses the maximum likelihood methods to estimate the coefficients of the equation. The maximum likelihood estimation procedure has a number of desirable statistical properties. All parameter estimates are consistent and also efficient asymptotically. In addition, all parameter estimates are known to be (asymptotically) normal, so that the analog of the regression t-test can be applied. In this case the ratio of the estimated coefficient to its estimated standard error follows a normal distribution. To test the significance of all or subset of coefficient in the logit model when maximum likelihood is used, several options analogous to R2 are possible (Pindyck and Rubinfield, 1981). One simple option is to calculate log likelihood ratio. The log likelihood ratio test follows a chi-square distribution with j degrees of freedom (where j is the number of parameters in the equation other than constant) and is calculated as;

$$\Theta = \frac{L_\theta}{L_{max}}$$

The appropriate test follows directly from the fact that,

$$-2 \log \Theta = -2 (\log L_o - \log L_{max})$$

where L Θ is the value of the likelihood function L when all parameters (other than constant) are set equal to zero. Lmax is the value of likelihood function when all variables are included in the model.

A second option is to calculate the residual as follows:

$$\hat{e} = Y_i \overset{n}{-} P_i$$

These residuals will be positive for those adopting cover cropping and negative otherwise. From these values it is easy to calculate an analog to R2. Let,.

3 Results and Dicussion

Characteristics of selected farmers Descriptive statistics presented in Table 1 indicate that the average values of the explanatory variables, except age, appear to be higher for cover cropping adopters than those for non-adopters. The adopters had significantly higher levels of education larger farms and more farming experience than the non-adopters. The adopters reported substantially more contacts with extension personnel, easy access to credit, higher farm income, and belonged more to farmers associations. Most (72%) were males.

Model Estimation

In a stepwise regression analysis, the important explanatory variables were selected and maximum likelihood estimates of the coefficients (Biis) were computed. The selection of the explanatory variables was as expected. The estimated coefficients of the parameters of the logit model of adoption of cover cropping technology are presented in Table 2.

The Chi-square is significant at 1 percent level and implies that the independent variables taken together influence the adoption of cover cropping soil conservation technology. The analogous R2 shows that 73 percent of original variance of the dependent variable was explained by the model. The model correctly predicted all the adopters.

Variables other than age of the farmer were positively related to the adoption behaviour of the farmer. On the basis of asymptotic t-test, education level, farm size, farm income, farming experience, age, extension contact, credit access and farmers association membership were significantly influencing the adoption of soil conservation technology. However, the values of estimates given in Table 2 are not comparable with one another, because the magnitude of the estimates depend on the unit of measurement, and because they are expressed as indices. Thus they have little interpretative value unless transformed into probabilities. Therefore, the predicted probabilities of cover cropping adoption for the selected farmers were calculated.

$Zi = 2.3019$ and $Pi = 0.8627$.

That is, a farmer with these resources is likely (86%) to adopt cover cropping technology. The probabilities for individual farmers are computed in a similar manner and their sum (ΣPi) predicts the number of adopters. The mean probability of an adopter was 0.83, while that of non-adopter was 0.14. Table 2 shows that all the cases were correctly predicted.

Impact of Policy Changes On Cover Cropping Adoption

The effect of alternative policy changes on adoption of cover cropping may be derived from the logistic regression results. A comparison of the estimated number of adopters, given their present circumstances and following a policy change, provides a measure of the impact of that policy. Farm size, credit access, and extension contact were important determinants of adoption of soil conservation. It was predicted that with the existing resources, 72 perent of the farmers would adopt cover cropping (Table 3). If all the farmers have access to credit, other factors remaining unchanged, the level of technology adoption would increase to 76 percent, an increase of 6 percent over the previous valuation. Increasing the frequency of extension contacts had the greater impact, it increased the number of adopters by 23 percent. Credit to all the farmers had a smaller impact than increased frequency of extension contacts. Farm size had a very small increase in the adoption of cover cropping which is expressed in view of the high proportion of the farmers (89%) cultivating small farm sizes.

The policies adopted in combination had a greater predicted impact than the policies adopted in isolation, because of interactive effects. For example, combining the policies of increased land allocation to farmers, total credit use and increased frequency of extension contacts increased the number of adopters by 21 (ie, 93-72), while their added effect was 21 (2 + 4 + 15).

4 Conclusion

TThe study examined the factors affecting adoption of cover cropping soil conservation technology through multivariate logistic regression model. Educational level, age, farm size, extension contact, credit access, membership of farmers' association, farm income and farming experience were significant determinants of adoption of cover cropping technology. Increasing land allocation to farmers, increasing extension visits and more liberal access to credit are likely to increase the adoption of cover cropping technology. Therefore, more liberal credit policy, increased land allocation and increasing the extension contacts between farmers and extension personnel are critical for policy designed to increase agricultural production through adoption of cover cropping soil conservation technology.

References

1. Babalola, O. Soil Management and Conservation in Nigeria. In: Agronomy in Nigeria. M. O., Akoroda (ed). 2000; 216 -223
2. Evans P.T. "Designing Agro Forestry Innovations To Increase Their Adaptability: A case study from Parraguay". Journal of Rural Studies, 2000; 4(1) 44-55.
3. Food and Agricultural Organisation (FAO). Soil tillage in Africa: Needs and challenges. Soil Bulletin, 2001, 68, 5-7.
4. Green, DAG, Ngongola DH 1993. "Factors affecting fertilizer adoption in less developed countries: An Application of Multivariate logistic Analysis in Malawi". Journal of Agricultural Economics, 1993; 44(1): 99-109
5. International Institute of Tropical Agriculture (IITA). Annual Report Abstracts, IITA Ibadan 2003.
6. Joshi, PK and Parshad R. Factors affecting land augmentation. A case of Alkali Soils. Agricultural Situation in India 1989; 44(5): 329-334

7. Malla, PB Logit Analysis of Technology Adoption by Rice farmers in Dhanusha District, Nepal. Research Paper Series No.22 A/D/C-APROSC, Kathmandu, Nepal 1982.
8. Matthews-Njoku, E C (2005). Farmers' Adoption of Improved Soil Conservation and Management Practices in a rainforest zone of Nigeria. Global Approaches to Extension Practice2005; 1(1): 24-31
9. Ofoh, MC Sustainable soil erosion control practices on small-scale farmlands in south eastern Nigeria – a review. International Journal of Agriculture and Rural Development2001; 2: 150-154.
10. Ohajianya, DO Socio-economic determinants of multiple uses of water for irrigation in Kaduna state, Nigeria. Journal of Modeling and Simulation Techniques in Enterprises, AMSE France 2004; 25(1): 67-77
11. Ohajianya, DO Enwerem VA Echetama J A and Anaeto, F C Comparative Analysis of Organic and inorganic fertilizer use in cassava production in Imo State. International Journal of Agriculture and Rural Development 2007; 9: 30-34.
12. Okezie, CA and Amaefule CC Economics of Soil Conservation Practices Among Food Crop farmers in the Rainforest Zone of Abia State, Nigeria. International Journal of Agriculture and Rural Development 2006; , 7 (2): 1-6.
13. Parshad R Correlates of Adoption of Alkali Soil Reclamation" Indian Journal of Extension Education 1992; 28(3/4): 28-37.
14. Pindyck, RS .Rubinfeld DL Econometric Models and Economic Forecasts (Second Edition), Internation Student Edition, McGraw-Hill International Book Company, New Delhi1981; .273-310.
15. Raintree, JB Strategies For Enhancing The Adoptability Of Agroforestry Innovations". Agroforestry Systems 1983; 1(2): 173-187.
16. Rogers, EM Diffusion of Innovation, The Free Press, New York 2003.
17. Shakya, PB Flinn JC Adoption of Modern Varieties and Fertilizer use in Eastern Terai of Nepal". Journal of Agricultural Economics 1985; 36(3): 409-419
18. Sharma, VP Factors Affecting Adoption of Alkali Land Reclamation Technology: An Application of Multivariate Logistic Analysis. Indian Journal of Agricultural Economics 1997; 52: 244-251