FACTORS THAT INFLUENCE FARMERS AWARENESS TO RENEWABLE ENERGY ADOPTION IN SOUTH-SOUTH NIGERIA

Abstract: The study examined factors that influence farmer's awareness to renewable energy adoption in south-south Nigeria. The result showed that (44.09%) of respondents had high RE awareness, (27.80%) had medium awareness level about RE while (28.12%) of the respondent had low-level RE awareness. The empirical results from the analysis revealed that age, educational level and extension visit were significant at 1% level, cooperative membership was significant at 5% level while farm size and farm experience were significant at 10% level of probability. The result of the marginal effect analysis showed that the likelihood of being in the high, medium and low RE awareness group increases with increase in age, farm size, farm experience, cooperative membership and extension visit. The study therefore recommended that all relevant stakeholders should strive to provide farmers with renewable energy related extension messages.

Key words: Agricultural production; Ordered probit; Willingness to use.

Introduction

Energy is an important tool for socio-economic growth and development of any nation (Akuru & Animalu, 2009). It is a major requirements of human society and very vital for technological advancement. The role of energy in sustenance of economic activities as well as its contribution to increasing standard of living of the populace cannot be over emphasized and as a result, there is increasing demand of energy in various sectors of the nation. Energy is the foundation of growth and development in Nigeria because it serves as a tradable commodity for earning the nations income, which in turn is used to assist various government developmental projects Sambo, (2005). Due to population pressure, inevitable industrialization, more agricultural production and improving living standards, the demand for energy in Nigeria is rising Akuru & Kamper, (2016).

The current energy generation capacity in Nigeria stands poorly at 7,566.2 MW with a little 15.61% of this generated from renewable sources while a larger percentage is based on fossil fuels (Ogbonnaya et al., 2019) which is considered too little considering the potential the country has for renewable and conventional energy utilization. The country is endowed with great amount of renewable and non-renewable energy resources but despite the availability of these energy resources, it is unable to meet increasing energy demand and is yet to explore available renewable energy (RE) potentials with a wide range of less environmental and climatic impacts especially in the agricultural sector (Igbinovia, 2014). Agriculture requires and uses energy as a significant input to production in the form of fuel to power machinery and equipment, to heat or cool farm buildings, to light farm buildings, to dry crops, and indirectly in fertilizers and chemicals generated off the farm. Hence the growth and development of the agricultural sector require a reliable and sustainable energy source which is currently underutilized in Nigeria's agricultural sector due to poor information on renewable energy utilization (Chilakpu et al., 2018).

Information, as regards the benefits of RE utilization in agriculture that is available to farmers, is inadequate in South-South Nigeria and this has led to low-level awareness and adoption of RE technologies among farmers especially in the rural areas where technological advancement is taken with suspicion (Beckman & Xiarchos, 2013). Also, the level of awareness of renewable energy sources and technologies in many parts of the world, both economic and environmental, is generally low (Chel & Kaushik, 2010) and this affects farmers adoption of RE sources as a farmer is more likely not to want to use a technology he does not know or understand its benefit.

Fortunately, some studies have been conducted over the years to determine the factor influencing renewable energy adoption in agriculture: (Wall et., 2021; Zakaria el., 2020; Ali et al., 2016; Akinwale & Adepoju, 2019). However a vast majority of these research has focused on assessing determinants of renewable energy adoption. However not much have been done to determine factors that influence farmers awareness to renewable energy adoption especially in south-south Nigeria**.** This paper therefore tries to describe farmer's renewable energy awareness level and estimate factors that influence their awareness level on renewable energy adoption in the study area using the ordered probit regression model.

Materials and Methods

Study Area

The study was conducted in South-South Nigeria. The region is bordered to the South by the Atlantic Ocean and to the East by Cameroon. The South- South States occupy 85,303 square kilometers of land and are made up of six states which are the major oil-producing states in Nigeria. The states include Akwa Ibom, Bayelsa, Cross River, Delta, Edo and Rivers and are divided into 18 Agricultural zones (3 per state) and 126 local government areas for administrative convenience (Agba, *et al* 2010). The National Population Commission (NPC, 2006), stated that the population of the South-South States as of 2006 was 21,014, 655. However, the predominant occupation of people in the zone is farming.

Sampling and data

A multistage sampling technique was used for selecting respondents (farm households) for the study. In the first stage, three states were chosen at random from the six states in the south-south geopolitical zones. In the second stage, two agricultural zones were chosen at random from each of the three states, for a total of six agricultural zones. In the third step, two LGAs were chosen at random from each of the six agricultural zones, for a total of 12 LGAs. In the fourth stage, two communities were randomly selected from each of the 12 LGAs giving a total of 24 communities with a sampling frame of 413, 133 farm households used for the study. A proportionate random sampling method was used to select 95% confidence level of farm households from the farm household population of 413,133 gotten from the ADP's using the following formula:

$$\boldsymbol{n} = \frac{\boldsymbol{N}}{\mathbf{1} + \boldsymbol{N} * (\boldsymbol{e})^{\mathbf{2}}}$$

Where:
n = sample size,
N = size of target population,
e = limit of tolerable error (level of significance = 0.05) and
1 = constant.

$$n = \frac{413{,}133}{1+413{,}133 * (0.05)^2}$$

n = 399.999 = 400

Out of 400 copies of the questionnaire administered, 313 copies were used for the analysis. The remaining 87 were not used due to insufficient data provided and Covid-19 restrictions at the time of data collection.

Analytical frame work

Ordered Probit model and Multinomial Logit Model

When it comes to choice concerns, it has been discovered that there are some intrinsic advantages that make the Ordered Probit Model superior to the Multinomial Logit Model. Both the Multinomial logit model and the ordered probit model support two or more categories, although the ordered probit model is recognized to be more appropriate due to the ordering nature of the dependent variable. The computed coefficients in the ordered probit model cannot be interpreted directly, but they can be used to estimate the probabilities of the dependent variable at various levels, as well as the corresponding marginal probabilities (Bayram Işik et al., 2009).

According to Katchova (2013), the presence of two intercepts, which are the threshold parameters, indicates the existence of three distinct groups. The multinomial probit model, which allows for two or more categories, has been discovered to suffer from the assumption of independence of irrelevant alternatives as it is believed that errors are believed to be independent for each category. In order to bypass this issue, the ordered probit model allows the dependent variable (awareness level) to take on ordinal values Greene, (2003). (Okoye et al., 2010) also mentioned that the Ordered Probit model approach has been extensively used in the estimation of models with ordered type, which basically requires the probit relationship function.

The latent continuous metric is critical to the researcher's observation of ordinal outcomes, as detailed below. Y*, which is the latent continuous variable, is a linear function of some variables, X and a normally distributed disturbance term:

$$Y_i^* = X_i\beta + \varepsilon \qquad (1)$$

The latent variable Yi* could be coded as 0,1,2,3,...,m as it displays itself in ordinal categories. The response of category m is thus observed when the underlying continuous response falls in the *m*-th interval as:

$$Y^* = 0 \; if \; Y^* \leq \delta 0 \qquad (2)$$

$$Y^* = 1 \; if \; \delta 0 < Y^* \leq \delta 1 \qquad (3)$$

$Y^* = 2 \; if \; \delta 1 \; < Y^* \; \leq \delta 2$ (4)

$Y^* = 3 \; if \; \delta 2 \; < Y^* \; \leq \delta 3$ (5)

Where $\delta 1$ (i=0, 1, 2, 3) are the unobservable threshold parameters which will be estimated together with other parameters in the model. $\delta 0$ is normalized to a zero value when an intercept coefficient is included in the model Greene, (2000) and therefore only m-1 additional parameters are estimated with βs. Similar to the models for binary data, the probabilities for each of the observed ordinal response which in this study had 3 responses (0 = low level, 1= medium level and 2= high level) are given as:

$$prob\ (Y = 0) = P(Y^* \leq 0) = P(\beta'\mathrm{X} + \ \varepsilon i\ \leq 0) = \ \emptyset(-\beta'\mathrm{X}) \quad (6)$$

$$prob\ (Y = 1) = \emptyset(\delta 1 - \beta'\mathrm{X}) - \ \emptyset(\beta'\mathrm{X}) \quad (7)$$

$$prob\ (Y = 2) = 1 - \emptyset(\delta 1 - \ \beta'\mathrm{X}) \quad (8)$$

where 0 < δ0< δ1<...< δm-1 …. n is the cumulative normal distribution function such that the sum total of the above probabilities is equal to one. The probability that Yi falls into the jth category is given by:

$$prob(Y_i = j) = \emptyset\left(\delta_j - \beta' X_i\right) - \emptyset\left(\delta_{j+1} - \beta' X_i\right) \quad (9)$$

j=0,1,2,...J,

Where Yi represents the upper and lower the shold values for category *j*, respectively. The log likelihood function is the sum of the individual respondents' log probabilities:

$$L = \sum_{j+1}^{j} \sum_{yi=j} \log\ (\emptyset\left(\delta_j = \beta' X_i\ \right) - \emptyset(\delta_i - \beta'\, X_i)) \quad (10)$$

Marginal effects are estimated to determine how much each explanatory variable influences (increases or reduces) the likelihood of respondents in each of the three dependent variable categories. The marginal effects of an ordered probit model can be estimated as done by (Chen et al., 2002).

$$\frac{\partial P(Y_i = j)}{\partial X_k} = \ \emptyset\ \left[\delta_{j-1} = \sum_{k=1}^{k} \beta_k\, X_k\right] - \ \emptyset\left[\delta_j - \sum_{k-1}^{k} \beta_k\, X_k\right] \beta_k \quad (11)$$

Where:

$\frac{\partial P}{\partial X_k}$ is the partial derivative of the probability with respect to explanatory variable Xk. A positive (negative) marginal effect of X_k suggests that the probability of a respondent selecting that particular category increases (decreases) with X_k.

Model specification

Ordered probit regression Model

The ordered Probit Regression Model was used to investigate the elements that influence farmers' awareness of renewable energy in the research area. The Ordered Probit Model is the most suited model since the dependent variable has discrete values that have a natural ordering (Abdel-aty, 2001). Respondents were asked a series of questions about their level of awareness, which were then used to classify the farmer's level of awareness as 1,2,...J, where J is a positive integer. The following is the ordered probit model for this study:

$$Z_{i=1,2,..j} = b_0 + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4 + b_5X_5 + b_6X_6 + b_7X_7 + b_8X_8 + b_9X_9 + b_{10}X_{10} \quad (12)$$

Where;

Z = awareness level (0 = low level) (1 = medium level) and (2 = high level).

The independent variables are as follows:

X1 = Gender (1=Male, 0=Female)

X2 = Age in years

X3 = Educational level (years spent in school)

X4 = Household size

X5 = Farm size (ha)

X6 = Farm experience (years)

X7 = Cooperative Membership (1= Yes, 0= No)

X8 = Access to credit (1=Yes, 0=No)

X9 = Extension Agent Visits (number of visits)

X10 = off farm income (naira).

bi = Parameters to be estimated.

Results

Renewable energy awareness of respondents

Socio-economic factors also have an impact on awareness, adoption decision and the success of any adoption decision depends on its dissemination among potential users. Table 1.0 presents the result of the study. The result showed that (44.09%) of respondents had high RE awareness, (27.80%) had medium awareness level about RE while (28.12%) of the respondent had low-level RE awareness. This result is in line with the findings of (Singh & Jirli, 2018) that agricultural stakeholders has a high level of awareness towards information communication technology but disagrees with the findings of (Kendall et al., 2017) who highlighted low awareness and adoption of Precision agriculture on family farms in China.

Table 1.0 Distribution of respondents by awareness level

RE Awareness level	Frequency	Percentage
Low level	88	28.12
Medium level	87	27.80
High level	138	44.09
Total	**313**	**100.00**

Source: field survey 2020

***Factors that influence farmers level of awareness of Renewable* energy**

The result in table 1.1 presents ordered probit model analysis used to estimate the determinants of farmer's awareness level of RE adoption in south-South Nigeria. Three categories of awareness level: low, medium and high formed the dependent variable as 1, 2 and 3 respectively while socio-economic and institutional factors formed the explanatory variables. Out of 10 explanatory variables specified in the model, 6 significantly influenced farmer's awareness level to adopt RE in agricultural production. According to Katchova (2013), the presence of two intercepts, which are threshold parameters, implies the presence of three distinct categories. The cut1 and cut2 threshold parameters are significant at the 5% level, implying that the ordered probit model with the three different attitudes is extremely appropriate.

Table 1.1 Factors that influence farmers level of awareness of Renewable energy

Variables	Coefficients	T-value	Marginal effects		
			Prob (Z=1)	Prob (Z=2)	Prob (Z=3)
Gender	0.01017	0.07	-0.003	-0.001	0.004
Age	0.0270***	4.28	-0.009***	-0.002***	0.010***
Educational level	0.0712***	4.30	-0.023***	-0.005***	0.028***
Household size	-0.0137	-0.46	0.004	0.001	-0.005
Farm size	0.0616*	1.79	-0.019*	-0.005*	0.024*
Farming experience	0.0150*	1.89	0.005*	-0.001*	0.006*
Cooperative membership	0.1676**	1.97	-0.037**	-0.009*	0.046**
Credit access	-0.0975	-0.59	0.031	0.007	-0.038
Extension visit	0.3398***	4.53	-0.107***	-0.025***	0.132***
Ln off farm income	0.1187	0.79	-0.053	-0.012	0.065
Cut1	2.117**	3.09			
Cut 2	1.214**	2.12			
Observations	313				
LR chi2 (10)	72.04				
Prob > chi2	0.0000***				
Log likelihood	-301.69361				
Pseudo R2	0.3267				

Source: Field survey 2020 Note: *, ** and * represent significance at 10%, 5% and 1%**

The log-likelihood value of -301.694 implies that the explanatory variables used in the ordered probit model are appropriate. The chi-square statistics is highly significant at ($p \leq 0.0000$). The explanatory power of the factors as reflected by Pseudo R2 was high (0.327) and significant indicating that the hypothesized variables are actually responsible for about (33%) of the variations in the level of awareness of RE. In terms of consistency with *a priori* expectations on the relationship between the dependent and the explanatory variables, the model seem to have behaved well. The parameter estimates of the ordered probit model only provided the direction of the effect of the explanatory variable on the dependent variable (level of awareness) but did not present the actual magnitude of change or probabilities in the coefficients. Thus the marginal effects of the ordered probit model result measure the expected change in probability of a particular level of awareness on RE. According to (Wollni et al., 2010), the coefficient estimates of the ordered probit model are difficult to interpret. They did, however, propose focusing on the marginal effects after estimating the ordered probit model.

The empirical results of the study revealed that age, educational level, and extension visit were significant at the 1% level of probability, cooperative membership was significant at the 5% level of probability, and farm size and farm experience were significant at the 10% level of probability. The coefficient of the age of the farmers was positive and significantly related to farmer’s level of awareness of RE adoption at 1% level. In other words, an elderly farmer is likely to have a higher RE awareness level than younger ones. This could be attributed to the years of farming experience and exposure. Maturity may increase a farmer's desire to learn new things. This backs up the findings of (Rahman et al., 2018) that an increase in the age of a farmer increases awareness of information communication technology but disagrees with the findings of (Daberkow & Bride, 2003) that the age of farmers decreases the likelihood of precision agriculture awareness level.

The coefficient of the educational level was positive and significantly related to farmer’s level of awareness of RE adoption at 1% level. This means that as one's educational level rises, so does one's desire to learn more. This finding is consistent with the findings of (Ashraf et al., 2015), who found a substantial link between education and awareness level of citrus farming practices in Pakistan. Salehin et al., (2009) discovered a substantial association between education and awareness because education instills in farmers a desire to employ cost-effective technology. There was a positive relationship between RE awareness and extension visits, which shows that farmers who had access to extension services tend to have a higher probability of being aware of RE. This is an indication that extension visits play an important role in educating farmers on various agricultural practices that are capable of enhancing productivity. This study agrees with the findings of (Oduniyi, Oluwaseun and Antwi, 2018) who found that information received through extension services is statistically significant and had a positive influence on climate change awareness in the study area.

The coefficient of cooperative membership was positive and significantly related to farmer’s level of awareness of RE adoption at 5% level. In other words, belonging to a cooperative society increases farmer's RE awareness level. This can be traced to the experiences and knowledge shared among members on new farming practices. This result supports the findings of (Rahman et al., 2018) who found that an increase in cooperative membership by farmers increases awareness of information communication technology. Farm size and farm experience were statistically related to farmer's awareness of RE at (10%) probability level, indicating that an increase in farm size and farm experience increases the likelihood of renewable energy awareness.

The marginal effect result is presented in Table 1.1. The marginal effect analysis for age suggests that the likelihood of being in high RE awareness group increased by (1%) with higher age, the likelihood of being in the moderate RE awareness group increased by (0.25%) while the likelihood of being in the low RE awareness group increased by 0.9% with an increase in age. The marginal effect analysis for farm size suggests that the likelihood of being in the high RE awareness group increased by (2.4%) with higher farm size, while the likelihood of being in the moderate and low RE awareness group increased by (0.5%) and (1.9%) respectively with an increase in farm size.

Marginal effect analysis for farm experience suggests that the likelihood of being in the high RE awareness group increased by (0.6%) with higher farm experience, while the likelihood of being in the moderate and low RE awareness group increased by (0.1%) and (0.5%) respectively with an increase in farm experience. Marginal effect analysis for cooperative membership suggests that the likelihood of being in a high RE awareness group increased by (4.6%) with cooperative membership, while the likelihood of being in the moderate and low RE awareness group increased by (0.9%) and (3.7%) respectively with an increase in cooperative membership.

The marginal effect analysis for extension visit suggests that the likelihood of being in the high RE awareness group increased by (13.2%) with higher extension visits, while the likelihood of being in the moderate and low RE awareness group increased by (2.5%) and (10.7%) respectively with an increase in extension visits. Extension education provided by extension agents raises farmers' knowledge and access to technological learning and enhanced production inputs that have the potential to increase output (Oparinde et al., 2018).

Conclusion

This study was carried out to estimate factors that influence farmers level of awareness of RE in the study area. The estimate was archived using an ordered probit regression model. The results from the analysis revealed that age, educational level and extension visit were significant at 1% level, cooperative membership was significant at 5% level while farm size and farm experience were significant at 10% level of probability. The result of the marginal effect analysis showed that the likelihood of being in the high, medium and low RE awareness group increases with increase in age, farm size, farm experience, cooperative membership and extension visit. Based on the findings of this study, it is recommended that all relevant stakeholders work to provide farmers with renewable energy-related extension messages in order to encourage more farmers to adopt renewable energy, which will increase agricultural production and make their agricultural production systems more resilient to climate change.

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