Impact of oil spillage on technical efficiency of Cassava farmers in the Niger Delta region of Nigeria

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Abstract
Food production and food security in Niger Delta Region (NDR) have been hampered by oil spillage leading to poor agricultural output with possible negative implications on welfare of farming households. A four-stage sampling procedure was used. The states of Bayelsa, Delta, and Rivers were randomly selected from the four major oil-producing states in NDR. Nine Local Government Areas (LGAs): 2, 3, and 4, respectively, were selected from Bayelsa, Delta, and Rivers based on the prevalence of oil spillage. A total of 45 communities were chosen in the LGAs comprising 10, 15 and 20 communities proportionately selected in size from Delta, Rivers and Bayelsa States, respectively. Age, household size, farm size, years of formal education and farming experience of cassava farmers in Oil ₚillage group were 55.8±6.4 years, 6.3±2.3 persons, 2.0±0.8 hectares, 12.5±5.2 and 9.0±3.8 years, respectively. The Non-Oil Spillage group had 49.8±6.0 years, 5.7±2.0 persons, 2.2±0.6 hectares, 13.5±4.9 and 10.5±6.8 years. Average technical efficiency achieved through the stochastic production frontier model of the OS group was 62.0%, while the NOS group was 77.0%, respectively. Technical efficiencies were significantly different between OS and NOS groups. Above a quarter (25.9%) of the OS farmers had higher TE rates above their means. Similarly, NOS farmers with higher TE above their average rates were 17.0%. Oil spillage reduced the technical efficiency of cassava farming households by 12.9%. Most of the farmers in NOS locations (92.0%) had higher welfare than those in OS locations (25.0%). Oil spillage reduced the technical efficiency in cassava farming including welfare of cassava farming households in the Niger Delta region of Nigeria.

Keywords: Impact, oil spillage, technical efficiency, cassava farmers, Niger Delta

Introduction
Massive crude oil deposits found in the Niger Delta have undergone exploration for years by the government of Nigeria and international oil companies. Environmental experts from Nigeria, United States of America and United Kingdom have rated Niger Delta region as the most oil-affected ecosystem and degraded area in the world, (Suku et al, 2023). Liquid petroleum products are generally noted as oil and are made up of hydrocarbons. Its release into the ecosystem is termed an oil spill (Thakur & Koul, 2022). Leakage of pipelines due to long usage, activities of oil thieves, and improper use of equipment are the main causes of oil spillage in the region. Oil spills could be

caused by deliberate acts such as sabotage, oil bunkering, and lack of maintenance of engineering equipment and tanker accidents. According to Ukhurebor et al. (2023), oil spills can occur through natural occurrences like hurricanes and earthquakes. The history of oil spills in Nigeria is shocking and appears to be one of the worst on earth (Ocholi, 2022). The oil industry whose confine is within the Niger Delta region has added so much value to the economy of Nigeria and this fact has not been controverted, but crude oil exploration business has made the Niger Delta region one of five most severely crude oil degraded environments in the world, (Adeola et al., 2024).

Cassava is an essential crop for enhancing food security in regions facing drought, famine, and civil strife (Marengo et al., 2022). Its remarkable adaptability in planting and harvesting methods, combined with its resilience to poor soil conditions and pests, makes cassava a reliable food source. It is a cost-effective carbohydrate option for urban populations, making it especially valuable for busy city dwellers who need accessible and convenient food solutions. Embracing cassava can help strengthen communities and provide stability during difficult times.

Cassava stands out as a critical dietary energy source for low-income consumers across many regions of tropical Africa, notably within bustling urban areas. Remarkably, farmers in one-third of the villages in cassava-growing regions regard it as their most vital crop (Sanginga, 2022). In fact, in half of the countries assessed, cassava is recognised as the leading food crop. While maize is considered the most important crop in Malawi, Burundi, and Kenya, it is worth noting that yam claims this title of first among equals solely in Nigeria. This highlights cassava's immense value and potential to improve food security in the region (David, 2024).

Cassava plays a vital role in calorie intake across Africa, surpassing both maize and sorghum. While FAO statistics show that cassava contributes less protein than cereals, this underestimation overlooks the potential nutritional value of cassava leaves, which are often disregarded as food (Delaquis, 2023). By recognising these leaves as a protein source, we can appreciate the full benefits of cassava in the African diet. (Immanuel et al., 2024) Raising productivity and efficiency in the agricultural sector has been given much-needed attention in the area of feeding Nigeria's growing population.

This is reflected in the adoption of new technological approaches required to improve farm output and income in developing economies (Khan et al., 2022). However, output growth is assessed by both technological growth and the efficiency with which available technologies are used. Thus, efficiency as a way of improving agricultural production has produced a large number of studies focusing on agricultural development. According to Immanuel et al. (2024), cassava has five major advantages over other food crops, and this involves implementing strategies to reserve crops during periods of famine, ensuring the availability of essential rural food staples, cultivating cash crops to cater to both local and international markets, utilizing crops for industrial purposes, and maximizing revenue opportunities from overseas markets.

Statement of the Problem

Human well-being and survival fundamentally depend on the delicate layer of soil that covers much of the Earth's land. Alarmingly, land degradation has impacted over one billion individuals, affecting nearly 40% of the planet's land surface (Weeraratna, 2022). Oil spills significantly contribute to this crisis, leading to severe land degradation that disproportionately affects the poorest rural communities, often leaving them without vital resources (Nuhu et al., 2022). Addressing land degradation is not just an environmental issue but a crucial step toward improving the lives of those in need.

Land is one of the most important inputs needed for farming, and as such, any negative effect on its fertility and its ability to produce has serious economic implications for countries whose economy is dependent on the primary sector for its growth and development. A good example is Africa, where farming is vital to the growth, development and livelihoods of the rural dwellers whose dependence is on agricultural production (Natarajan et al., 2022). Efficiency is a major concern in productivity, mostly in evolving agricultural economies where resources are in short supply and chances to apply, including using modern sciences, are becoming scarce and expensive (Adisa et al., 2024). Raimi et al. (2022) in their study recorded that oil-polluted soil could reduce the yield of cassava, thus, land degradation or pollution has negative implications on agricultural productivity, which also reduces the efficiency of the inputs used in the affected area.

Oil spillage has therefore produced a setback in the agrarian economy, resulting in decreasing agricultural productivity, crop outputs and fish catch, thereby increasing poverty and welfare loss (Babatunde 2023). The farmlands are facing severe infertility due to oil spills and gas flaring, drastically hindering food production for these communities. The farmlands are suffering from extreme infertility caused by oil spills and gas flaring, critically limiting food production for our communities. Similarly, the creeks and rivers, once teeming with fish and vital for our diets, are now blanketed in oil films. This contamination has driven fish away, depriving the communities of essential protein sources and forcing many to migrate elsewhere (Igbani et al., 2024). Across the Niger Delta area, literature has it that 65 per cent of the population have their livelihood on agriculture while the other 35 per cent depend on financial assistance from abroad (Siloko, 2024).

In 2020, global production of cassava reached an impressive 302.66 million metric tons, with Africa leading, contributing 193.62 million metric tons. Among these nations, Nigeria shines as the premier cassava producer in the world, generating around 60 million metric tons (FAO, 2022; Onyediako and Adiele, 2022). The trend is clear: cassava's total harvested area has expanded significantly in recent years, and Nigeria is at the forefront with a remarkable 7.7 million hectares harvested in 2020 (FAOSTAT, 2022). However, it is crucial to note that despite being the largest producer, over 90% of Nigeria's cassava is consumed locally (Onyediako & Adiele, 2022). This highlights the potential for growth in local consumption and international trade, ensuring cassava remains a vital part of Nigeria's economy and food security. To fully unlock the potential of the cassava industry, focus must be on key areas such as export opportunities, industrial applications, food security, and economic development. By investing in these sectors, we can drive growth and create lasting benefits for communities and economies alike. Increased and enhanced production, processing and packaging are needed to leverage the current technologies and innovations. The production differentials presently found in Niger Delta region require a holistic approach in public and private sectors to change for a positive narrative. This implies closing the production gap between supply and demand.

From the foregoing, pertinent research questions are:

1. What are the demographic and socioeconomic characteristics of cassava farmers?
2. What is the technical efficiency of farmers affected by oil spillage?
3. What is the impact of oil spillage on the technical efficiency of farmers affected by oil spillage?

Objectives

The overall objective of the study is to determine farmer's technical efficiency and impact of oil spillage on production of cassava farmers in Niger Delta region of Nigeria. Specific objectives include:

i. Examine demographic and farm characteristics of Cassava farmers.
ii. Estimate the technical efficiency of farmers affected by oil spillage.
iii. Estimate the impact of oil spillage on the technical efficiency of the cassava farmers.

Materials and Methods

Study Area

The Niger Delta is a significant farming region in Nigeria, making notable contributions to the country's farming sector. Nigeria is third-largest cassava producer in the world, for which the Niger Delta is a subset, following Indonesia (Daku & Okechukwu, 2023). Due to its rich vegetation, many indigenous people rely on farming for their livelihoods. A significant body of research has explored the profound impact of various environmental challenges on farming activities in the Niger Delta, highlighting urgent need for effective solutions to support local agriculture. These challenges affect productivity, soil fertility, access to farmland, and the transportation of goods to markets. Some research has focused on crop diseases.

Historically, the Niger Delta was a landscape rich in farming and vibrant community activities before the onset of oil production. Today, much of this land is shared with oil companies focused on crude oil extraction. Unfortunately, their operations have devastating effects on the remaining lands, limiting the resources available to the local population and undermining their livelihoods. It's crucial to address these challenges to protect the community's future.

Farmlands vital for crop production are vanishing daily due to oil spills and widespread pollution. Research into environmental impacts of oil exploration and production in Niger Delta region has uncovered alarming evidence that oil spills inflict severe damage on farmlands, water sources, mangrove forests, fishing activities, and marine resources. Consequently, countless families are being uprooted from their communities, losing not only access to clean drinking water and ancestral homes but also their agricultural land and fishing grounds. They are left grappling with contaminated freshwater sources and dwindling fish populations, threatening their livelihoods and well-being (Ogidi & Akpan, 2022).

Nnadi et al. (2022) contend that while oil companies have made substantial contributions to Niger Delta region and its communities, adverse impacts of crude oil exploration and production far overshadow these benefits. The relentless extraction processes have led to the contamination of vital streams and rivers, the destruction of lush forests, and a significant decline in biodiversity. Alarmingly, research reveals that, over the past 50 years, exploration/production activities in Niger Delta have resulted in spillage of approximately 9 to 13 million barrels of oil, highlighting a severe environmental crisis that cannot be ignored.

Prince & Nwankwoala (2022) conducted a significant study on the impact of oil spills on farming, specifically examining horticultural crops in Rivers State, Nigeria. Utilising multistage sampling, they collected data from 17 local government areas, providing a comprehensive overview of the situation. The analysis of 296 questionnaires highlighted a stark contrast: the average size of horticultural farms affected by crude oil pollution was notably smaller (1.04 hectares) compared to unpolluted farms (1.17 hectares). More critically, the output of key crops, such as fruits, bananas, peppers, okra, leafy vegetables, and melons, demonstrated a troubling decline on polluted farms (15.98 tons) versus their non-polluted counterparts (18.75 tons). This alarming disparity underscores the urgent need for effective measures to address the detrimental effects of oil pollution on agriculture.

This study was conducted in three selected states within Niger Delta region. It encompasses nine states, namely Abia, Akwa Ibom, Bayelsa, Cross River, Delta, Edo, Imo, Ondo, and Rivers, along with their 185 local government areas where oil and gas production is vital for Nigeria's Economy. The region is home to approximately 31 million people, representing about 25% of Nigeria's population. It includes 40 ethnic groups and is composed of around 13,000 small communities where approximately 250 languages are spoken. Land area of the Niger River delta is roughly 75,000 km², accounting for 12% of Nigeria's total landmass. There are around 600 oil fields produced from about 5,000 wells, and although oil production is concentrated in specific areas, the region is interlaced with approximately 10,000 km of pipelines. The prevalence of small settlements in the region can be attributed to the ecosystem, which offers limited space for human habitation, particularly due to the presence of islands. The Niger Delta ecosystem is classified as a tropical rainforest, supporting a wide variety of plant and animal species both in water and on land. (Keke et al., 2023).

i. Sampling and Data Collection

Four-stage sampling procedure was used to select the sample. Stage one was purposive selection of three states chosen from four (4) major oil producing states in Niger Delta (states that have suffered oil spillage in the last ten years, and include Bayelsa, Delta and Rivers States (Okonkwo 2022). Stage two was purposive selection of four Local Government Areas (LGAs) from Delta State, two LGAs from Bayelsa State and three LGAs in Rivers State. These selected LGAs from each of the chosen states have records of farmlands that have been affected by oil spillage, as well as farmlands not affected by oil spillage. The third stage involved proportionate selection of twenty communities in Delta State, ten communities in Bayelsa State, and fifteen communities in Rivers State. The fourth and final stages involved random selection of three cassava farming households from each community in Delta State, three cassava farming households in Bayelsa State and two cassava farming households from Rivers State that farmed in oil-spilt locations. Also, eight cassava farming households in Delta State, nine in Bayelsa State and seven in Rivers State were chosen from locations where there is no oil spillage proportionate to the size of the population. A total of 475 cassava farming household heads were used for this study, out of which 450 cassava farming household heads were suitable for analysis.

ii. Method of Data Analysis

Model Specification and Estimation

Objective 1: Objective one was met by the application of descriptive and inferential statistics. Means, standard deviations, percentages and frequencies were applied in analysing demographic variables of farmers, such as input/output variables and distribution of efficiency levels.

Objective 2: The Stochastic frontier production function was used in analysing the technical efficiency of cassava farming households. Variables like cassava yield and farm inputs were used. The Stochastic Frontier Production Model was applied to evaluate the technical efficiency of farmers in two locations to determine whether the oil spillage affects cassava yield or not. Cassava is a major crop farmed in the area of study. The output quantities of cassava were meticulously recorded in local units before being converted to kilograms for consistency. To thoroughly analyse this data, we employed the Battese & Coelli (1995) model, which effectively captures technical inefficiency within a stochastic frontier production function based on cross-sectional data. This model not only estimates key parameters of the stochastic frontier but also accounts for time-varying technical inefficiency effects. The process of specifying an inefficiency stochastic frontier model for cross-sectional data begins with a foundational definition of the stochastic frontier production function. Stochastic Frontier Production Model (SFPM) put forth by Battese & Coelli (1995) enhances original frameworks proposed by Aigner et al. (1977), ensuring a robust analysis and insightful conclusions.

$$Y_i = F(X_i : \beta)\exp(V_i - U_i), \qquad i = 1, 2, \ldots \ldots . . N \ldots \ldots \ldots \ldots \ldots \ldots \ldots . . (1)$$

Where,

Y_i = output of cassava farm

X_i = real input used by the cassava farm

β = vector of parameters estimated

Vi - U_i = is double error term (Aigner et al., 1977)

V = Random variable assumed to be independently and identically distributed N (O, δ^2) and independent of U

U = Random variable that accounts for technical inefficiency, assumed independently distributed as a truncation of the normal distribution with mean μ and variance σ^2

Whereas values of Vi represent the occurrences that are outside the control of the cassava farmer, values of Ui, however, show the technical inefficiency of cassava production. The coefficients (β) represent model parameters that are to be determined. The ratio between the standard deviation of errors of technical inefficiency (U) and model specification errors (V) is represented by (λ):

This ratio is formally expressed as:

$$\delta^2 = \delta_v^2 + \delta_v^2 \qquad and \qquad \gamma = \frac{\delta_v^2}{\delta^2} \qquad \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (2)$$

Values of γ range from 0 to 1, such that the value of 0 with the traditional average response function for the nonnegative random variable, μi, is absent from the model, i.e. perfect efficiency in production. Value one shows that all deviations from the frontier are due to technical inefficiency entirely, i.e. random error on production is zero. Variables of the Stochastic Frontier Production Model can be evaluated using maximum likelihood estimation techniques. Maximum likelihood estimation of conditions stated on statistical distributions of v and u, makes it possible to calculate the conditional mean of ui :

$$e_i = v_i + u_i \qquad \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (3)$$

Estimation of Technical Efficiency

Technical Efficiency (TE) was evaluated according to Okoye *et al*. (2008) as indicated below:

$$TE = \frac{Y_i}{Y_i^*} = \frac{f(X_i\beta)\exp\,(V_i - U_i)}{f(X_i\beta)\exp\,(V_i)} = \exp(-U_i) \qquad \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (4)$$

The technical efficiency of the individual cassava farm was estimated as the ratio of real output Yi to corresponding frontier output Yi*, all in the original units. Technical efficiency has a value of between 0 and 1. Measurement of farm-specific technical efficiency requires estimation of a non-negative error ui and a random normal error term vi. The Stochastic Frontier Production Model was applied in analysing the technical efficiency of cassava-producing farmers and detailed model specifications were discussed in the subsequent section.

Inefficiency Model

Ui =The technical inefficiency effect is assumed to be independent of Vi, which is the deviation from the optimum output attributed to technical inefficiency

Where Ui is a function of socioeconomic variables, which is specified as follows:

$$U_i = a_o + \sigma_1 Z_1 + \sigma_2 Z_2 + \sigma_3 Z_3 + \sigma_4 Z_4 + \sigma_5 Z_5 + \sigma_6 Z_6 + \sigma_7 Z_7 + \sigma_8 Z_8 \ldots\ldots (5)$$

Where:

Ui= Technical inefficiency effects

Z_1= Age in years

Z_2= Household size in numbers

Z_3= education in years

Z_4= years of farming experience

Z_5 = Status of respondents in the household (House head=1, 0 otherwise)

Z_6= Access to extension services (yes=1, 0 otherwise)

Z_7= off farm income (off farm income=1, 0 otherwise)

Z_8= Membership of Association (yes=1, 0 otherwise)

σ_1 to σ_8 = parameters to be estimated

Analysis of efficiency was first done following the works of Aigner et al. (1977), approach of estimating the stochastic frontier production functions model provided in Equation (1). Study specified a stochastic frontier production model using a Cobb-Douglas production function for cassava-producing farmers as:

$$lnY = \beta_0 + \beta_1 lnX_{1ij} + \beta_2 lnX_{2ij} + \beta_{3ij} lnX_{3ij} + \beta_4 lnX_{4ij} + \varepsilon i \ \ldots \qquad (6)$$

Where subscripts ij refer to ith observation on the jth farmer

In = logarithm to base e

Y = total quantity of cassava cultivated in kilograms

X_1 = farm size in hectares

X_2 = labour in man-days

X_3= quantity of planting stocks in kilograms

X_4 = fertiliser applied in kilograms

εi = error term (V_i-U_i)

Objective 3: In analysing objective three, the study made use of the estimated results of the Cobb-Douglass production model in objective two. The mean technical efficiency of the oil spillage and non-oil spillage groups was used as a baseline that separates efficient cassava farmers from those who are not efficient. The impact of oil spillage on the technical efficiency of cassava farmers was estimated using propensity score matching methodology. The propensity score matching approach was used to examine the impact of farming on production efficiency through technical efficiency in oil-spillage cassava enterprises. The method compares the technical efficiency of oil spillage-affected cassava enterprise households with their counterfactual group that did not cultivate their cassava in oil spillage-affected locations. In evaluation practice, it is expected that the proportion of farmers who farmed in oil-spilt affected locations is bound to be smaller when compared to their counterparts who farmed in non-oil-spilt affected locations

Propensity scores are estimated with a probit model (Sianesi, 2004). Predicted propensity scores are applied to estimate the treatment effect. According to Becker & Ichino (2002) average treatment effect on treated (ATT) is a variable of concern in the propensity score matching model. Hence, we employ ATT to estimate the way farming oil spillage affected farmlands on technical efficiency. ATT is computed by matching cassava farmers who farmed in oil spillage-affected areas and cassava farmers who farmed in non-oil spillage-affected farmlands that are nearest in terms of their propensity scores. Here, the treated group are referred to as cassava farmers who farmed in oil spillage-affected farmlands and ATT is calculated:

ATT= E (T/1=1) = E(Y/1)/D=1) - E (Y (0)/D=1………………………………(7)

Where E(Y/1)/D = 1 represents the expected technical efficiency outcome of cassava farmers that farmed in oil spillage-affected farmlands, and E (Y (0)/D denotes the alternative technical efficiency of non-oil spillage-affected cassava farmers. The controlled estimates represent what the technical efficiency outcome of oil-spillage-affected cassava farmers would be if they had not engaged in non-oil-spillage-affected cassava farming enterprise activities.

In the literature, various matching techniques have been developed to effectively pair oil-spilt and non-oil-spilt cassava farmers based on similar propensity scores, allowing for an accurate calculation of Average Treatment Effect on Treated (ATT). This study strategically employs both nearest-neighbour and kernel-based matching approaches for enhanced reliability. When it comes to estimating treatment effects, Average Treatment Effect (ATE) is the most frequently referenced measure, reflecting the average difference in outcomes within the entire sample. However, our true focus lies in understanding the impacts specifically on those individuals who experienced the oil spill. This targeted analysis is known as Average Treatment Effect on Treated (ATT), which provides crucial insights into the real consequences of the treatment for the affected group. Additionally, considerations for Average Treatment Effect on Untreated (ATU) are valuable in providing a holistic view. Ultimately, ATE can be seen as a weighted combination of ATT and ATU, but for this research, our primary goal is to derive a thorough and significant estimation of the ATT.

First, the study generated the technical efficiency and results from objective 2 and then profiled the groups of farmers into low-efficiency and high-efficiency status using the mean of the technical efficiency (See Tables 6 and 7). Results from these tables were then used for propensity score matching using the nearest neighbour and kernel-based matching approach.

Matching methods with replacement were employed, which matched each treated observation i to the control observation j with similar characteristics. The study went further to match the units of variables or covariates using the propensity scores. Several matching methods, as detailed in the literature, were used. They include Nearest Neighbour Matching. In our matching process, we ensure that for each treated observation \(i \), we find a controlled observation \(j \) that is closest in terms of the covariate value \(x \). Using kernel matching, we enhance this approach by matching each treated observation \(i \) with multiple controlled observations. The weight assigned to each match is inversely related to the distance between the treated and controlled observations, allowing for more robust comparisons. This technique effectively identifies non-treated individuals with propensity scores that closely align with those of the treated farmers. To maintain the integrity of our analysis, we decided to exclude 18 observations.

Results and Discussion

Table 1: Summary of Farmers' Characteristics

Characteristics	Values		
	Oil spill affected farmers	Non-oil spill affected	Pooled
Age(years)			
Minimum	41	36	36
Maximum	68	68	68
Mean	55.76	49.77	51.26
Std. Deviation	6.41	6.00	6.62
Sex (% of farmers)			
Male	44.6	56.5	53.60
Female	55.4	43.5	46.40
Household size			
Minimum	2	2	2
Maximum	13	16	16
Mean	6.29	5.7	5.87
Std. Deviation	2.26	1.99	2.07
Marital Status (% of farmers)			
Single	2.7	4.4	4
Married	85.7	80.8	82
Divorced	7.1	11.8	10.70
Widowed	4.5	3	3.30
Years of formal education			
Minimum	1	1	0
Maximum	20	21	21
Mean	12.47	13.52	13.26
Std. Deviation	5.21	4.85	4.96
Years of farming experience			
Minimum	2	2	2
Maximum	35	40	40
Mean	10.51	9.01	9.38
Std. Deviation	6.81	3.79	4.76
Farm size (hectare)			

Minimum	1.05	1.03	1.05
Maximum	5	3.8	5
Mean	2.01	2.17	2.13
Std. Deviation	0.79	0.57	0.63
Association membership (% of farmers)			
No	42.9	29.6	32.90
Yes	57.1	70.4	67.10
Source: Field Survey, 2022			

Stochastic Frontier Production Function Estimates of Cassava Farmers

Results of the stochastic frontier production function for selected oil spillage and non-oil spillage farms are shown in Table 2. Sigma-squared (s^2) in Table 2 for oil-spilt and non-oil spilt areas are (0.04 and 0.06) and significantly different from zero at a 1% level. Thus, a good fit and the correctness of the specified distributional assumption of the composite error term. The result showed (MLEs) of the stochastic frontier production function for cassava farmers in oil spillage-affected areas. Three out of four inputs used in the model were statistically significant at a 1 per cent degree of probability. They include farm size, fertiliser and planting material. The result showed that farm size is an important factor in cassava production, with a coefficient of 0.564, implying that a 10% increase in a hectare of land cultivated would increase cassava output by 5.6% at a 1% significance level. Thus, land as a factor of production is very valuable in cassava production in the oil spill location area. This result conforms with findings of Ayibakiri & Ebisine (2022), which inferred that farm size is one vital factor in agricultural production. Planting material was also an important input and was significant at 1% with a coefficient of 0. 36. This result implies that a 10% increase in the use of planting materials in cassava production would raise output by 3.6%. Fertiliser was also one input in cassava production with a coefficient of 0.1203, which was statistically significant at 1%. This means that a 10% increase in the application of fertiliser in cassava production would increase output by 1.2%.

Maximum likelihood estimates of the stochastic frontier production function for cassava farmers in non-oil spill-affected farms revealed that three (3) out of four inputs used in the model were statistically significant at one per cent. They include farm size, fertiliser and planting material. The Result in Table 2 further showed that planting materials were a valuable variable in cassava production in non-oil spill areas, with a coefficient of 0.49, implying that a 10% increase in a hectare of land cultivated would increase output of cassava by 4.9% at 1%. This means that planting material as a factor of production is very valuable in cassava production in non-oil spillage-affected farms. The result also showed that farm size was an important factor in cassava production in this location, with a coefficient of 0.411, implying that a 10% increase in a hectare of land cultivated would increase output of cassava by 4.1% at a 1% level of significance. This result conforms with findings of Siloko (2024), who inferred that farm size is a valuable factor in agricultural production. Fertilizer was also significant at 1% probability level with an estimated coefficient of 0.111. This means that a 10% increase in fertilizer applied in cassava farms would increase output by 1.1%.

From Table 2, one could deduce that farm size, fertiliser and cassava stocks are all significant at one per cent degrees in both locations, implying that they are key inputs that influence the output of cassava in the region. However, while 3 out of the 4 inputs used for the model are significant in oil spill location, the same 3 out of the 4 inputs used were also significant in the non-oil spill location, meaning that they are key factors in cassava production in both locations. It is noted that variance parameters of the model, such as sigma squared, likelihood ratio and gamma in both

Table 2: **Maximum Likelihood Estimate of Stochastic Frontier Production Function**

	Oil Spill Affected Farms			Non-oil Spill Farms		
Variable	Coefficient	Standard error	z-statistics	Coefficient	Standard error	z-statistics
Production factor						
Constant	5.5256	0.5794	9.54	7.7908	0.2864	27.21
Farm size	0.5644***	0.0986	5.73	0.6709***	0.0401	16.73
Labour	0.0804	0.0721	1.12	0.1255**	0.0582	2.15
Fertilizer	0.1203***	0.0413	2.91	0.0963**	0.0449	2.15
Planting material	0.3626***	0.0746	4.86	0.1458***	0.0512	2.85
Diagnostics						
Likelihood ratio	6.3235***			54.36***		
Sigma squared	0.0477***	0.0103	4.62	0.1512***	0.0152	9.95
Gamma	0.8245***			0.9648***		

Source: Computation from field survey, 2022

locations are all significant, implying the existence of technical inefficiencies in both locations.

Note: *** significant at 1% and ** significant at 5%

Technical Efficiency of Cassava Farmers in Oil Spill and Non-Oil Spill Affected Areas

Table 3 showed that the technical efficiency of sampled farmers was less than one (1.00) in the oil spill-affected area. This implies that cassava farmers in oil spill-affected areas are producing below optimum output. Distribution of technical efficiency shows that the most efficient farmer has a technical efficiency of 0.93, that is (93.11%), while the least efficient farmer has a technical efficiency of 0.19, that is (19.27%), with a mean technical efficiency of 0.77, that is (77.51%). A mean technical efficiency of 77% means that an average farmer was able to achieve about 77% of optimal output from a given set of inputs under a given technology. Thus, the mean technical efficiency shows a reasonable average level of technical efficiency of a farm. Cassava farmers were not optimally efficient, as their observed output is 23% less than the optimum output. Hence, the output of cassava farmers can be raised by 23% through improved resource allocation with no additional cost.

In a non-oil spillage-affected location, the technical efficiency of sampled cassava farmers was less than one (1.00). This implies that cassava farmers in non-oil spillage-affected locations are equally producing below the maximum frontier output. Distribution of technical efficiency shows that the most efficient farmer has a technical efficiency of 0.93, that is (93.12%), while the least efficient farmer has a technical efficiency of 0.19, that is (19.27%), with a mean technical efficiency of 0.81, that is (81.01%). A mean technical efficiency of 81.01% means an average farmer was able to achieve about 81% of optimal output from a given set of inputs under a given technology. A mean technical efficiency of 81% indicates a reasonable average level of technical efficiency of a farm. Also, results showed that cassava farmers were not optimally efficient, as their observed output is 19% less than the maximum output. Hence, the output of the cassava farmers can be raised by 19% through efficient resource allocation with no extra cost in the non-oil spill affected area.

Frequency Distribution of Technical Efficiency

Table 3 shows that farmers in the oil spill-affected area had about 58.04% of the population with technical efficiency of 31% to 70%, while the remaining 41.96% had technical efficiency within the range of 71% and 90%, as shown in Table 3. In the non-oil spill-affected farms, the distribution of technical efficiency of farmers showed only 44.97% had technical efficiency of between 1% and 80%, while the remaining (55.03%) had technical efficiency of more than 80%. Result conforms with study of Lee et al. (2022) in Niger Delta Region who revealed that average technical efficiency of rice farmers falls within range of 75%.

3: Frequency distribution of the technical efficiency of farmers in oil spill and non-oil spill locations

Technical Efficiency Level (%)	Oil Spill Affected Farms	Non-oil Spill Affected Farms
≤ 30	0(0.0)	1 (0.30)
31 to 40	1(0.89)	0(0.0)
41 to 50	6(5.36)	0(0.0)
51 to 60	17(15.18)	6(1.78)
61 to 70	41(36.61)	43(12.72)
71 to 80	36(32.14)	102(30.18)
81 to 90	11(9.82)	158(46.75)
91 to 100	0(0.0)	28(8.28)
Total	112(100)	338(100)
Mean	68.48%	80.51%
Minimum	39.90%	19.27%
Maximum	86.57%	93.11%

Source: Computation from field survey, 2022

Note: Figures in parentheses are percentages

Table 4: Analytically-derived Stochastic Frontier Cost Function

	Oil Spill Affected Farms	Non-oil Spill Affected Farms
Variable	Coefficient	Coefficient
Production factor		
Constant	0.0232	0.0016
Price of land (rent)	0.5005	0.6461
Price of labour (wages)	0.0713	0.1208
Price of Planting Material	0.3215	0.1404
Price of fertilizer	0.1067	0.0927
Output (adjusted frontier output)	0.8868	0.9630

Source: Computation from the field survey 2022

Table 5: Summary of test of means - Technical Efficiency

Group	**Observation**	**Mean**	**Standard error**	**t-value**
Non-Oil spill	338	80.51	.0049	11.63
Oil spill	112	68.47	.0100	
Combined	450	77.51	.0050	
Difference		12.03	.0103	

Distribution of Cassava Farmers by Technical Efficiency Level

Table 6 shows the summary of group means of cassava farmers by efficiency level. To disaggregate the efficiency levels of farmers based on whether they are technically efficient or not, the study made use of the regression results generated from objective two. From the results in objective two, the mean technical efficiency of 450 farmers was estimated and then used to separate farmers who were technically efficient or not, as shown in Table 6. Based on this index, all farmers whose technical efficiency was lower than the mean of technical efficiency of the two groups were adjudged to be technically inefficient, while those whose technical efficiency was higher than the mean were taken to be technically efficient farmers, as shown in Table 7. A look at Table 7 shows that only 38% of the farmers fell into the category of high technically efficient farmers in the oil spillage group, while 62% of them fell into the category of farmers that are low technically efficient. This means that the majority of farmers in the oil spillage group are not highly technically efficient. On the other hand, the farmers in the non-oil spillage group exhibited different levels of technical efficiency. A cursory look at Table 7 revealed that 63% of farmers in the non-oil spillage group fell into the category of high technically efficient farmers, while only 38% of them fell into the category of those that are low technically efficient.

Test of Mean Difference between Oil Spill and Non-Oil Spill Location Farmers

A test of mean difference between cassava farmers in the two areas was accomplished by a t-test of mean difference, and results are presented in Table 5. The test was based on the hypothesis that there is no significant difference in the efficiency (technical) of oil spill-affected and non-oil spill-affected crop farmers, as stated earlier. Results of the t-test show that there is a significant difference ($p<0.01$) between the technical efficiencies of the two categories of cassava farmers. This signifies that non-oil spill-affected cassava farmers produced more output from a given level of inputs than their oil spill-affected cassava farmers counterparts. This also implies that non-oil spill-affected cassava farmers can produce more output at a minimum cost than oil spill-affected crop farmers. Therefore, null hypotheses were rejected for technical efficiency. Thus, non-oil spill-affected cassava farmers were more technically than oil spill-affected cassava farmers.

Table 6: Summary of the group means for Technical, Allocative and Economic efficiencies

Variable	Observation	Mean	Standard deviation	Minimum	Maximum
TEF	450	77.51	10.81	19.27	93.11
EEF	450	59.00	02.29	51.74	65.07
AEF	450	75.29	08.81	60.50	98.70

Table 7: **Distribution of farmers by technical efficiency level**

	Oil Spill Affected Farmers		Non-Oil Spill Affected Farmers	
	Frequency	Percentage	Frequency	Percentage
High Efficiency	43	38.39	208	61.54
Low Efficiency	69	61.61	130	38.46
Total	112	100	338	100

Source: Field Survey, 2022

Impact Analysis of Oil Spillage on the Technical Efficiency of Cassava Farming Households

Table 8 illustrates that the estimated propensity score from the probit regression is 0.2478. In determining these propensity scores, we meticulously fitted all collected data on covariates into the probit model, carefully refining the selection by reducing the number of covariates until we achieved an optimal match. This rigorous process ensured that only the most significant covariates influencing program participation were retained. Notably, these variables were chosen because they remain unaffected by the decision to farm or not on oil-spillage-affected lands, and they are also expected to stay consistent over time. The findings from the probit model of the propensity score are displayed in Table 8. As highlighted by Smith and Todd (2005), these results are critical for verifying the consistency of the estimated causal effects, which could be influenced by the choice of exogenous variables used to calculate the propensity score. Table 9 reveals that several covariates show statistical significance and are linked to farming in oil spill locations. This evidence indicates that participation in farming within these areas was largely driven by observable covariates, with hidden covariates playing a negligible role. Consequently, this suggests that the results obtained from the program assessment using the propensity score matching (PSM) approach are both unbiased and consistent, reinforcing their reliability.

The primary aim of estimating the propensity score was to effectively balance the distributions of covariates between the two farmer groups. By establishing a sufficient common support region for both groups, we successfully eliminated differences in covariates between the matched sets. These actions are essential prerequisites for ensuring the reliability of our subsequent program impact assessments. We then implemented the common support condition (see Fig. 1), along with the balancing property, to reinforce our findings.

Table 8: Predicted Propensity Score Match (P score)

Variable	Observation	Mean	Standard Deviation	Minimum	Maximum
P score	417	0.2478	0.1993	0.0146	0.9455

Source: Field Survey 2022.

Table 9: Propensity score matching and covariate balancing test estimates

Variable	**Sample**	**Mean Treated**	**Control**	**% Reduction Bias**	**% |bias|**	**t-test**	**p>|t|**
Age	Unmatched	55.86	49.77	96.9		9.09	0.000
	Matched	55.65	55.99	-5.3	94.5	-0.38	0.701
Sex	Unmatched	0.37	0.41	-7.4		-0.68	0.499
	Matched	0.38	0.44	-11.4	-53.5	-0.84	0.404
Marital Status	Unmatched	0.55	0.43	23.8		2.19	0.029
	Matched	0.55	0.58	-4.8	79.9	-0.35	0.723
Household size	Unmatched	6.39	5.73	29.0		2.83	0.005
	Matched	6.23	6.32	-4.0	86.3	-0.29	0.769
Years of formal Education	Unmatched	12.46	13.58	-23.0		-2.14	0.003
	Matched	12.55	12.28	5.7	75.1	0.40	0.687
Years of farming Experience	Unmatched	10.59	9.01	28.8		3.08	0.002
	Matched	10.57	9.31	22.9	20.6	1.71	0.089
Access to credit	Unmatched	0.37	0.42	-11.0		-1.01	0.314
	Matched	0.36	0.36	0.1	99.1	0.01	0.994
Member of any Association	Unmatched	0.43	0.30	27.8		2.60	0.010
	Matched	0.42	0.40	2.8	89.8	0.20	0.839

Source: Computation from Field Survey

Table 10: Propensity Score Match showing treatment assignment and common support

Treatment assignment	Off support	On support	Total
Untreated	16	322	338

Treated	2	110	112
Total	18	432	450

Source: Field Survey 2022

Table 9 offers compelling insights into the balancing of covariates before and after applying propensity score matching. The standardised bias difference between the treatment and control groups—specifically, oil-spillage-affected versus non-oil-spillage-affected farmers—provides a clear metric for assessing bias. Notably, the discrepancies in the raw (unmatched) data are significantly greater than those seen in the matched samples, highlighting the effectiveness of the matching process. This approach not only ensures a strong covariate balance between treatment and control groups used in the analysis, but it also enhances the credibility of the findings. Furthermore, Table 9 demonstrates that, before matching, several variables reveal statistically significant differences; however, post-matching, all covariates align as anticipated, affirming the robustness of propensity score matching.

Table 11: **Distribution of observational bias**

Sample	Pseudo R^2	LR$\chi2$ (ρ-value)	Mean bias
Unmatched	0.186	94.19 (0.000) ***	31.0
Matched	0.016	4.77 (0.782)	7.1

Source: Author's Computation

Table 11 indicates a low pseudo-R2 value, yet insignificant likelihood ratio tests strongly support the hypothesis that both groups possess the same distribution for covariates X after matching (see Table 11). Findings demonstrate the effectiveness of the matching procedure in balancing the characteristics between the treated group and the matched comparison group. The low pseudo-R2 value highlights the relatively random allocation of the program (Pradhan & Rawlings, 2002). This suggests that treated farmers share similar overall characteristics, facilitating a robust match between treated and control farmers. Importantly, these results have been utilised to assess the impact of oil spillage among groups of farmers who have comparable observed traits. The third stage carried out involved assessing the quality of the match. To achieve this, three criteria were used, which were t-test, joint significance and common support.

The t-test values for matched units showed no statistical difference between treated and control groups since for all matched units the p>/t/ values were greater than 0.1 (Table 11).
For the joint significance factor, Pseudo R^2, p>chi^2 and common support. The pseudo-R2 and mean bias before matching were 0.186 and 31.0, respectively. These were reduced to 0.016 and 7.1 after matching (Table 11). This implies a significant reduction in bias as a result of matching. Since, after matching, it is expected that Pseudo R^2 and mean bias should be close to zero.

For p>chi^2, it is expected that after matching that it should be greater than 0.1, thus denoting no statistical difference between the treated and control group of the matched units. The estimate before matching was 94.19 and after it was 4.77

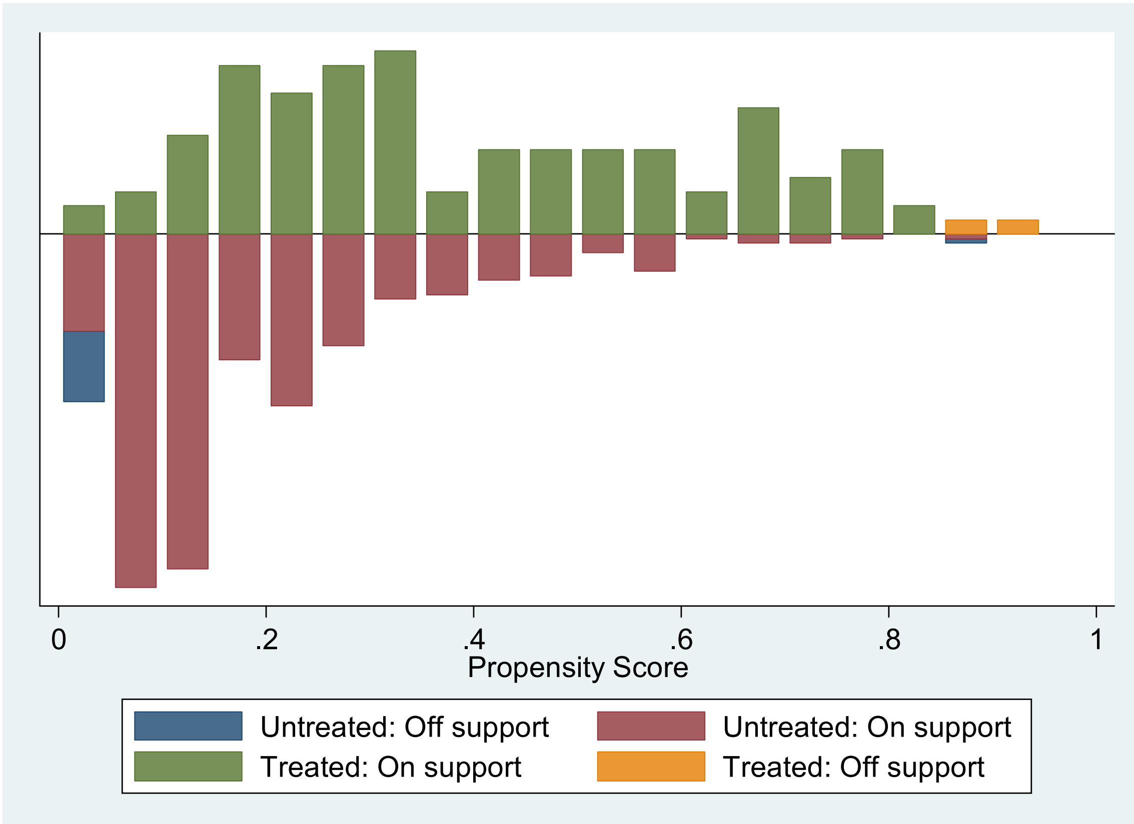

Figure 1. Common Support for Propensity Score Match (p-score)

The last test carried out was common support, as shown in Figure 1. It is a visual representation of the propensity scores. From the graph, which shows density distributions of propensity scores for oil spillage-affected farmers and non-oil spillage-affected farmers, there was a considerable (good) overlap, which shows that the matching estimate was good. The three criteria used in assessing the quality of the match thus confirm that the match was good. This leads to the next stage, which is to evaluate the impact of oil spillage on the technical efficiency of cassava farmers having similar observed characteristics. The outcome variables are the technical efficiency and welfare indexes of farmers in both oil-spilt locations and those not affected by oil spillage.

Impacts of Oil Spillage on the Technical Efficiency of Cassava Farmers

The consequences of oil spillage on the technical efficiency of cassava farming households were rigorously assessed using the two most commonly utilised matching methods in the literature: Nearest Neighbour Matching (NNM) and Kernel-Based Matching (KBM). The findings are illustrated in Table 12. The NNM results reveal a significant and adverse impact of oil spillage on technical efficiency. This analysis quantifies the average difference in technical efficiency between closely matched pairs of cassava farming households, where each pair belongs to a distinct farming status. Importantly, our focus is on the Average Treatment Effect on the Treated (ATT), which provides critical insights into how oil spillage specifically affects the technical efficiency of farmers directly impacted by such incidents. Specifically, the NNM and KBM causal effect of farming on oil-spillage-land on technical efficiency suggests that the technical efficiency of farmers who farmed in oil spillage-affected locations was lowered by 0.1115 – 0.1153 than those farmers not affected by oil spillage. The result of the analysis reveals that farming on oil-spilt land indeed had a technical efficiency-reducing effect on the farm households between 11.15% and 11.53%. NNM and KBM showed that farming on oil spillage-affected land exerted a negative and significant effect on the probability of technical efficiency. This implies that the reduction in productivity generated through farming on oil spillage-affected land leads to a reduction in farmers' technical efficiency. These findings agree with Lee *et al*, (2022) who carried out similar studies in the Niger Delta region.

Table 12: Impacts of oil spill on Average Treatment on Treated (ATT), Average Treatment on Untreated (ATU) and Average Treatment Effect (ATE) -Technical efficiency

Variable	Sample	Treated	Controls	Difference	Standard Error	T-ratio
Efficiency	Unmatched	0.6848	0.8051	-0.1203	0.0103	-11.63
Index	ATT	0.6850	0.7965	-0.1115	0.0141	-7.92
KBM	ATU	0.8060	0.6936	-0.1124	-	
	ATE	-	-	-0.1122		
Efficiency	Unmatched	0.6848	0.8051	-0.1203	0.0103	-11.63
Index	ATT	0.6850	0.8033	-0.1153	0.0189	-6.10
NNM	ATU	0.8059	0.6974	-0.1085	-	
	ATE	-	-	-0.1102		

It is crucial to recognize that the endeavour to enhance cassava production while ensuring environmental sustainability is significantly undermined by farmland pollution in the Niger Delta region of Nigeria. This study reveals the alarming extent to which oil spills have adversely affected the technical efficiency of cassava farming households. Furthermore, it highlights how these spills have systematically reduced the overall efficiency of cassava cultivation in the Niger Delta, emphasizing the urgent need for action and remediation.

5.3 Policy Recommendations

The following were recommended for policy formulations based on the outcome of this study:

1. Government at all levels in the Niger Delta region could do more by encouraging young people to go into farming in the oil spill affected location through agricultural programmes such as young farmers club and farm settlement scheme.
2. More females should be encouraged into farming in the oil spill-affected location, and this could be achieved through incentives such as making land available for farming at reduced cost or through a scheme such as the FADAMA programme.
3. In order to increase farm-level efficiency in the oil spill-affected location, increased use of planting materials and fertiliser should be considered by the farmers through farm inputs subsidies from the government or bulk purchases from farmers' cooperative ventures.
4. The Federal government of Nigeria should also ensure that necessary measures are put in place to remediate areas that have already been affected by oil pollution so as to make more land available to the farmers.

5. Farmers in oil-polluted locations should seek additional means of livelihood by diversifying their sources of income. They should take farming as a secondary occupation, as this will help reduce welfare loss in the farm households.

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