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Enhancing fertilizer-use-efficiency through fertilizer microdosing as climate-smart practices among crop farmers in North Central, Nigeria

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The impact of climate change, soil fertility depletion, and land degradation has necessitated the continuous use of fertilizer to enhance crop productivity. However, the high cost of fertilizer, coupled with improper use of fertilizer leading to environmental issues, has encouraged efficient use of fertilizer. This study draws on farm-level data to assess the link between the implementation of fertilizer microdosing technology and fertilizer use efficiency among cereal crop farmers in North Central, Nigeria, due to its agroecological importance, high cereal production, and vulnerability to climate change. We used the Heckman two-stage model to explore the adoption and intensity of adoption since it presents a more precise estimation by effectively addressing the endogeneity arising from latent sample selection biases. We examined the mechanism of the effect of the adoption of fertilizer microdosing technology on fertilizer use efficiency using a 2SLS instrumental variable regression to control for unobserved variables. This study found that adoption of fertilizer microdosing technology is gender-sensitive; thus, its application is more common among male farmers. The results show that there is a positive relationship between the adoption of fertilizer microdosing technology and fertilizer use efficiency. The estimated elasticities of fertilizer microdosing technology adoption for maize, sorghum, millet, and maize-sorghum are similar, and the average elasticity of fertilizer microdosing technology adoption is around 0.6. Statistically, a 1% increase in fertilizer microdosing technology adoption is associated with a 0.6% increase in fertilizer use efficiency. These results suggest massive promotion of this technology for use among farmers since it can help reduce fertilizer wastage and ensure a climate-smart practice.

KEYWORDS

fertilizer microdosing, fertilizer use efficiency, climate change, 2SLS, Nigeria

Introduction

Farmers make repeated land-use and management decisions while facing diverse resource endowments, the depletion of soil fertility, climate change impact, and significant environmental constraints to the production of suitable food crops (Erkossa et al., 2014; Makurira et al., 2011; Akinwale et al., 2025). Although rich in natural resources compared to other continents, the productivity of agriculture in Africa falls below the global average due to limited use of productivity-enhancing technologies and the impact of climate change (Camara et al., 2013; Haug and Hella, 2013; Adegunsoto et al., 2024; Kolapo and Sieber, 2025). Increased agricultural productivity and improved use of farming inputs such as fertilizer have to be at the top of agendas for sustainable agricultural growth because the loss of soil fertility and soil moisture pose the greatest threats to agricultural production (Dar and Gowda, 2013; Giordano and Clayton, 2012; Kolapo et al., 2025a,b). Research conducted at the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) suggests that land degradation affects more than half of Africa, resulting in a loss of approximately US\$42 billion in income and 5 million hectares of productive land each year (ICRISAT, 2015). The majority of farmlands produce poor yields due to poor farming techniques, nutrient deficiency and lack of water as a result of climate change (Akinwale et al., 2025; Kolapo et al., 2025c; Kamara et al., 2025). Land degradation is particularly acute in sub-Saharan African regions where long-term overuse of soil and low, unpredictable rainfall are prime reasons for poor food production owing to climate change (Kolapo et al., 2022a). Despite the fact that Nigeria is blessed with enormous areas of land, land degradation has greatly lowered the quality of cultivable land, resulting in lower crop yields (Kolapo et al., 2022a). Farmers have been compelled to continue cultivating increasingly marginal soils, thus encouraging the use of fertilizer to improve soil nutrients and increase crop yield (Kamara et al., 2025; Kolapo et al., 2022b). There is increasing evidence that fertilizer use has risen in countries with large-scale fertilizer promotion programs, including Ethiopia, Zambia, Malawi, and Nigeria (Omonona et al., 2019). However, the conventional methods of fertilizer application often lead to large quantities of fertilizers being used by resource-poor farmers in Africa, including Nigeria, which is not always available for use by the farmers (Kolapo et al., 2024b). The conventional fertilizer application methods in Nigeria include the broadcasting method, where fertilizers are spread on the farm plots (Omonona et al., 2019). Another fertilizer application method includes banding, which involves placement, localized placement, etc. Many smallholder farmers in sub-Saharan Africa lack the resources to acquire large quantities of fertilizer, hence a considerable proportion of them stop fertilizer application over time, which has resulted in low agricultural productivity (Kolapo et al., 2024a). To overcome these challenges, fertilizer microdosing technology was introduced to resource-poor farmers in Africa in the last decade to ensure efficient fertilizer use and increase crop productivity (ICRISAT, 2015), also serving as a climate-smart strategy to adapt to climate change impact (Kolapo and Kolapo, 2023). In Nigeria, fertilizer microdosing technology is gradually gaining popularity among smallholder farmers (Orkaa and Ayanwale, 2020).

Fertilizer microdosing is a precision farming technique in which small and affordable quantities of fertilizer are applied directly to the crop at planting or shortly after planting in order to increase fertilizer use efficiency and improve productivity (Ibrahim et al., 2015a). The main objective behind fertilizer microdosing is to minimize the cost of fertilizer and investment risk, and to increase investment return to poor farmers who cannot otherwise afford to apply the recommended amount of fertilizer (Camara et al., 2013). The fertilizer microdosing method typically uses between a third and a fourth of the typically recommended fertilizer rate (Camara et al., 2013). The cost of fertilizer microdosing as compared to using the recommended rate therefore reduces by a similar ratio, between a third and a fourth. However, the labor requirements of the fertilizer microdosing method are higher and, due to this, farmers have tried a new method of applying fertilizer microdosing that mixes fertilizer with seed to minimize additional labor costs (Pender et al., 2008). In earlier on-station and on-farm fertilizer microdosing research, yield increases of up to 130% yield over the farmers' common practice of no fertilizer application are reported (Camara et al., 2013; Ibrahim et al., 2015b). Other ex-post studies also indicate the positive yield impact of fertilizer microdosing (Murendo and Wollni, 2015). The 'agronomic efficiency' of crops and varieties (Mwangi, 1996), agro-climatic variables and existing soil quality conditions are deemed as important drivers for improving crop productivity through fertilizer use. Studies on the economic returns of fertilizer microdosing report profit increases ranging from marginal (Abdoulaye and Sanders, 2006) to 88% (Abdoulaye and Sanders, 2005) using partial budgeting analysis. Other than yield benefits, the fertilizer microdosing technology is further promoted for its potential to reduce fertilizer-related emissions, water contamination problems and also adaptation strategy to climate change impact.

However, studies on application of fertilizer microdosing techniques and its relationship with fertilizer use efficiency of cereal crop farmers in Nigeria is scanty or non-existence. To the best knowledge of the researchers, this is the one of the few studies in Nigeria to evaluate fertilizer use efficiency of smallholder cereal crop farmers through the applications of fertilizer microdosing technique. Orkaa and Ayanwale (2020) previously examined the determinants of fertilizer microdosing techniques among underutilized indigenous vegetable farmers in South-west Nigeria; they however failed to ascertain its current application among the cereal crop farmers. Also, there is a dearth of knowledge on fertilizer use efficiency of the users of fertilizer microdosing technology vis-a-vis conventional fertilizer application procedures in Nigeria which is the main objective of this study. This study emphasizes the extent to which fertilizer microdosing has improved fertilizer use efficiency of sole and mixed cropping system in Nigeria. Although a sizeable portion of literature on the yield impact of the fertilizer microdosing technique (Biazin and Stroosnijder, 2012; Ibrahim et al., 2015b; Twomlow et al., 2010) and on the cost-benefit (Camara et al., 2013; Abdoulaye and Sanders, 2005, 2006) exist, little is known about the fertilizer use efficiency (which is a better indicator of crop assimilation efficiency or nutrients loss rate) of the use of the technology (Wei et al., 2022). Presently, the yield and fertilizer use efficiency implications of fertilizer microdosing are

important criteria to evaluate and scale-up its spread across Nigeria. This study investigates the relationship between fertilizer microdosing practices and fertilizer use efficiency among growers of maize, sorghum and cowpea using farm-level data in Nigeria. We use household survey data that includes information on output, costs, and prices on various production activities performed by farmers in the current system. This paper contributes to the literature by addressing the gap regarding the yield and fertilizer use efficiency implications of adopting fertilizer microdosing technique. The study provides information relevant to decision making with respect to promoting technologies that improve the yield, fertilizer use efficiency, adaptation to climate change and livelihoods of smallholder farmers in Nigeria and in areas with similar environmental and socio-economic conditions.

Conceptual framework

Various models have been developed to assess the adoption of specific innovations (Kolapo and Tijani, 2025; Kolapo et al., 2024a; Kolapo and Didunye, 2024; Kolapo et al., 2023, 2022b, 2021a,b,c,d). The determinants of a dichotomous choice are generally estimated using logit or probit models (Toluwase et al., 2017; Mwalupaso et al., 2019; Kolapo and Ayeni, 2020; Kolapo and Yesufu, 2020), and those of multiple choice are often assessed using ordinary least squares (OLS), the tobit model, the multivariate probit model (MVP), and the Multinomial logit Selection Model (MNLS; Khonje et al., 2018; Kolapo et al., 2020c,e). However, it is impractical and biased to estimate the decision and intensity of adoption separately using these methods, principally because these two stages are inseparable. The second stage is conditional on the first. In other words, only when farmers decide whether to adopt fertilizer microdosing Technology can they choose the area of land to be allotted to its application (Birhanu et al., 2017). Therefore, modeling the process in this study required a two-stage estimate that simultaneously accounted for the decision and depth of adoption. Both the Heckman two-stage model and double-hurdle estimation have been demonstrated to have analytical superiority in this regard (Birhanu et al., 2017); however, the former presents a more precise estimation by effectively addressing the endogeneity arising from latent sample selection biases (Heckman, 1979). Accordingly, this study used the Heckman two-stage model (comprising a sample selection and an outcome equation) to identify the factors influencing farmers' adoption of fertilizer microdosing Technology. Following Heckman (1979), we first formulated a binary probit model following the random utility model as a benchmark for estimating adoption decisions. We then exploited a modified OLS model to estimate the determinants of adoption intensity, where the inverse mills ratio (IMR) was incorporated as an additional independent variable to correct the sample selection bias. Here, referring to Li et al. (2017), we considered the adoption intensity as a continuous variable comprising of the area (ha) of land allotted to the application of fertilizer microdosing Technology.

The first stage assumes the existence of an underlying relationship as follows:

$$Y_{da}^* = \alpha X_{da} + \varepsilon_{da} \quad (1)$$

where Y_{da} is an unobserved variable that measures the conditional probability that an individual decides to adopt fertilizer microdosing technology, that which is observed can be expressed as:

$$Y_{da} = \begin{cases} 1, & \text{if } Y^*_{da} > 0 \\ 0, & \text{if } Y^*_{da} < 0 \end{cases} \quad (2)$$

where Y_{da} denotes a dichotomous variable that takes the value of one if a cereal farmer adopts fertilizer microdosing Technology; otherwise, it is zero. X_{da} refers to a vector of independent variables associated with adoption decisions. α indicates a vector of parameter coefficients to be estimated, reflecting the effect of the independent variable on the adoption decision. ε_{da} is a normally distributed error term.

The algebraic representation of the second stage model is as follows:

$$Y_{ia} = \beta X_{ia} + \rho \sigma \text{IMR} + \varepsilon_{ia} \quad (3)$$

where Y_{ia} is a continuous interval variable representing the adoption intensity measured by the areas of land in ha allotted to the application of fertilizer microdosing Technology by the i th cereal farmers. Y_{ia} is only observed when Y_{da} equals 1. Y_{ia} gradually increases to the total land area allotted for its application, indicating a gradual increase in adoption intensity from low to high. X_{ia} shows a vector of explanatory variables for the adoption intensity, β is a vector of parameter coefficients to be estimated, and ε_{ia} is the error term. ρ denotes the correlation between ε_{da} and ε_{ia} . σ is the standard deviation of ε_{ia} . IMR contains information on the unobserved factors affecting the first decision and helps improve the parameter estimates and correct selection bias in the second stage (Birhanu et al., 2017); it was obtained from the first stage, and the formula is as follows:

$$\text{IMR} = \frac{\phi(\alpha X_{da})}{\Phi(\alpha X_{da})} \quad (4)$$

where ϕ and Φ are the normal density function and the cumulative density function of a standard normal distributed variable, respectively. Sample selection bias exists if IMR is statistically significant. hence, the OLS regression may bring about a biased estimate, which can be effectively corrected by the Heckman two-stage model, indicating that it is appropriate for estimation.

Research method

The study was carried out in North Central Nigeria. The area is located between latitude 8 °N and 10 °N and Longitude 3 °E and 10 °E (Kamara et al., 2025; Akinwale and Afodu, 2024b). North central Nigeria is characterized by a Tropical Continental Climate marked by a wide variation of annual temperature regime and a restricted rainfall, with temperatures and rainfall varying with location and period of the year. The Mean annual temperature ranges from 24 to 37 °C, while the Mean annual rainfall is between 100 and 200 cm³ (Kolapo et al., 2024b; Kassali et al., 2024; Kolapo, 2023; Jimoh et al., 2023; Rabirou et al., 2022). The climate of north central Nigeria is characterized by a rainy season

which extends from April to October, and a dry season which starts in December and lasts till March (Kolapo and Abimbola, 2020; Kolapo et al., 2020a,b,c,d,e). The recession of harmattan for the rains is heralded by the moist Tropical Maritime Air Mass of the Southwest Trade winds. This point is usually marked by hot sunny days with temperatures being highest about March to April. Soil resources of the area are either friable, porous, coarse-grained sandy or lateritic usually gray or reddish in color, and generally low in fertility (Ogunleye et al., 2020). The soil supports a wide variety of crop species, including cereals such as Maize, Rice, Millets, and Sorghum and legumes like cowpea, groundnut (Kolapo and Kolapo, 2020; Toluwase and Kolapo, 2017; Kolapo and Fakokunde, 2020). These crops supply much of the average farm family's subsistence food requirements as well as a marketed surplus for income.

The study employed a multistage sampling procedure to choose those who participated. In the initial phase, two states, Benue and Kwara, that are part of the same agro-ecological region, were purposefully chosen. Using a purposive sample, two local government areas (LGAs) were chosen from each state in the second step, taking into account the large number of smallholder soybean farmers in these areas. Five villages were chosen at random from each of the four LGAs for the third stage. In accordance with Tesfahunegn et al. (2016), the sample size for the study was established using the sample determination formula as outlined by at a 95% confidence level and a 5% margin of error. This allowed for the selection of 12 farmers from each of the five villages that had previously been chosen in order to provide 480 respondents who were interviewed for the study. Structured questionnaires were used to collect data from the respondents. Data on socioeconomic characteristics such as age, gender, educational status, farming experience, farm size, household size access to financial supports, membership of farmers association, access to weather information, access to irrigation facilities, access to extension services, years stayed in the community were collected. Furthermore, data on varieties of soybean being cultivated, costs of inputs and outputs, yield and income from soybean production, access to machinery receiving training and skill acquisition on fertilizer microdosing, types of fertilizer application methods implemented on their farm, etc. were all collected. Data enumerators were incorporated during data collection after receiving training before the start of data collection. Data was collected with the use of the ODK application. Data cleaning was carried out which were later transferred into STATA 15 for data analysis.

Gatekeeper permission was also obtained from the community leaders of the selected communities in the Local Government Areas in Benue and Kwara States. The ethical principles of respect for person, anonymity and confidentiality, beneficence, and principle of justice were all observed in the course of the study. For instance, data collection was only done after informed consent had been obtained from the respondents. Respondents were asked for their consent verbally before the commencement of the interview. Informed consent was obtained verbally from the respondents and only those respondents who gave their consent verbally were interviewed. All respondents, irrespective of their ethnicity and creed, were treated fairly and equally throughout the conduct of the study.

Estimation of fertilizer use efficiency (FUE)

Currently, little is known about the relationship between fertilizer microdosing technology and fertilizer use efficiency (FUE), there are however, a large body of evidence on the relationship between farm size and fertilizer use efficiency (FUE; Wei et al., 2022), farm size and productivity, which this study can draw on (Wang et al., 2015; Muyanga and Jayne, 2019; Sheng et al., 2019; Yan et al., 2019; Yao and Hamori, 2019).

Following (Wei et al., 2022; Wang et al., 2015; Muyanga and Jayne, 2019; Sheng et al., 2019; Yan et al., 2019; Yao and Hamori, 2019), the model in this paper is as follows:

$$\ln FUE_i = \alpha + \gamma \ln A_i + \delta (\ln A_i)^2 + \sum_k \beta_k X_{ki} + \varepsilon_i \quad (5)$$

where subscript i denotes the farm household; FUE, the dependent variable, denotes fertilizer use efficiency; A denotes fertilizer microdosing use; X are various control variables, including soil quality, irrigation access, access to climate information, etc.; γ and β_k are estimated coefficients; and ε is the random error term. Both fertilizer microdosing use and FUE are in logarithm in the model, so that the coefficient of fertilizer microdosing use is its elasticity. The square-term of fertilizer microdosing has been added into the model to capture the potential non-linear relationship between fertilizer microdosing use and FUE. Equation 5 can be estimated using the ordinary least squares (OLS) regression, or the weighted least squares to correct for heteroscedasticity. The obtained coefficients of fertilizer microdosing use (γ and δ) may be biased from the real relationship between fertilizer microdosing use and FUE.

This is attributed to the potential endogeneity problem. For example, farmers with more knowledge and skills are more likely to use fertilizer microdosing for fertilizer application on larger part of their farm. Therefore, the OLS estimate of the coefficient on fertilizer microdosing use reflects both the effect of fertilizer microdosing use and the selection effect on the FUE.

To address this potential concern, an instrumental variable regression was adopted to control for unobserved variables. The number of years a farmer has stayed in farm village was used as an instrumental variable, which was also used by Wossen et al. (2017), to identify access to fertilizer subsidies. New technologies are first introduced to leaders in each community for farm trials where these leaders are farmers who have stayed for a longer number of years in such community. However, the number of years a farmer has stayed in a community or village is unlikely to be correlated with farmer's knowledge and skills because some farmers might network out of their villages/communities to acquire more farming knowledge and skills. Meanwhile, because the acquisition of new skills is limited in rural areas in Nigeria due to lack of extension services among others, adoption of new technology (fertilizer microdosing) and number of years stayed in villages are closely correlated. To test the effectiveness of the instrumental variable, this study first conducted the under-identification test and weak identification test; the test results showed that the null hypothesis of under-identification and weak identification both can be rejected. Then, the correlation between the number of years stayed in a village and adoption of fertilizer microdosing technology was tested; the Shea's partial R^2

and the P value of F -statistic suggested that the correlation between number of years stayed in a village and adoption of fertilizer microdosing technology was statistically significant.

This study then conducted Durbin-WuHausman test on the endogeneity of fertilizer microdosing technology adoption; the test results showed that for the samples of maize, sorghum, and maize-sorghum, the null hypothesis that fertilizer microdosing technology is the exogenous explanatory variable can be rejected; but for the samples of millet, the null hypothesis cannot be rejected. Therefore, the number of years stayed in a village can be regarded as a valid instrumental variable for fertilizer microdosing technology adoption. The instrumental variable regression can capture the effect of fertilizer microdosing technology adoption on FUE while excluding the selection effect. A two-stage least squares (2SLS) estimation was implemented by using the number of years stayed in a village as the instrumental variable with other control variables.

According to Cassman et al. (1998), FUE, the dependent variable, is defined as the ratio of grain yield to the quantity of applied fertilizers per unit area, which is the indicator of FUE commonly used in agronomy:

$$\text{FUE} = Y/F = (Y_0 + \Delta Y)/F = (Y_0/F) + (\Delta Y/F) \quad (6)$$

where Y is the grain yield obtained with an applied fertilizer of F ; Y_0 is the grain yield without fertilizer inputs; ΔY is the incremental increase in grain yield that results from fertilizer application; $\Delta Y/F$ is often called the agronomic efficiency, and it represents the product of uptake efficiency from the applied fertilizers. Therefore, higher FUE means that a higher proportion of fertilizers is converted into grain, and a smaller proportion of fertilizers is lost (Figure 1).

Results

Summary of descriptive statistics

The descriptive statistics of the sampled households are presented in Table 1. Results show that the average ages of the respondents were 46.20 ± 15.58 years. This implies that majority of the farmers are in their active age and are vibrant and productive. The result is similar to Solaja et al. (2024), Ajiboye et al. (2023), and Bamiro et al. (2023) who found that smallholder farmers in Nigeria are in their productive age. Majority (75.42%) of the farmers were married. Thus, the use of family labor for crop production might be possible. About 50.63% of the sampled respondents were male indicating that cereal production is almost equally distributed among the two genders in term of its production. The average years of education of the farmers were 7.346 ± 3.21 years. This implies that considerable proportion of the farmers are literate and can read and write. The average household size is 7.24 persons. Farm Experience indicates that the average years into cereal production were 19.972 ± 13.746 years. This shows that the farmers had been in cereal production for a long period of time and must have accumulated experience over the years. Membership of association results also indicate that the majority 76.16% of the respondents belong to associations. Being a member of associations including farmers' cooperative societies in rural dwellings are important

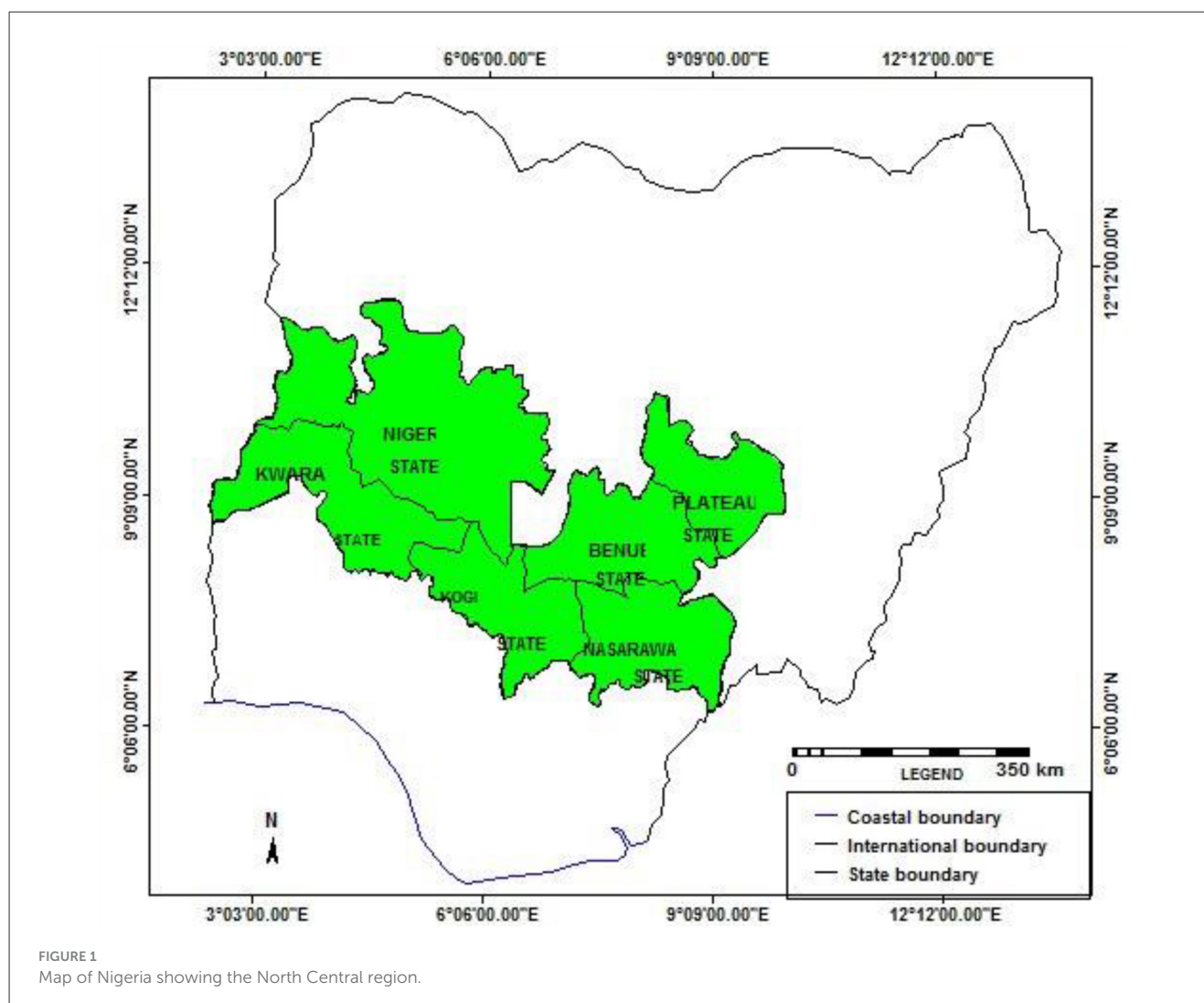
forms of social networks that help farmers get external information about new technologies and innovations and also provide different forms of support to help farmers increase their farm output. The average land cultivated by the farmers indicates that sampled farmers were predominant smallholder farmers in the region. The majority (79.2%) of the respondents do not have access to credit indicating that the farmers lack financial support. The average number of years the respondents had stayed in their community was 29.79 ± 16.93 years. The majority (76.46%) of the respondents owned their farmland and thus might not be faced with the problem of land tenure security. About 45.35% of the respondents had access to weather information while about 32.85% had access to irrigation. The soil quality was reported by the respondents, and the options are measured from 1 to 5, with 1 representing very good condition and 5 representing very poor condition.

Result from the Heckman two-stage regression model

Factors of adoption and intensity of adoption of fertilizer microdosing practices

The result of the Heckman two stage regression model presented in Table 2 reveal several significant factors influencing the adoption (first stage) and intensity of adoption (second stage) of fertilizer microdosing technology among the cereal farmers. In this study, Stata software (version 15) was used to estimate the parameters of the Heckman two-stage model and identify the factors that affected the adoption decision and intensity of fertilizer microdosing technology by the sampled households. The results are summarized in Table 2. The model passed the chi-squared test at a significance level of 1%, indicating that it fit reasonably well. We report the coefficients of the explanatory variables, standard deviations, t -value, and IMR (lambda). lambda was found to be statistically significant and positive at the 5% level, suggesting a selection bias in the sample, and that the Heckman two-stage model was suitable for our analysis. Finally, we conducted a variance inflation factor (ViF) test among the independent variables and the IMR to ensure the validity of the results and avoid multicollinearity problems. The maximum and mean ViF were 2.46 and 1.13, respectively, indicating that there was no multicollinearity problem.

Gender was positive and statistically significantly associated with the likelihood of adoption of fertilizer microdosing technology. This implies that adoption of fertilizer microdosing technology is gender sensitive. Thus, male farmers are more likely to use fertilizer microdosing technology when compared with their female counterparts. This might be attributed to the disproportionate access to resources and technology among farmers in Nigeria which tend to be biased toward the female farmers. Furthermore, a negative coefficient of variable age suggests that as the age of farmers increases, there is a decrease in the likelihood of adopting fertilizer microdosing technology. This implies that younger male farmers may be more inclined toward adopting modern practices compared to their older counterparts. Older farmers are more inclined to traditional fertilizer application system, hence the low level of adoption of fertilizer microdosing technology among them. This result



agrees with Kolapo and Didunyemi (2024) that young farmers are more likely to use new agricultural innovations. With a positive significant coefficient of years of resident in community, it indicates that as the number of years a farmer has resided in her community increases, there's a higher likelihood of embracing a fertilizer microdosing technology. This could be attributed to increased familiarity with local agricultural dynamics and networks over time. Smallholder farmers are known to networking among each other within or outside their communities and in the process, they are bound to inform each other of new method of farming which ultimately increase the use of fertilizer microdosing technology for efficiency fertilizer use and increased yield. The positive coefficient of per capita income is highly statistically significant, suggests that higher per capita income correlates with higher likelihood of adopting fertilizer microdosing technology. This indicates that financial resources play a role in facilitating the adoption of modern agricultural techniques. This agrees with Kolapo et al. (2023) that having access to financial resources can help facilitate adoption of new innovations. The significant p -value of access to weather information, indicates that having considerable level of access to quality weather information enhances the probability of utilizing fertilizer microdosing technology. This implies that better access

to up-to-date information facilitates the adoption and uptake of agricultural innovations among the farmers. This agrees with Kolapo et al. (2024a,b) that information accessibility plays a vital role the adoption of modern agricultural technology. Variable soil quality was positive and significant indicating that as the farmers with poor soil quality are more likely to use fertilizer to enhance their soil nutrients and thus utilizing the fertilizer microdosing technology as an application method for efficient fertilizer use and increased yield.

With regard to adoption intensity of fertilizer microdosing technology by the cereal farmers, we also found a negative and statistically significant coefficient of age variable. This implies that as age of the farmers increases, there is higher likelihood that they allotted smaller plot of land for the application of fertilizer microdosing technology. As previously stated, older farmers are more inclined to protecting norms and tradition, hence they are more likely to embracing traditional methods of fertilizer application in their cereal production. This agrees with Kolapo and Kolapo (2021); Kolapo et al. (2021a,b), and Toluwase et al. (2017) who found a similar result that new technology application is a thing among the younger farmers. Conversely, the variable gender was positively and statistically significantly associated with the adoption intensity of fertilizer

TABLE 1 Summary of descriptive statistics.

Variable	Mean	Std. dev.	Max.	Min.
Age (years)	46.20	15.58	18	80
Marital status (married)	0.7542	0.4275	4	1
Gender	0.5063	0.500	1	0
Years of education	7.346	3.21	8	0
Household size	7.245	3.584	14	1
Farm experience (years)	19.972	13.746	53	6
Membership of association (%)	0.7616	0.4971	1	0
Access to extension services	0.7313	0.4437	1	0
Frequency of extension contact (#)	6.908	12.592	15	0
Access to credit (yes = 1, no = 0)	0.792	0.6472	1	0
Amount of credit obtained (Naira)	12324.896	15706.13	25,000	0
land size cultivated (ha)	1.8716	0.5583	2.937	0.0625
Years stayed in community	29.79	16.93	75	2.2
Owned_land (%)	0.7646	0.4785	1	0
Access to climate information	0.4535	0.710	1	0
Access to irrigation	0.3285	0.176	1	0
Soil quality	0.979	0.713	5	1

microdosing technology. The reveals that male farmers are more likely to allot more plot of farmland for the application of fertilizer microdosing technology when compared to their female counterparts. This finding agree with [Kolapo and Ayeni \(2020\)](#) and [Kolapo and Yesufu \(2020\)](#) who found that uptake of innovation are common among the male gender. This underscores the influence of gender bias to resources use, highlighting the importance of addressing gender barriers to encourage widespread adoption of fertilizer microdosing technology. In addition, access to climate information were found to be positive and statistically significant suggesting that farmers who have access to quality weather information have a higher likelihood of allotting greater proportion of their farmland to fertilizer microdosing practices. Smallholder farmers are known to be constrained with access to quality information on modern innovation techniques that could enhance their productivity. Thus, when they eventually assessed the needed information, they are more likely to devote large area of their farm land to the new innovations considering the benefits they would derived from its application (fertilizer microdosing technology).

Fertilizer microdosing practices and fertilizer use efficiency relationship

Presented in [Table 3](#) are the results of the fertilizer microdosing adoption-fertilizer use efficiency relationship together with control

TABLE 2 Parameter estimates of the Heckman two-stage model.

Variable	Coefficient	Standard error	t-value
First stage (decision to adopt)			
Gender	0.5605***	0.2045	2.864
Age	−0.4626***	0.1434	−4.535
Education	0.5371	0.4771	0.104
Marital status	0.270*	0.105	1.804
Membership in association	−0.3023	3.048	−0.492
Household size	−0.2089	0.2068	−1.304
Farming experience	−0.4086	3.065	−1.325
Number of extension visits	0.4029	0.4043	0.676
Years resident in community	0.5235***	0.0605	8.623
Credit	0.6023	0.5016	1.394
Per capita income	0.7260***	0.2081	3.215
farmland size	0.4051	0.4057	0.917
Access to climate information	0.6309**	0.3130	2.374
Access to irrigation	0.7052	0.6058	0.893
Soil quality	0.3285***	0.1144	2.861
Constant	0.0003	0.0007	0.264
Intensity of adoption (second stage)			
Gender	0.5415***	0.1015	−6.282
Age	−0.359***	0.103	−3.471
Education	0.4008	4.071	0.110
Marital status	0.6170	0.5194	0.801
Membership in association	−0.4023	0.4048	−0.474
Household size	−0.7090	0.6068	−1.322
Farming experience	−0.5086	0.4065	−1.321
Number of extension visits	0.3029	0.3043	0.671
Years resident in community	0.5523	0.5460	1.624
Credit	0.4023	0.4016	1.392
Per capita income	0.6260	0.6181	1.203
Farmland size	0.4051	0.6057	0.895
Access to climate information	0.5464***	0.285	2.674
Access to irrigation	0.6052	0.5058	0.911
Soil quality	0.5003	0.5014	0.281
Constant	1.0892***	0.2579	5.164
Lamda	0.3808**	0.1732	2.322
Rho	0.7657		
Wald chi ² (15)	164.92		
Prob > chi ²	0.0000		

***, **, * represent significance level at 1%, 5%, and 10%, respectively; Standard error clustered at village level.

TABLE 3 Estimation result of fertilizer microdosing technology-fertilizer use efficiency nexus.

Variable	Maize		Sorghum		Millet		Maize-sorghum	
	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS
Adoption of fertilizer microdosing technology	0.0185* (0.0094)	0.0627*** (0.0096)	0.0147 (0.0145)	0.0357*** (0.0125)	0.0065** (0.0033)	0.1022*** (0.0211)	0.0080** (0.0041)	0.5605 (0.6004)
Gender	0.0020*** (0.0006)	0.0022*** (0.0006)	0.0015*** (0.0005)	0.0011** (0.0005)	0.0069 (0.0518)	0.0009 (0.0014)	0.0020 (0.0026)	0.0007 (0.0018)
Age	−0.0090*** (0.0014)	−0.0098*** (0.0014)	−0.0067*** (0.0014)	−0.0059*** (0.0013)	0.0314 (0.4643)	0.0014 (0.0038)	0.0018 (0.0087)	0.0027 (0.0019)
Education	−0.0019 (0.0014)	−0.0017 (0.0014)	0.0022* (0.0013)	−0.0005 (0.0008)	0.0048 (0.0045)	0.0001 (0.0006)	−0.0006 (0.0008)	−0.0003 (0.0007)
Marital status	−0.0001 (0.0005)	−0.0001 (0.0005)	−0.0004 (0.0004)	0.0001 (0.0003)	0.0005 (0.0016)	0.0005 (0.0003)	−0.0001 (0.0006)	0.0027 (0.0089)
Membership in association	0.0006 (0.0007)	0.0004 (0.0007)	0.0002 (0.0006)	0.0003 (0.0005)	0.0094*** (0.0024)	0.0013** (0.0003)	0.0003 (0.0004)	0.0016 (0.0027)
Household size	0.0015 (0.0011)	0.0017* (0.0010)	0.0008 (0.0009)	0.0007 (0.0007)	−0.0047 (0.0035)	−0.0002 (0.0003)	−0.0008 (0.0005)	−0.0031 (0.0317)
Farming experience	0.0010*** (0.0002)	0.0012*** (0.0002)	0.0009*** (0.0002)	−0.0007*** (0.0002)	0.0037 (0.0057)	0.0003 (0.0022)	0.0007 (0.0014)	−0.0005 (0.0031)
Number of extension visits	0.0003** (0.0001)	0.0004*** (0.0002)	0.0004** (0.0002)	0.0003** (0.0001)	−0.0015*** (0.0005)	0.0001 (0.0001)	0.0003*** (0.0001)	−0.0005** (0.0002)
Years resident in the community	0.0003 (0.0002)	−0.0001 (0.0002)	−0.0001 (0.0002)	−0.0001 (0.0002)	0.0003 (0.0007)	−0.0002 (0.0002)	−0.0009*** (0.0003)	−0.0018*** (0.0005)
Credit	0.0006 (0.0019)	0.001 (0.002)	−0.0006 (0.0019)	0.0006 (0.0013)	−0.0016 (0.0066)	0.0015 (0.0097)	−0.0003 (0.0015)	0.0026 (0.0043)
Per capita income	−0.0003* (0.0002)	0.0001 (0.0001)	−0.0006** (0.0003)	−0.0005* (0.0003)	0.0002* (0.0001)	0.0001* (0.0001)	0.0002 (0.0005)	0.0002 (0.0031)
farmland size	−0.0022*** (0.0008)	−0.0026*** (0.0008)	−0.0018** (0.0007)	−0.0015*** (0.0006)	0.0081*** (0.0026)	−0.0001 (0.0004)	0.0007 (0.0005)	−0.0011 (0.0086)
Access to climate information	0.0013** (0.0006)	−0.0009 (0.0007)	−0.0002 (0.0007)	−0.0007 (0.0005)	0.0032 (0.0022)	0.0001 (0.0005)	0.0001 (0.0006)	0.0003 (0.0009)
Access to irrigation	0.4603* (0.2775)	−0.9109*** (0.2671)	0.0334 (0.3497)	−1.3134*** (0.3399)	2.7306*** (0.6223)	0.0002** (0.0001)	0.0003 (0.0006)	0.0005 (0.0004)
Soil quality	0.3788*** (0.1007)	−0.1234 (0.0968)	0.159 (0.1282)	−0.3558*** (0.1362)	−0.0586 (0.221)	−0.0011 (0.0026)	−0.0002 (0.0011)	0.0007 (0.0018)
R ²	0.457	0.573	0.436	0.572	0.378	0.483	0.319	0.548

***, **, * represent 1%, 5%, and 10% level of significance, respectively.

variables. The estimated coefficients of fertilizer microdosing adoption are positive and most of them are statistically significant at the 1% level for maize, sorghum millet and maize-sorghum. The estimated coefficients from the OLS of fertilizer microdosing adoption, namely elasticities, for maize, sorghum, millet and maize-sorghum are 0.0627, 0.0357, 0.1022, and 0.5605, respectively, which indicates that the use of fertilizer microdosing technology has a positive and statistically significant effect on FUE. The results of the 2SLS estimation using the number of years stayed in community as instrumental variable to identify adoption of fertilizer microdosing technology are compared with the results of the OLS estimation. While the OLS estimate of the coefficient on fertilizer microdosing usage reflects both the effect of fertilizer microdosing adoption and the selection effect on the FUE, the 2SLS estimate captures mostly the former. The estimated coefficients of fertilizer microdosing adoption using 2SLS are still significant but smaller in magnitude than those using OLS. This implies that both the fertilizer microdosing adoption and the selection

effect play important roles in the positive relationship between fertilizer microdosing adoption and fertilizer use efficiency. Overall, the results of the 2SLS estimation still suggest a positive fertilizer microdosing adoption –fertilizer use efficiency relationship, though they are not exactly the same as those of the OLS estimation. This result is similar to [Wei et al. \(2022\)](#) and [Wang et al. \(2015\)](#).

Furthermore, statistically significance variables were found among the control variables. For maize producers, gender has a positive impact on fertilizer use efficiency, the older the farmer is, the lesser the fertilizer use efficiency, the higher the farm experience, the higher the fertilizer use efficiency is, the higher the number of extension visits, the higher the fertilizer use efficiency is, per capita income has a negative impact on fertilizer use efficiency, access to irrigation, soil quality and access to climate information has a positive impact on fertilizer use efficiency. For sorghum, while gender has a positive impact on fertilizer use efficiency, age on the other hand reduce fertilizer use efficiency. Education, farming experience, and number of extension visits all had a positive

TABLE 4 Estimation result of yield and intensity of fertilizer use.

Variable	Maize		Sorghum		Millet		Maize-sorghum	
	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS
Fertilizer use intensity								
Adoption of fertilizer microdosing technology	−0.0002 (0.0002)	−0.0009*** (0.0003)	−0.0018*** (0.0005)	−0.0004 (0.0005)	0.0033*** (0.0008)	0.0015** (0.0007)	−0.0003 (0.0015)	0.0026** (0.0013)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R ²	0.465	0.293	0.284	0.193	0.633	0.188	0.133	0.293
Yield								
Adoption of fertilizer microdosing technology	0.0001* (0.0001)	0.0002 (0.0005)	0.0002** (0.0001)	0.0003 (0.0006)	0.0005 (0.0004)	−0.0018*** (0.0005)	−0.0004 (0.0005)	0.0033*** (0.0008)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R ²	0.391	0.145	0.432	0.453	0.223	0.368	0.325	0.153

***, **, * represent 1%, 5%, and 10% level of significance, respectively.

TABLE 5 Estimated results for all the crops.

Variable	Fertilizer use efficiency		Fertilizer use intensity		Yield	
	2SLS	OLS	2SLS	OLS	2SLS	OLS
Adoption of fertilizer microdosing technology	0.6405*** (0.0033)	0.0080** (0.0041)	0.0533*** (0.0121)	0.0144*** (0.0054)	0.0802*** (0.0168)	4.7080*** (0.4333)
Gender	0.0009** (0.0004)	0.0020*** (0.0006)	0.0035*** (0.0009)	0.0041*** (0.0010)	0.0104*** (0.0017)	1.2936*** (0.1578)
Age	0.0014* (0.0008)	0.0018** (0.0007)	0.0053*** (0.0015)	0.0038*** (0.0013)	0.0123*** (0.0028)	0.6407** (0.2685)
Education	0.0001 (0.0006)	−0.0006 (0.0008)	−0.0003 (0.0007)	−0.0009 (0.0017)	0.0048** (0.0025)	0.0643 (0.2612)
Marital status	0.0005 (0.0003)	−0.0001 (0.0006)	0.0027*** (0.0009)	0.0026*** (0.0006)	0.0058*** (0.0017)	−8.0492*** (1.1737)
Membership in association	0.0003 (0.0003)	0.0003 (0.0004)	0.0016** (0.0007)	0.0006 (0.0005)	0.0028** (0.0013)	0.9878*** (0.3489)
Household size	−0.0002 (0.0003)	−0.0008 (0.0005)	−0.0031** (0.0017)	−0.0022** (0.0010)	0.0053* (0.0030)	6.3564*** (1.1194)
Farming experience	0.0003* (0.0002)	0.0007* (0.0004)	−0.0005* (0.0003)	0.0005* (0.0003)	0.0010* (0.0006)	0.0914*** (0.0244)
Number of extension visits	0.0001 (0.0001)	0.0003*** (0.0001)	−0.0005** (0.0002)	0.0004** (0.0002)	0.0007 (0.0005)	0.0026* (0.0014)
Years resident in the community	−0.0002 (0.0002)	−0.0009*** (0.0003)	−0.0018*** (0.0005)	−0.0004 (0.0005)	0.0033*** (0.0008)	0.0028* (0.0017)
Credit	0.0015** (0.0007)	−0.0003 (0.0015)	0.0026** (0.0013)	0.0062*** (0.0020)	0.0074** (0.0035)	0.0055*** (0.0019)
Per capita income	0.0001* (0.0001)	0.0002 (0.0005)	0.0002** (0.0001)	0.0003 (0.0006)	0.0005 (0.0004)	0.0044*** (0.0012)
farmland size	−0.0001 (0.0004)	0.0007 (0.0005)	−0.0011* (0.0006)	−0.0002 (0.0011)	0.0007 (0.0018)	0.0070*** (0.0020)
Access to climate information	0.0001 (0.0005)	0.0001 (0.0006)	0.0023** (0.0009)	−0.0006 (0.0010)	0.0027 (0.0019)	0.0045*** (0.0016)
Access to irrigation	0.0325*** (0.0106)	0.0327** (0.0164)	0.3789*** (0.1002)	0.1207*** (0.0227)	0.4351*** (0.1225)	0.0011** (0.0005)
Soil quality	0.0114 (0.0203)	0.0351 (0.0243)	0.3274*** (0.0801)	0.0774** (0.0312)	−0.4513*** (0.1064)	0.00013*** (0.0004)
R ²	0.546	0.536	0.249	0.436	0.392	0.398

***, **, * represent 1%, 5%, and 10% level of significance, respectively.

impact on fertilizer use efficiency while per capita income and farm size reduced fertilizer use efficiency. For millet, membership in association increased fertilizer use efficiency, number of extension visits had a negative impact on fertilizer use efficiency, the higher the per capita income is, the higher the fertilizer use efficiency is, farm size and access to irrigation had a positive impact on fertilizer use efficiency. For maize-sorghum, the higher the number of extension visits.

To examine the mechanism of the effect of Adoption of fertilizer microdosing technology on fertilizer use efficiency, we replaced fertilizer use efficiency with fertilizer use intensity and grain yield, and re-estimated the models using OLS and 2SLS. The estimation results are presented in Table 4. The results suggest that Adoption of fertilizer microdosing technology has a significant positive effect on the fertilizer use intensity, and also has significant effect on yield. In other words, the positive effect of Adoption of fertilizer microdosing technology on FUE is due to both increase in yield and the reduction in fertilizer use. This is similar to the result of [Muyanga and Jayne \(2019\)](#) and [Sheng et al. \(2019\)](#).

After we estimated all the samples of various crops, the average adoption of fertilizer microdosing technology elasticity was obtained. The estimated results are presented in Table 5. For all crops, the elasticity of adoption of fertilizer microdosing technology is around 0.6, in other words, holding other factors constant, a 1% increase in adoption of fertilizer microdosing technology is associated with a 0.6% increase in fertilizer use efficiency.

Robustness check (quantile regression)

A robustness check was carried out to investigate the effect of adoption of fertilizer microdosing technology on fertilizer use efficiency more comprehensively. We used the quantile regression to explain this effect. As shown in Table 6, the estimated coefficients of adoption of fertilizer microdosing technology are positive and statistically significant. For different crops, as the quantile increases, the estimated coefficients of adoption of fertilizer microdosing technology show different trends. The results of quantile regression suggest that the main finding of this study, that there is a positive relationship between adoption of fertilizer microdosing technology and fertilizer use efficiency is robust.

Discussion

The impact to climate change, depletion of soil fertility, and land degradation necessitates the continuous use of fertilizer to enhance crop productivity. The recent high cost of fertilizer as a result of many factors including Russia-Ukraine war among others has necessitate efficient use of fertilizer. In addition, improper use of fertilizer application such as broadcasting method have been observed to be linked to environmental issue due to run-off. Thus, an efficient method of fertilizer application that will reduce fertilizer wastage and serve as climate smart practices could be found in the use of fertilizer microdosing technology. Inadvertently, fertilizer microdosing technology could be regarded as a multipurpose technology that could help farmers adapt to the impact of climate change while also helping to reduce fertilizer wastage. This dual purpose thus necessitates the need for adoption of this technology among smallholder farmers in Nigeria.

This study draws on a farm-level data to assess the link between adoption of fertilizer microdosing technology and fertilizer use efficiency among cereal crop farmers in Nigeria. This study found that adoption of fertilizer microdosing technology is gender sensitive, thus its more common among male farmers. The application of fertilizer microdosing technology is labor intensive, which could be endure by the male gender. This might be one of the reasons why its application are more common among male farmers. Another reason could be attributed to disproportionate access to information and resources among the two genders. Men are more likely to assess information on new innovations and production resources when compared to their female counterparts. Likewise, older farmers are more inclined to traditional farming system, hence, younger farmers are more likely to apply this technology.

Our estimation suggests a positive fertilizer microdosing adoption–fertilizer use efficiency relationship. Indicating that the application of fertilizer microdosing technology led to fertilizer use efficiency among the farmers. In addition, gender was positively associated with fertilizer use efficiency. Male farmers that are more like to be more efficient with their fertilizer. This might be attributed to the fact that they are found to have adopted this technology in the study region. Furthermore, younger farmers are more efficient with fertilizer application which might be connected to the fact they use this technology more than the older farmers

TABLE 6 Parameter estimates of the quantile regression.

Crop	15th	30th	45th	60th	75th
Maize	0.2987*** (0.0906)	0.1894*** (0.0684)	2.2521*** (0.1585)	0.4705*** (0.1089)	1.2936*** (0.1578)
Sorghum	0.5714*** (0.1580)	0.2385*** (0.0809)	1.8995*** (0.5862)	0.4489*** (0.1561)	0.6407** (0.2685)
Millet	0.2627*** (0.0323)	0.6205*** (0.0863)	1.2451*** (0.4518)	0.3218*** (0.1018)	0.0643 (0.2612)
Maize-sorghum	0.0551*** (0.0107)	0.0437** (0.0084)	14.1277*** (1.6821)	2.9339*** (0.7456)	8.0492*** (1.1737)
All crops	0.0005 (0.0004)	−0.0002 (0.0004)	0.0725*** (0.0134)	1.1754* (0.7942)	0.9878*** (0.3489)
Control variables	Yes	Yes	Yes	Yes	Yes

***, **, * represent 1%, 5%, and 10% level of significance, respectively.

who are more inclined to traditional fertilizer application system that usually leads to fertilizer wastage. This finding are similar to that of Wang et al. (2015), Muyanga and Jayne (2019), Sheng et al. (2019), Yan et al. (2019), and Yao and Hamori (2019). Educated farmers with considerable years of experience who also had access to extension services are likely to be efficient with fertilizer application. Smallholder farmers might have undergone training and seminars on this technology through their access to extension agents. This will no doubt help facilitate the use of this technology having gotten enough information about its benefits.

Conclusion

This study investigates the relationship between adoption of fertilizer microdosing technology and fertilizer use efficiency among producers of maize, sorghum, millet and maize-sorghum using farm-level data from north central Nigeria. The results show that there is a positive relationship between adoption of fertilizer microdosing technology and fertilizer use efficiency. The estimated elasticities of fertilizer microdosing technology adoption for maize, sorghum, millet and maize-sorghum are similar, and the average elasticity of fertilizer microdosing technology adoption is around 0.6. Statistically, a 1% increase in fertilizer microdosing technology adoption is associated with a 0.6% increase in fertilizer use efficiency. These estimates are robust to various control variables, to employing the 2SLS estimation by using the number of years stayed in community as the instrumental variable, and to quantile regression. The factors that influenced the adoption and intensity of adoption of this technology have also been discussed. These results suggest that massive promotion of this technology for use among the farmers can facilitates fertilizer use efficiency especially during this period of high costs of fertilizer and climate change issues. Ensuring an efficient use of fertilizer through the use of this technology can help reduce environmental issues and adapt to the impact of climate change.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. Written informed consent was obtained from the [patients/ participants OR patients/participants

legal guardian/next of kin] to participate in this study in accordance with the national legislation and the institutional requirements.

Author contributions

AK: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. IO: Methodology, Project administration, Supervision, Validation, Visualization, Writing – review & editing. WA: Formal analysis, Investigation, Methodology, Project administration, Visualization, Writing – review & editing. AE: Data curation, Investigation, Methodology, Project administration, Visualization, Writing – review & editing. SS: Supervision, Methodology, Investigation, Resources, Writing – review & editing.

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