



VALIDITY OF SELF-REPORT TO MEASURE FARM SIZE: EVIDENCE FROM NORTHERN GUINEA SAVANNAH OF BORNO STATE, NIGERIA

¹Shehu, A., ²Kadafur, M. I. and ¹Goni, I. C.
¹Department of Agricultural Economics and Extension, Abubakar Tafawa Balewa University, Bauchi, Nigeria.
²Department of Socio-economics, International Institute of Tropical Agriculture, Kano, Nigeria
Corresponding Authors' E-mail: abbasecons@gmail.com Tel.: +2348034107403

ABSTRACT

The study was explored to examine the validity of self-report to measure farm size: Evidence from Northern Guinea Savannah of Borno State, Nigeria. Multi-stage sampling procedure was used to select 667 respondents. The data were collected using Universal Transverse Mercator (UTM-area) direct measure and interview of a household head. Data were analysed using both descriptive statistics (count, percentage and mean) and inferential statistics (multiple regression and intra-class correlation). The results found the F-value of 2.7778 significant at P≤0.001 implying that the model was reliable; and the deterministic coefficient was found to be 3.3% meaning that socio-economic characteristics were not the major determinants of selfreported farm size precision because 96.7% variations were accounted by other variables. The regression coefficient was 0.0128 signifying that if years of education increased by 1 year, the precision in self-reporting farm size will increase by 0.0128%. The intra-class correlation using two-way mixed effects model (where; people effects are random and measures effects are fixed) connotes that there is no agreement between two methods of measurement as depicted by average measure of intra-class correlation of 0.066. It was then concluded that farmers' selfreported farm size was not valid and the only socio-economic factor that is affecting it was education. The study therefore, recommended that the use of any available application for measuring farm size during surveys like UTM-area measure which available at play store and compatible with Androids phone should be used.

Keywords: Farm size measure, Intra-class correlation, Measured farm size, Self-report, Validity

INTRODUCTION

Farm is an establishment (single unit with a legal or informal management structure) that has its principal or secondary activity in farming, with the production of agricultural products and biological assets as seeds and animals; and for which full economic data on key business variables, such as costs and revenues, can be collected and made available (Poppe & Vrolijk, 2019; and Fuglie *et al.*, 2017). Farm size plays a critical role in agricultural sustainability; increasing farm size shows clear benefits for environmental protection (Ren *et al.*, 2019; and Ju, *et al.*, 2016).

Farms are integral part to the Nigerian economy and, more broadly, to the nation's social and cultural fabric. A healthy agricultural sector helps ensure a safe and reliable food supply and improves energy security. It contributes to employment and economic development, traditionally in small towns and rural areas where farming serves as a nexus for related sectors from farm machinery manufacturing to food processing. It contributes to the nation's economic growth overall, providing crucial raw inputs for the production of a wide range of goods and





services, including many that generate substantial export value. For instance, in 2019 farms contributed 8.76 trillion Naira directly to the Nigeria GDP representing about 22.12% of a total gross domestic product (GDP) (NBS, 2019). It occupies 19,747,805 ha of land coverage of the total land area of 19,747,805 ha land area of Nigeria (World Bank, 2017).

Farms that are complex, along many dimensions of their business operations, have existed for decades. In fact, it has always been common for families that own and operate farms to also be engaged in other businesses and occupations (Sumner, 1982; and U.S. Department of Agriculture and Economic Research Service, 2017). Farm size is often related to farm complexity, but the measurement of farm size itself is complex. The most useful measures of size differ by enterprise and purpose. Often, in comparisons across farms with different commodity enterprises, size is measured by farm value of production. Area of land harvested, number of livestock, and quantity of production or sales are all useful metrics for comparing farms with the same enterprise or mix of enterprises. The presence of multiple locations for farming activities or multiple addresses for farm management sites creates complexities in farm operation and management and, with those complexities, the potential for significant mistakes in data collection. Geographic dispersion may also increase survey burden. Respondents in charge of multi-farm operations might be surveyed multiple times for the same data fields, leading to their frustration and their lower willingness to participate or to their providing less accurate responses. When separate records are kept for the different locations of a farm, location-based estimates are more reliable (National Academies of Sciences, Engineering, and Medicine, 2019). Use of farmers' perception to ascertain sizes of their field is also source of error in measurement of the size of farms. Employing computer aid devices might be more precise. Desiere and Jolliffe (2017) attributed inverse land and productivity relationship to measurement error.

To get household measures of farm size, we can draw on several approaches. First, we can get survey data on the amount of farm size using questionnaire. Before we can draw reliable inferences from survey data, we need to know the direction and magnitude of biases from measurement errors of farmers (Vadez *et al.*, 2003). If we intend to calibrate the information on farm size from surveys, we should also take into account factors likely to affect measurement errors in surveys. For example, formal education might affect the size and the direction of errors when estimating field size. People knowing the basics of arithmetic might make smaller errors when estimating the size of their fields because they are more adept at computations. Indigenous people are often illiterates; they may likely not measure their plot accurately. Second, we can make direct measurements of farm size using a measuring tape and a compass or computer aided device like UTM-area measure. Direct measures provide more accurate estimates of farm size but require more time and cost.

Economists have long argued that agricultural statistics are largely a public good. Bonnen (1977) points out how improving the quality of agricultural statistics can improve public policy through a better understanding of policies' effects on society. Key users of the information produced by the agricultural statistics agencies and researchers include the other researchers and other government policy makers, National Assembly, program administrators and managers, federal statistical agencies (including for international reporting), State and local government officials and farm and industry groups interested in public policy issues (including nature conservation). Publicly available data also contribute to the efficient operation of markets and are used by farmers, ranchers, and other businesses for planning and forecasting.

The broad objective of the study was to estimate and compares the size of farms using direct measurement and self-reported measurement methods. The specific objectives were to





describe socio-economic factors influencing precision in the self-reported farm size; and determine the validity of self-reported farm size.

MATERIALS AND METHODS

The Study Area

The study was carried out in the northern guinea savannah of Borno State. It is situated between latitudes 100 30'N and 100 45'N and longitudes 120 23'E and 130 13'E. It consists of three (3) Local Government Areas (LGAs) namely; Biu, Hawul and Kwayakusar. The study area has a population of about 352,886 with 2019 projected population estimate of about 531,459 based on 3.2% population growth rate. It covers an area of 69,435 km² (Borno State Agricultural Development Programme [BOSADP], 2001).

Sampling Procedure and Sample Size

Multi-stage sampling procedure was used to select the population for the study. In the first stage, the three (3) LGAs namely; Biu, Kwayakusar and Hawul of the Northern Guinea Savannah (NGS) ecological zone of the State were selected, this was due to the fact that they are the major maize producing areas and, hence used for the intervention in the State. In the second stage, three (3) districts namely; Mirnga, Biu North and Biu East, Kwayakusar, Wandali, Miltha, Kwayabura, Sakwa and Kidang were randomly selected from each LGAs. In the third stage one (1) community was randomly selected from each district, giving a total of nine (9) communities. In the fourth stage, a list of maize farmers was obtained from Borno State Agricultural Development Program (BOSADP) office from which 40% of total population of maize farmers was drawn using systematic random sampling giving a total of 667 respondents (Table 1).

Community	Number of registered farmers	Proportion used		
Mirnga	266	106		
Mainahari	166	66		
Tum	147	59		
Jalingo	133	53		
Kinging	126	50		
Kwayabura	186	74		
Wandali	206	82		
Kwayakusar	266	106		
Ngabu	166	66		
Total	1667	667		

 Table 1: Selected Respondents based on Sampled Communities

Method of Data Collection

The data were collected using two methods: direct measure we used a UTM-area measure software downloaded from Play store on our android tablets to make direct measurement of the respondents' farm(s). Interview of a household head: Interview was conducted for the male household heads without referring to the information already gathered through method 1. The household heads were asked to estimate the total area of land in their possession. The estimates were recorded in hectares.

Analytical Techniques

Data were analysed using both descriptive and inferential statistics. Descriptive statistics was used to describe the socio-economic characteristics of the respondents. Multiple regressions were used to analyse the socio-economic determinants of farm measurement error and intra-class correlation was used to analyse the reliability of self-reported farm size. This





model was used to determine the socio-economic factors that influence the accuracy in self-reported data. The implicit form of the model is:

$$\begin{split} Y &= f(X_1, X_2, X_3, X_4, X_5, X_6, X_7) & \dots(1) \\ & \text{The explicit form of the multiple regression model is presented as:} \\ Y_i &= b_0 + b_1 X_1 + b_2 X_2 + b_3 X_3 + b_4 X_4 + b_5 X_5 + b_6 X_6 + b_7 X_7 + u & \dots(2) \\ & \text{where;} \end{split}$$

Y= % change in self-reported farm size

The explanatory variables included in the model include:

 $X_1 = Sex$ (Dummy) (D = 1 if male and 0 otherwise);

 X_2 = Education (years of formal education);

X3 = Household size (Number of people);

 $X_4 =$ Marital status (Married=1, Single = 0);

 $X_5 =$ Farm size (ha);

 $X_6 = Age (years);$ and

 $X_7 =$ Farming experience (years)

RESULTS AND DISCUSSION

Continuous Socio-economic Characteristics of the Respondents

Table 2 represents the socio-economic characteristics of the respondents. The result depicts that the average age of the respondents was 45 years meaning that the respondents were in their active age to take appropriate measure of their farms. The standard deviation of 14 showed a little variation of ages in the study area. The findings were in line with Kadafur *et al.* (2017). Also, the average years of formal education was 8 years with a standard deviation of 6, this implies that most of the respondents had some secondary school education with wide variation within the respondents' years of education. This corroborates the findings of Kadafur *et al.* (2017) and Duniya (2018) who their studies found about 50% had some secondary school education.

The average years of farming experience was 22 years with a standard deviation of 12. This showed that the farmers were experienced with wider variation within their experience as showed by the standard deviation. This is in line with Shehu *et al.* (2019) who found that farmers were experienced with 20 years farming experience and a standard deviation of 11.94 in north-east Nigeria. Further to Table 2, the average household size of the respondents was 8 persons with a standard deviation of 4. This showed the large household sizes in the study area with also little variation. It also means farmers needs big farms to cater for their food needs. It is in line with Kadafur *et al.* (2017) who also found 8 people as an average household size in the study area. The average self-reported reported farm size and measured farm size were 1.14 and 1.27 with a standard deviation of 0.9 and 8.05, respectively. This showed the farmers had small farms and there is wide variation within self-reported farm size but there exist in measured farm size. That showed error exist between the two measurements. This corroborates the findings of Vadez *et al.* (2003) that found farmers' biases in reporting deforestation. The average percentage change of the self-reported farm size and measured one was -0.29 ha with little variation of 0.4.





Variable	Minimum	Maximum	Mean	S.D	
Age	18.00	86.00	45.43	13.98	
Education	0.00	30.00	8.04	5.94	
Farming Experience	2.00	56.00	21.80	11.55	
Household Size	1.00	24.00	8.32	4.11	
Self-reported farm size	0.10	5.00	1.14	0.90	
Measured farm size	0.10	196.00	1.27	8.05	
Percentage Change	-4.00	0.99	-0.29	0.40	

Table 2: Continuous Socio-economic Variables

Qualitative Socio-economic Characteristics of the Respondents

The qualitative Socio-economic characteristics were presented in Table 3. The results revealed that majority (74.70%) of the respondents were males this was probably due to the culture of the area that restricted females with economic activities within their homes. This is in line with Shehu *et al.* (2019) and Kadafur *et al.* (2017) whom in their studies found majority (92% and 81.1%, respectively) of farmers were males in north-eastern Nigeria and Southern guinea savannah of Borno State, respectively.

Table 3: Non-continuous Socio-econon	nic Variables
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Variable	Frequency	Percentage		
Sex				
Female	150.00	25.30		
Male	443.00	74.70		
Marital status				
Single	11.00	1.85		
Married	504.00	84.99		
Widowed	73.00	12.31		
Divorced	5.00	0.84		
Educational level				
Adult education	28.00	4.72		
Junior high school	24.00	4.05		
No education	161.00	27.15		
Post-secondary	99.00	16.69		
Primary	114.00	19.22		
Secondary	167.00	28.16		
Group membership				
Non-member	276.00	46.54		
Member	317.00	53.46		

Further in Table 3, it was reported that majority (84.99%) of the respondents were married; implying the existence of early marriage in the study area. This is in line with Shehu *et al.* (2019) and Kadafur *et al.* (2017) who found majority (88.4% and 89.2%) were married in north-eastern Nigeria and Northern guinea savannah of Borno State, respectively.

The education level of the respondents was found to be low, this was depicted by less than half (28.16%) that attended secondary schools. This is in line with Shehu *et al.* (2019) and Kadafur *et al.* (2017) who in their work found 29.7% and 24.1%, respectively, the people that





attended secondary schools. More than half (53.46%) were group members in the study area. This showed farmers form associations to pull benefits together in the study area.

Factors Influencing Precision in Self-reported Farm Size

Table 4 showed the socio-economic factors influencing precision in self-reported farm size, the deterministic coefficient was found to be 3.3% implying that socio-economic characteristics were not the measure determinants of self-reported farm size precision. This results means, 96.7% variations were accounted by other variables. The F-value was found to be 2.7778 (P \leq 0.001) this showed the model was reliable. This is in line with Kormos and Gifford (2014) who found that the considerable amount (79%) of unexplained variance between self-reports and objective measures by socio-demographics factors.

Only years of education was found to be positively significant ($P \le 0.001$), this implies those with higher education were able to estimates their farms accurately. The regression coefficient was 0.0128; this showed that if a year of education increases by 1 year, the precision in self-reporting farm size will increase by 0.0128%. This is in line with Vadez *et al.* (2003) who found that the educational level of the plot owner had an important weight on his estimation error, with more educated men making more accurate estimations.

This corroborates the findings of Vadez *et al.* (2003) who found bias in reporting deforestation and Desiere and Joliffe (2017) who argue that the inverse relationship between farm size and productivity was an artifact of systematic over reporting of production by farmers on small plots, and under reporting on larger plots.

Variables	Coefficient (B-value)	Std. Error	T-value
Constant	-0.3613	0.0953	-3.7924
Constant	-0.0006	0.0022	-0.2858
X ₁ (Age)	-0.0012	0.0492	-0.0252
X_2 (Sex)	-0.0070	0.0307	-0.2296
X ₃ (Marital status)	0.0128	0.0031	4.07***
X ₄ (Years of education)	0.003	0.003	0.076
X ₅ (Farming experience)	-0.043	0.034	-0.053
X ₆ (Group membership)	-0.004	0.004	-0.039
\mathbb{R}^2	3.30%		
F-value	2.7778***		

Table 4: Determinants of Precision in Measuring Farm Size

Intra-class Correlation using People Effects and Measures Effects

The result (Table 5) of intra-class correlation using two-way mixed effects model (where; people effects are random and measures effects are fixed) showed that there was no agreement between two methods of measurement, this was depicts by average measure of intraclass correlation of 0.066 (less than 0.7). This connotes that the farmers self-reported farm size was not reliable. This finding corroborates the findings of Vadez *et al.* (2003) that found farmers' biases in reporting deforestation; Kormos and Gifford (2014) and Kee *et al.* (2017) whom reported bias in self-reported height and weight.





Measure	Intra-class Correlation ^b	95% Confidence Interval		F-Test	with [Frue V	alue 0
		Lower Bound	Upper Bound	Value	\mathbf{Df}_1	\mathbf{Df}_2	Sig.
Single Measures	0.034ª	-0.047	.114	1.070	591	591	.20 4
Average Measures	0.066 ^c	-0.098	.205	1.070	591	591	.20 4

Table 5: Intra Class Correlation

a. The estimator is the same, whether the interaction effect is present or not.

b. Type A intra-class correlation coefficients using an absolute agreement definition.

c. This estimate is computed assuming the interaction effect is absent, because it is not estimable otherwise.

CONCLUSION AND RECOMMENDATIONS

Based on the study findings, it can be concluded that, farmers' self-reported farm size was not valid and the only socio-economic factor that is affecting it was education. However, most of the determinants of precision were not socio-economic. It was then recommended that the use of any available application for measuring farms during surveys like Universal Transverse Mercator (UTM-area) measure which are usually available at play store and compatible with Androids phone should be used.

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