Livelihood Impact of Good Agronomic Practice on the Output and Income of Cassava Cooperative Farmers in Adani Omor Zone of ATASP-1

Obiekwe Ngozi Josephine [1], Obianefo Chukwujekwu Aloysius [2*], Okoroji Nma Okechukwu [3], Ezeaputa Chima Perpetua [4], Nzeocha Chibuzo Chinwendu [5]

[1-2, 5] Department of Agricultural Economics, Nnamdi Azikiwe University, Awka, Nigeria

[3] Department of Cooperative Economics and Management, Nnamdi Azikiwe University, Awka, Nigeria

[4] Anambra State Polytechnic, Mgbakwu, Awka North Local Government Area, Nigeria

* Corresponding Author: **Obianefo Chukwujekwu Aloysius**

Article Info

ISSN (online): 3107-6602
Impact Factor (RSIF): 8.20
Volume: 02
Issue: 03
Received: 05-03-2026
Accepted: 04-04-2026
Published: 03-05-2026
Page No: 28-38

Abstract

This study examined the livelihood impact of Good Agronomic Practices (GAP) on cassava output and income among cooperative farmers in the Adani Omor Zone ATASP-1. Data was collected from a random sampling of 317 cassava farmers. The analytical tools used include the mean threshold from a five-point Likert scale and propensity score matching (PSM). The study revealed that several GAP components remained at the trial stage, evidenced by a grand mean of 4. Timely planting (90. 5% adoption; mean = 5), organic manure application (90. 5% adoption; mean = 5), and timely harvesting (72. 2% adoption; mean = 5) were completely implemented. According to logistic regression analysis, adoption probability fell with age (odds ratio = 0. 974) but rose with credit access (odds ratio = 1. 969), agricultural experience (odds ratio = 1. 026), and education (odds ratio = 1. 060). The treatment effect improved balance and lowered the normalized distance from 0.581 to 0.035. Which includes control variables in impact analyses, showed that using certain techniques boosted cassava yield by around 5.15 units (t = 2.74**) and farm revenue by roughly ₦136,261 (t = 2.17**). The findings showed that although using GAP produces major increases in production and income, livelihoods are limited by the absence of a consistent change from testing to sustained adoption—particularly for capital-intensive and technologically sophisticated innovations. The study therefore recommends that ATASP-1 coordinators should strengthen credit access, extension depth, and input delivery systems to help translate technology dissemination into sustained livelihood improvement.

Keywords: Good Agronomic Practices, Livelihood, Cooperative, Cassava Farmers, Output

1. Introduction

In Nigeria, especially given the rising population, rural poverty, and climatic volatility, food security in basic crops is a major policy issue. The Federal Government has started several agricultural development initiatives under the Ministry of Agriculture and Food Security to raise output, balance food supply, and improve rural life in response. Supported by the African Development Bank, the most prominent of these projects is the Agricultural Transformation Agenda Support Program Phase I (ATASP-1). ATASP-1 was conceived at a time when Nigeria faced critical challenges in food security occasioned by low productivity and production, and sub-optimal harvested area (AfDB, 2025) [4]. The ATASP-1 was designed to increase crop productivity, strengthen value chains, and improve the income and livelihood outcomes of smallholder farmers within designated Staple Crops Processing Zones (AfDB, 2025) [4]. Apart from the production targets, ATASP-1 specifically situated agriculture as a pathway to inclusive rural development through the linkage between farmers and extension services, improved inputs, mechanization, and markets; they equally embedded livelihood improvement within its programme Log Frame.

However, because of cassava's importance to national food security and rural household economies, it occupied a strategic position within ATASP-1 intervention. Though Nigeria is among the top cassava producers worldwide, the crop still serves two purposes for the nation: it is a main cuisine as well as a main source of income for millions of small farmers (Osuafor *et al*., 2020; FAO, 2022) [20, 9]. Using the autoregressive distributed lag (ARDL) technique based on FAO (2022) trend data, Omoluabi and Ibitoye (2024) [19] forecast Nigeria's cassava yield at 68.09 million tons, making the country the biggest producer of cassava worldwide and a major player in the world food scene. Resistant to poor soils and varying precipitation, cassava is particularly well suited for smallholder farming systems; yet, livelihoods reliant on cassava are still quite precarious. Moreover, empirical studies have shown that cassava farmers run the risk of several livelihood hazards including rising input costs, price volatility, pest and disease outbreaks, climate shocks, and limited access to credit and markets (Willett *et al*., 2019; Oyekola *et al*., 2021) [27, 21]. These dangers hence show themselves in several forms of poverty and vulnerability influencing not only agricultural output but also family income stability, food availability, and long-term well-being. Additionally, a recent survey conducted in southeast Nigeria found that even in locations with strong production potential, cassava farmers are in danger of losing their livelihood and are closely related to persistent income poverty and low asset accumulation (Isibor *et al*., 2024) [13].

In light of these difficulties, ATASP-1's primary outreach and productivity-boosting plan for cassava producers centred around GAP packages. Uchemba *et al*. (2021) [26] identified the following categories for these approaches: careful site selection, better land preparation via tractorization, procurement of supplies from reputable agro-dealers, utilization of premium cassava types such as TME 419, ridge planting, appropriate planting time, correct spacing and depth, balanced application of organic and inorganic fertilizers, chemical weed control, favorable processing conditions, and timely harvesting. These approaches should increase yields, lower production losses, enhance quality, and finally result in higher farm incomes and better living conditions for rural homes. Furthermore, Isibor *et al*. (2024) [13] and Su and coworkers (2019) [25] define livelihood opportunity as more than simply a means of earning money; it also encompasses the development of skills, resources, and choices that enable households to improve and sustain their quality of life over time. From this angle, it is expected that the adoption of GAP will affect livelihood results via direct productivity gains as well as indirect pathways such as more market involvement and income diversification.

Despite the increasing body of empirical research looking at the adoption and productivity consequences of better cassava technologies and agricultural methods, there remain certain gaps. Within the ATASP-1 intervention and other related programs, certain researchers (Abass, 2022; Acheampong, 2022; Habtewold, 2023; Iheyi, 2025) [1, 2, 10, 11] have documented favourable impacts of GAP adoption on yields and farm income in Nigeria's cassava and other main crops. But just a few publications used strong evaluation methodologies that took into account non-random adoption behaviour and directly based their analysis on the program-specific goal of enhancing livelihoods.

Realistically, not all ATASP-1 beneficiaries will adopt GAP practices at the same pace or intensity. Again, adopters often differ systematically from non-adopters in terms of education, asset base, access to information, and cooperative strength. However, failure to account for these differences can lead to biased estimates of programme impact. It is on this note that the study adopts the propensity score matching as a policy-relevant evaluation approach to isolate the effect of GAP adoption on key livelihood indicators, which are the cassava output and farm income, among cooperative farmers in the Adani Omor Zone of ATASP-1. By doing so, the study contributes evidence that is not only empirically relevant but also necessary for programme scaling decisions.

Specific Objectives of the Study

The specific objectives of the study are to:

1. describes the stages of GAP packages adopted by cassava farmers in ATASP-1, and
2. estimate the GAP adoption effect on the output and income of cassava farmers using PSM.

2. Empirical Review

Several related literatures exist to create a sound back-up to this present study's findings. None of the studies reviewed, none used PSM to examine the impact of adoption of GAP in the livelihoods of cassava farmers, this approach clarifies the novelty of this study.

The study Nwaobiala (2018) [15] examined the adoption of cassava agronomic practices among farmers in Abia and Imo States from a random sample of 120 respondents. To analyze the data, he utilized regression analysis and descriptive statistics. The research showed a positive correlation between farmers' adoption of sound agronomic practices (GAP), such as timely weeding, the use of improved cassava types, and fertilizer application, with higher yields and higher income levels. However, the research discovered that the full potential of GAP in increasing output and improving living conditions was still constrained by the restricted availability of credit institutions and a lack of extension services. By comparing those involved in out-grower programs with independent farmers.

Later research by Ojiako *et al*. (2018) [17] looked at the profitability of growing cassava on small-scale farms in Southern Nigeria. Using a comparative analysis approach, the study assessed real and possible investment returns. It highlighted the need for good agronomic practices (GAP) in raising output. They found that farmers participating in structured out-grower schemes, who were more likely to adopt GAP, such as improved varieties, timely weeding, and fertilizer application, recorded significantly higher net returns, which were estimated at 35 to 40% above those of independent farmers.

By means of a case study concentrating on extension initiatives and farmer approval patterns, the CARA Development Foundation investigated in 2024 the results of good agricultural practices (GAP) on raising Nigeria's cassava output. The research revealed that, in contrast to the 8 to 11 tonnes per hectare seen among traditional farmers, agriculturalists who adopted Good Agricultural Practices (GAPs), including enhanced stem cultivars, fast weed control, and soil fertility management, produced significantly more yields—from 15 to 20 tonnes per hectare. Adedigba (2019) [3] examined the impact of agricultural cooperative societies on the production of cassava crop yields for farmers in Ondo State, Nigeria. He examined the differences among non-cooperative and cooperative individuals using household survey information. The findings revealed that cooperative membership significantly raised the usage of GAP by improving farmers' access to inputs, extension services, and financial institutions. As a result, farmers who cooperated had higher production and income levels than those who did not. Moreover, the research revealed that the uptake process for co-op members was much influenced by factors like age, degree of education, farm size, savings mobilisation, market access, and market knowledge. In the Olayemi-Adeoluwa and Ogunwale (2025) [18] study on farmer adoption of enhanced cassava production methods in the Ogbomoso Agricultural Zone of Oyo State, Nigeria, descriptive statistics and regression models were used. The usage of modern technologies, such as timely weeding, fertilizers, automated land preparation, and high-yielding cassava kinds, was shown to be strongly connected to increased family income and cassava production. Both membership in a cooperative and participation in agricultural education were helpful in making a choice.

The International Institute of Tropical Agriculture (IITA, 2018) [12] also assessed the effectiveness of digital extension tools and cassava Good Agricultural Practices (GAP) in countries like Nigeria, Rwanda, and Tanzania. According to the study's conclusions, better cassava production and more household income were major results of the mix of better agricultural methods with internet-based advising tools.

Danso-Abbeam and Baiyegunhi's (2017) [7] research on the application of agrochemical management techniques among smallholder cocoa farmers in Ghana highlighted the need of understanding elements affecting adoption and their effects on productivity and sustainability. The study found a positive correlation between improved cocoa yields and higher farm income from the use of agrochemical methods, including pesticide usage, fertiliser application, and adherence to recommended safety guidelines. Furthermore, the study showed that involvement in agricultural organizations, farmer education, and credit availability significantly raised the likelihood of using advised agrochemical methods.

Mwebaze *et al.* (2024) [14] looked at the factors influencing East and Central Africa's smallholder farmers' acceptance of better cassava stems and intercropping techniques. The study mostly looked at how these things affect how much food and money farming makes. Better cassava types can help to generate more income and yields. Intercropping helps to diversify output, therefore lowering risk and improving food security is assisted by this. Adoption was greatly influenced by cooperative membership, credit accessibility, farmer education, and extension service availability. Shackelford *et al.*'s 2018 [23] research looked at several ways cassava is cultivated all around the world and how they affect the environment, as well as the way in which farming is carried out.

Good Agricultural Practices (GAP) have been shown to improve sustainability, raise production, and reduce soil erosion. Therefore, environmental results and financial prosperity are being connected to agricultural practices.

3. Materials and Methods

3.1. Study Area

Adani–Omor Zone of ATASP-1 was the study area, which spans through the Anambra State Local Government Areas (LGAs) of Ayamelum, Ogbarua, Orumba North, and Orumba South. In Enugu State, it covered Uzo-Uwani, Isi-Uzo, and Udenu LGAs. Adani is located at latitude 6.74° N and longitude 7.01° E; Omor is at latitude 6.52° N and longitude 7.03° E. The area is perfect for cassava growing, which features a tropical climate and rich alluvial soils. It has a dry season from November to March and a rainy season from April to October with a tropical temperature. The intensive crop production is aided by an average yearly rainfall between 1,500 and 2,000 mm. Mostly flat to somewhat undulating, the landscape helps automated farming and mass farming to be possible.

3.2. Population and Sampling Procedure

The population of this study is made up of all the cassava farmers participating in the Agricultural Agenda Support Programme phase-1 (ATASP-1) in Adani-Omor Zone (Anambra and Enugu). Based on the information from the Programme Monitoring and Evaluation Officer (PMEO) in 2025, the number of cassava farmers from various cooperative groups participating across the seven LGAs of Isi Uzo, Udenu, and Uzo-Uwani (Enugu); Ayamelum, Ogbaru, Orumba North, and Orumba South (Anambra) is 5847 farmers. This 5847 represents the sample frame for the study.

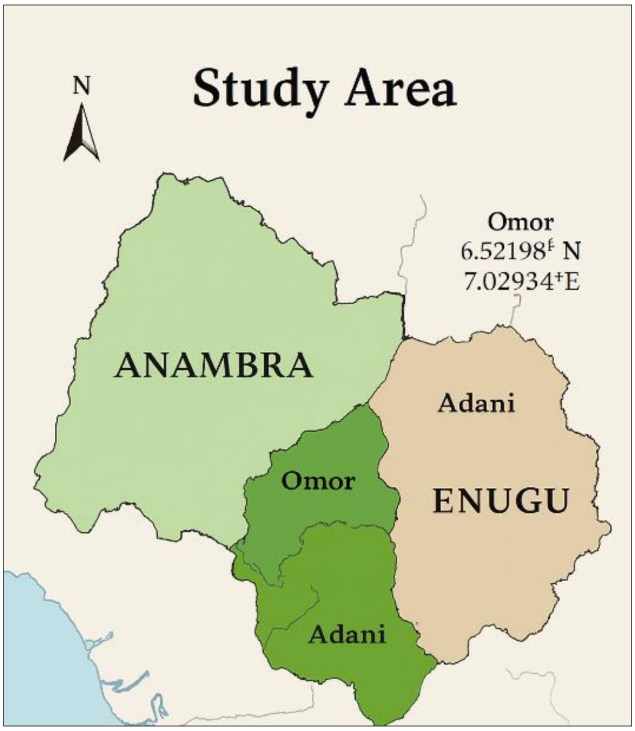

Fig 1: Map showing Adani-Omor Zone of ATASP-1

Table 1: Distribution of cassava farmers from Adani Omor zone of ATASP-1 Programme

State	LGA	Population
Enugu	Isi Uzo	951
	Udenu	2176
	Uzo-Uwani	256
Total		3383
Anambra	Ayamelum	22
	Ogbaru	1014
	Orumba North	953
	Orumba South	475
Total		2464
Grand Total		5847

Sources: ATASP-1 Programme Monitoring and Evaluation Officer, 2025

A multi-stage sampling technique was used to select the study respondents. The first stage involved the use of Cochran's (1977) sample size determination technique to calculate the appropriate sample size due to the cluster nature of the ATASP-1 programme intervention. This sample size technique has different steps of application.

Step one: The researcher(s) hope to achieve a minimum of 75% response rate from the respondents. Thus, the initial sample size (n_0) is calculated as:

$$n_0 = \frac{Z^2 * P * Q}{e^2}$$

Where:

n_0 = initial sample size, Z^2 = Z-score at 95% confidence level, P = probability of success, $Q\ (1 - P)$ = probability of failure and e^2 = error term. Thus, the initial sample size:

$$n_0 = \frac{1.96^2 * 0.75(1 - 0.75)}{0.05^2} \cong 288$$

The second step is to perform the correction of the finite population, which is defined as:

$$n = \frac{n_0}{1 + \left(\frac{n_0 - 1}{N}\right)}$$

Where:

N = entire population of cassava farmers in Adani Omor zone of ATASP-1, n_i = finite sample size, and n_0 remained as previously defined.

$$n_i = \frac{288}{1 + \left(\frac{288 - 1}{5847}\right)} \cong 274$$

Step three: there is a need to adjust for a minimum of 5% for non-response rate, using the below formula:

$$n_{adj} = \frac{n_i}{1 - r}$$

Where:

n_{adj} = Adjusted sample size at 5%, r = response rate, and 1-r = non-response rate (proportion of the sample that is expected not to participate in the survey or study).

$$n_{adj} = \frac{274}{1 - 0.05} \cong 288$$

Step four: due to the community/cluster approach of the programme, there is a need to take at-least, 10% cluster adjustment for design effect (DEFF), which is 1.1 in value:

$$n_{design} = n_{adj} * DEFF$$

Where:

n_{design} = Final sample size, DEFF = design effect values at 1.1 (10% increased of adjusted sample size)

$$n_{design} = 288 * 1.1 \cong 317$$

Thus, the final sample size is 317 cassava farmers.

In the second stage, Kumaison's (1997) proportionate formula, adapted in Ekwere and Edem (2014) [8] as used in Obianefo *et al.* (2022) [16], was used to allocate sample strata for the study. The Kumaison formula for strata distribution is stated as:

$$i_{th} = \frac{N_2}{N} * n_{design}$$

Where: *N* is the population of cassava farmers in Adani Omor, *N* is the total number of farmers in each LGA, and i_{th} is the strata distribution as populated in Table 2:

Table 2: Distribution of sample size according to LGA selection

LGA	Population	Strata
Isi Uzo	951	52
Udenu	2176	118
Uzo-Uwani	256	14
Ayamelum	22	1
Ogbaru	1014	55
Orumba North	953	52
Orumba South	475	26
Total	5847	317

Sources: Researcher's computation, 2025

The 317 cassava farmers from Adani Omor were randomly sampled from different programme clusters as populated in Table 2 through the assistance of the project extension officers.

The data from the survey were analyzed with a mean score of a 5-point Likert Scale and Propensity Score Matching (PSM) techniques. The PSM model is explicitly defined as:

Step 1: Treatment variables

Independent variable (Treatment):

GAP_i = 1 if farmer i adopted Good Agronomic Practices,

GAP_i = 0 otherwise.

Step 2: Covariates (Socioeconomic Variables)

These covariates are used to estimate the propensity score (the probability of adopting GAP):

Sex (Sex_i)

Age (Age_i)

Marital Status (MS_i)

Years of Education (Edu_Year_i)

Household Size (HHS_i)

Farming Experience ($Fexp_i$)

Access to Credit ($Credit_i$)

Income ($Income_i$)
Extension Visit ($ExtVisit_i$)
The propensity score model is therefore specified as:

$$\Pr(GAP_i = 1|X_i) = \Pr(GAP_i = 1|Sex_i, Age_i, MS_i, Edu_{Year_i}, HHS_i, Fexp_i, Credit_i, Income_i, ExVisit_i$$

Where: X_i is the vector of socioeconomic covariates.

Step 3: Outcome Variables
Cassava Output ($Output_i$)
Revenue ($Revenue_i$)

Step 4: Estimation Framework
After estimating the propensity scores, farmers who adopted GAP are matched with non-adopters who have similar scores. The treatment effect is then estimated as the difference in mean outcomes between matched groups:

$$ATT = E[Output_i(1) - Output_i(0)|GAP_i = 1]$$

$$ATT = E[Revenue_i(1) - Revenue_i(0)|GAP_i = 1]$$

Where:
- $Output_i(1)$ and $Revenue_i(1)$ are outcomes for adopters,
- $Output_i$ (0) and $Revenue_i$ (0) are counterfactual outcomes for non-adopters,
- ATT is the Average Treatment Effect on the Treated.

However, the final propensity model is as follows:

$$GAP_i = f(Sex_i, Age_i, MS_i, Edu_{Year_i}, HHS_i, Fexp_i, Credit_i, Income_i, ExVisit_i) + \varepsilon_i$$

Outcome Equations

$$Output_i = \alpha + \beta GAP_i + \gamma X_i + u_i$$

$$Revenue_i = \alpha + \beta GAP_i + \gamma X_i + u_i$$

Where:
β captures the effect of GAP adoption on cassava output and revenue,
X_i is the vector of socioeconomic covariates,
u_i is the error term.

4. Results and Discussion
4.1. Stage of Good Agronomic Technology adoption
The stage of GAP adoption on each technology disseminated by the ATASP 1 extension advisory unit is presented in Table 3. The data were captured with a 5 point Likert Scale to accommodate the 5 stages of adoption as reported in Obianefo *et al.* (2022) [16]. The grand mean of 4 is an indication that most of the technologies are at the trial stage, with only a few (timely planting, organic manure, and timely harvesting) fully adopted. Many of the technologies have not been fully adopted by the farmers. This approach of analysis is logical because one time use of a technology does not in any way imply sustained adoption.
For improved land preparation through tractorization, the Table revealed that 43.8% of farmers are aware, 39.1% are still evaluating, 5.4% are interested, 7.9% are at trial, while only 3.8% have adopted. The mean of 2 indicates that the practice remained at the evaluation stage. This does not reflect well on ATASP-1 participation since the programme's first phase is over, yet many farmers have not fully adopted tractorization. Given that tractorization calls for a lot of upfront investment, this finding suggests major financial limitations and risk aversion among farmers. Adedigba (2019) [3] and Olayemi-Adeoluwa and Ogunwale (2025) [18] reported similar results, with automated land preparation having the lowest acceptance rates among the cassava farmers because of high prices and lack of access to tools. Consistent with the findings of the CARA Development Foundation (2024) [6], the low adoption indicates that productivity improvements from automation are not yet ubiquitous, which might lower production efficiency and competitiveness.
Again, careful site selection revealed that 19.6% were reviewing (evaluation stage), 21.1% were at trial, and 59.3% had adopted. This habit is found at the trial stage with a mean of 4 places. Site selection is especially important since it influences the success of other farming methods. Adoption is greater than tractorization, but the reality that several farmers are still in the trial phase points to knowledge gaps and inconsistent application, which could compromise yield potential and lower returns on investment. This result corroborated Nwaobiala (2018) [15], who said that because of a lack of technical expertise, farmers sometimes only follow regionally relevant agronomic suggestions.
With a mean of 4, which denotes the trial stage, the statistics for obtaining supplies from licensed agro dealers revealed 3.8% awareness, 14.5% evaluation, 24.3% interest, 33.8% trial, and 23.7% adoption. This modest acceptance points to issues with affordability and poor links to the industry. Ojiako *et al.* (2018) [17] and IITA (2018) [12] found similar limitations: erratic input supply systems and pricing changes deter long-term adoption of certified inputs. Low yields and inefficiencies all along the cassava value chain are more likely to affect farmers who cannot find good inputs.
Similarly, the adoption rate for better cassava types like TME 419, which recorded 48.6% interest, 12.0% trial, and 39.4% adoption, with a mean of 4, puts the practice on the trial stage. Better kinds are appealing because of their increased yields and disease resistance, yet adoption is slowed by seed accessibility and distribution bottlenecks. This result supports Mwebaze *et al.* (2024) [14] and Shackelford *et al.* (2018) [23], who found that a main obstacle to varietal acceptance is still poor access to certified planting supplies. Such restrictions could hamper cassava's competitiveness and commercialisation in overseas as well as local markets.
Ridge planting appeals to 18.3% of farmers; 33.1% are in testing (trial stage); 48.6% have implemented it (adopted). The average is 4—the trial phase. Ridge planting increases yield and root growth; the somewhat greater uptake points to farmers' awareness of its advantages. This supports the 2024 CARA Development Foundation's conclusions [6] that farmers who used ridging had bigger yields. But partial uptake means that across all farms, yield potential is not entirely realised, therefore limiting overall production.
The Table showed that, with a mean of 5, suggesting full adoption, timely planting recorded 9.5% trial and 90.5% adoption. This high adoption demonstrated unequivocally that farmers saw the advantages of early planting for yield maximising. Nwaobiala (2018) [15] and Ojiako *et al.* (2018) [17] both recorded somewhat high acceptance rates, as they found that timely planting was among the most easily adopted

cassava practices because it is cheap and has obvious yield benefits. From an economic point of view, early planting increases profitability and food security by lowering the risk of crop failure and improving synchronization with market demand.

With a mean of 3, which corresponds to the interest stage, the Table revealed 3.8% awareness, 48.3% evaluation, 5.4% interest, 13.6% trial, and 29.0% adoption for advised spacing and planting depth. This reluctance to completely embrace the approach points to a lack of technological expertise and workforce limits. Abass (2022) [1] and Habtewold (2023) [10] also observed that labour intensity sometimes causes people to give up on perfect spacing. Notably, inadequate spacing lowers per-hectare yields, worsens nutrient competition, and causes ineffective land use.

For balanced application of inorganic fertilizer, the Table shows 7.6% evaluation, 17.4% interest, 35.3% trial, and 39.7% adoption, with a mean of 4, which indicates a trial stage. This result is consistent with the result of Danso-Abbeam and Baiyegunhi (2017) [7] and Oyekola *et al*. (2021) [21]; they noted that this moderate usage is probably limited by expensive fertilizer prices and limited availability. Such limitations could result in yield gaps when compared to possible production.

With an average of 3, which denotes the interest stage, chemical weed control registered 22.7% evaluation, 44.2% interest, 29.3% trial, and only 3.8% adoption. Cost, health problems, and lack of technical know-how seem to keep farmers from being too aggressive. Similar concerns were expressed by Danso-Abbeam and Baiyegunhi (2017) [7], who discovered that cost and safety issues were the main barriers to agrochemical use. Relying on manual weeding all the time increases labour costs and reduces agricultural output.

Organic manure had 4.1% awareness, 5.4% trial, and 90.5% adoption, with a mean of 5 indicating sincere adoption. CARA Development Foundation's (2024) [6] findings, which imply a broad adoption of organic soil amendments among cassava growers, support this conclusion. This total acceptance mirrors the availability and price of organic fertiliser. Organic fertilizer boosts resistance, enhances soil fertility, and promotes sustainable production. Timely collecting ultimately showed 27.8% adoption and 72.2% trial, with an average of 5. The rapid adoption rate demonstrated that farmers recognize that market value is directly related to harvest timing. Ojiako *et al*. (2018) [17] came to the same conclusion: By reducing post-harvest losses and maximizing price realization, timely harvesting improves domestic income, and the competitiveness of the market, and so raises household income. Danso-Abbeam and Baiyegunhi (2017) [7] also reported similar worries, finding that cost and safety concerns were the main obstacles to agrochemical use. Constant reliance on manual weeding raises labour expenses and lowers farm productivity.

Interestingly, the research revealed 4.1% awareness, 5.4% trial, and 90.5% adoption for organic manure, with a mean of 5, showing wholehearted adoption. This result is in agreement with CARA Development Foundation's (2024) [6] results, which suggest a widespread use of organic soil amendments among cassava farmers; this full acceptance reflects the cost and availability of organic manure. Organic manure increases resilience, improves soil fertility, and encourages sustainable productivity. Finally, timely harvesting had 27.8% adoption and 72.2% trial, with an average of 5. The high adoption rate showed that farmers understand there is a clear connection between harvesting on time and market value. Ojiako *et al*. (2018) [17] came to the same conclusion: harvesting on time greatly lowers post-harvest losses and maximizes price realization, so boosting market competitiveness and household income.

Table 3: GAP practice adoption stage by cassava farmers in ATASP-1

Technology	Aware	Evaluation	Interest	Trial	Adoption	Mean	Final adoption stage
Improved land preparation through tractorization	43.8	39.1	5.4	7.9	3.8	2	Evaluation
Appropriate site selection	0.0	19.6	0.0	21.1	59.3	4	Trial
Sourcing inputs from certified agro-dealers	3.8	14.5	24.3	33.8	23.7	4	Trial
Use of improved cassava varieties such as TME 419	0.0	0.0	48.6	12.0	39.4	4	Trial
Ridge planting	0.0	0.0	18.3	33.1	48.6	4	Trial
Timely planting	0.0	0.0	0.0	9.5	90.5	5	Adopted
Use of recommended spacing and planting depth	3.8	48.3	5.4	13.6	29.0	3	Interest
Balanced application of inorganic fertilizers	0.0	7.6	17.4	35.3	39.7	4	Trial
Chemical weed control	0.0	22.7	44.2	29.3	3.8	3	Interest
Use of organic manure	4.1	0.0	0.0	5.4	90.5	5	Adopted
Timely harvesting	0.0	0.0	0.0	27.8	72.2	5	Adopted
Grand mean						4	Trial

Source: Field Survey, 2025.

4.2. Systematic Mean Differences Before Matching

A crucial diagnostic phase in the propensity score matching approach is the evaluation of systematic mean disparities across adopters and non-adopters. Table 4 shows the descriptive statistics of the main covariates for the whole sample and for the treatment and control groups before matching. Since they point to non-random selection into adoption and the existence of noticeable variation between the two groups, the observed disparities in covariate means support the use of PSM.

The data revealed fairly minor mean variations across some demographic groups. With an SMD of -0.03, sex is generally the same across groups; this implies that adopters and non-adopters do not consistently differ in their gender makeup. Once more, house size showed a slight disparity with an SMD of −0.08, suggesting that family structure might not necessarily influence adoption choices directly. Similarly, the number of extension visits reported a small difference of −0.05, suggesting fairly similar exposure to extension services before matching.

Most socioeconomic and human capital factors, meanwhile, showed a significant mean difference, suggesting a consistent gap between those who adopt and those who don't. Age had a mean difference of -3.22 years; adopters were typically younger. Younger farmers may be more willing to use better methods, maybe because they are more open to new ideas, are more willing to take risks, or are better able to use new technologies. This age gap creates selection bias that has to be taken into account to prevent overestimation of adoption results.

Years of education showed a positive mean difference of 1.20 years in favour of adopters, suggesting that adopters have better educational achievement. This corresponded with the expectation that education would help people better understand technical advice and increase their capacity for decision-making. Uncorrected, this discrepancy could confuse the projected influence of adoption with the effect of education itself.

Groups also significantly differ in their farming experience; adopters say they have, on average, 2.47 more years of experience. This implies that adoption could be motivated by gathered practical experience as well as youthfulness rather than just by youthfulness. More seasoned farmers could better judge the advantages of fresh techniques and incorporate them into current production processes.

Table 4: Description of the Covariates before matching

Variable	Full Sample	Non-Adopters	Adopters	Systemic Mean Difference (SMD)
n	317	226	91	
Sex	0.38	0.38	0.35	-0.03
Age	48.71	49.63	46.41	-3.22
Marital status	2.36	2.33	2.43	0.1
Years of schooling	11.13	10.78	11.98	1.2
Farming experience	17.09	16.38	18.85	2.47
Household size	6.21	6.23	6.15	-0.08
Monthly income	105362.62	102526.11	112407.14	9881.03
Number of extensions visited	3.71	3.73	3.68	-0.05
Access to credit	0.62	0.58	0.74	0.16

Source: Field Survey, 2025.

Monthly income shows the most marked difference; adopters make, on average, ₦9,881 more than non-adopters. This significant disparity suggests that before adoption, adopters are in a stronger financial position, which might help them to absorb risks, buy complementary inputs, or pay for upfront expenses. This supports the worry that income might affect both adoption and outcome factors at once, which will make basic mean comparisons untrustworthy.

Furthermore, access to credit is quite different; adopters have a greater share of access, as shown by an SMD of 0.16. This strengthens the case that adoption behaviour depends on liquidity limitations and that farmers with better access to formal or informal credit markets are more likely to adopt modern methods.

4.3. Logistic Regression Estimates of Adoption Probability for Propensity Score Construction

The logistic regression estimates that were used to predict the likelihood of adoption and produce the propensity scores for the matching procedure are shown in Table 5. The model links farmers' adoption choices to a collection of socioeconomic covariates that earlier theories and empirical data had suggested might affect the uptake of technology. It should be observed that the model's main objective is covariate balancing rather than causal inference.

At the 5% level of probability, the age coefficient was negative and statistically significant. The odds ratio of 0.974 implies that, all else being equal, a unit increase in age lowers the chance of adoption by around 2.6%. Younger farmers are more receptive to adopting better agronomic methods because they are more open to innovation, have a higher risk tolerance, and have a longer planning perspective, as shown by earlier descriptive evidence from ATASP-1 and existing studies (Nwaobiala, 2018; Mwebaze *et al.*, 2024) [15, 14]. Similar age-related adoption trends have been observed in Nigeria and sub-Saharan Africa for cassava and other major crop systems (Danso-Abbeam and Baiyegunhi, 2017; Olayemi-Adeoluwa and Ogunwale, 2025) [7, 18].

The level of education's coefficient was positive and statistically significant at the 5% threshold. Each additional year of schooling increases the likelihood of GAP adoption by about 6%, as measured by an odds ratio of 1.060. According to the findings, human capital has an impact on farmers' ability to comprehend, analyze, and effectively implement improved strategies. Prior research has demonstrated that education is a significant factor affecting farmers' adoption of agricultural technology because it enhances information processing, decision-making, and responsiveness to extension messages (Uchember *et al.*, 2021; Adedigba, 2019; Shackelford *et al.*, 2018) [26, 3, 23], and this conclusion is consistent with those findings. Therefore, as Ojiako *et al.* (2018) [17] also discovered, education is a significant factor in selecting people for adoption inside ATASP-1.

The coefficient of farming experience was also positive and statistically significant at the 5% level of probability. With an odds ratio of 1.026, each year of farming experience increases the likelihood of adoption by around 2.6%. Farmers' increasing practical knowledge, which boosts their confidence in experimenting with new ideas, is implied by this. The claims made by Oyekola *et al.* (2021) [21] and Mwebaze *et al.* (2024) [14], who discovered that experienced farmers are more capable of assessing the benefits and dangers of novel technologies, are supported by this finding. Once again, the conclusion indicates that farming expertise exacerbates the model's identified negative age effect, demonstrating that experience—rather than age alone—is more important for adoption choices.

In addition, the coefficient of credit access was shown to be a significant and statistically positive factor in adoption at the 5% probability threshold. According to a ratio of 1.969, farmers who lack credit are almost twice as likely to implement GAP as those who do. This highlighted the significance of liquidity and financial inclusion in overcoming barriers to adoption, particularly in situations when superior practices require upfront investment or take time to yield results. IITA (2018) [12], Abass (2022) [1], and Danso-Abbeam and Baiyegunhi (2017) [7] all came to somewhat comparable findings, emphasizing that access to credit alleviates financial constraints and encourages the long-term use of productivity-enhancing technologies.

Table 5: Logistics regression estimate of the probability of adoption for propensity score

Parameters	Coeff.	Std. Error	t-value	Exp.	conf. Low	conf. High
(Intercept)	-5.941	3.277	-1.81	0.003	0.000	1.558
Sex	-0.279	0.272	-1.03	0.756	0.440	1.281
Age	-0.026	0.012	-2.24**	0.974	0.952	0.996
Marital status	0.137	0.127	1.08	1.147	0.898	1.482
Level of education	0.058	0.029	2.00**	1.060	1.002	1.124
Farming experience	0.025	0.013	1.93**	1.026	1.000	1.053
Household size	-0.003	0.054	-0.06	0.997	0.896	1.106
Income	0.403	0.277	1.45	1.496	0.870	2.589
Number of extension visits	-0.027	0.066	-0.41	0.973	0.854	1.108
Access to credit	0.677	0.285	2.38**	1.969	1.139	3.487

Source: Field Survey, 2025. Sig. at 10% (*), 5% (**), and 1% (***), the level of probability

4.4. Propensity Score Balancing and Overlap Assessment

The results of the propensity score balancing test, which compares mean values and standardized differences between treated and control groups before and after matching, are shown in Table 6. Whether the matching method successfully reduced obvious disparities between adopters and non-adopters and generated enough common support will depend on this stage being very important.

Before matching, treated and control groups show large differences across many covariates. With a sizable standardized difference of 0.581, the distance showed a clear absence of overlap and emphasized the presence of notable pre-treatment differences. Age, education, agriculture experience, monthly income, and credit access all exhibit modest variances as well; standardized differences above the accepted cutoff of 0.1 for balance. These trends reveal that before matching, adopters and non-adopters differed significantly, which makes it inappropriate to directly compare outcomes and possibly leads to skewed results. This discovery supports the large body of research that emphasizes that adopters often have advantages in human capital, resources, and access to services that also impact outcomes (Rosenbaum and Rubin, 1983; Caliendo and Kopeinig, 2008) [22, 5], as technology adoption is seldom arbitrary. Studies of agricultural technology have found similar selection problems: program effects are overestimated because pre-treatment imbalances are not taken into account (Abass, 2022; Habtewold, 2023) [1, 10].

Matching shows a clear increase in covariate balance for all factors. For important indicators including distance, age, education level, agricultural experience, monthly income, and access to credit, the normalized differences are either around zero or far lower than what is considered good. For instance, the age difference shrinks from -0.218 to -0.026 after matching, but the standard distance difference is much smaller, dropping from 0.581 before matching to 0.035 after matching. Before matching, there was a big difference in how easy it was to get credit and how good people were at school, but this difference is almost gone now. This finding suggests that the matching algorithm successfully restricted comparisons to farmers in the same region of common support and produced a counterfactual group observationally comparable to adopters, which is an essential requirement for a trustworthy estimate of the Average Treatment Effect on the Treated (Caliendo and Kopeinig, 2008) [5].

With only slight changes, the consistent differences in factors such as sex, family size, and frequency of extension visits—which were already somewhat well balanced before matching—remain well balanced following matching. But none of the covariates shows a standardized difference after matching that is big enough to make you worry about residual imbalance. The matched sample satisfies the balancing criterion; hence we are more certain that any future impact projections would mirror variations resulting from GAP adoption rather than pre-existing variations in observable characteristics (Rosenbaum and Rubin, 1983) [22].

Table 6: Propensity score balancing and overlapping assessment

Variable	Mean Treated Before	Mean Control Before	Std. Diff. Before	Mean Treated After	Mean Control After	Std. Diff. After
distance	0.332	0.272	0.581	0.332	0.328	0.035
Sex	0.356	0.380	-0.051	0.356	0.311	0.093
Age	46.656	49.244	-0.218	46.656	46.967	-0.026
Marital status	2.456	2.330	0.122	2.456	2.378	0.076
Level of education	11.889	10.878	0.219	11.889	11.822	0.014
Farming experience	18.667	16.615	0.211	18.667	19.233	-0.058
Household size	6.189	6.262	-0.031	6.189	6.411	-0.095
Monthly income	11.527	11.429	0.213	11.527	11.507	0.044
Number of extensions visited	3.656	3.742	-0.043	3.656	3.722	-0.033
Access to credit	0.733	0.593	0.318	0.733	0.722	0.025

Source: Field Survey, 2025.

4.5. Average Treatment Effect on the Treated for Cassava Output

Results from models with and without covariate controls are compared in Table 7, which shows the predicted average treatment effect on the treated for cassava production in ATASP-1. By comparing the estimated adoption effect with and without controlling for observable features, this comparison helps us determine the robustness of the prediction and if the estimated impact is significantly changed by accounting for these traits.

The findings indicated that in both model specifications, adoption has a statistically significant and beneficial impact on output. Including covariates in the model resulted in an increase in adoption of around 5.15 units, which was statistically significant at the 5% level. The model without covariate controls produces a very comparable estimate of 5.19 units, which is still statistically significant at the 5% level. These projections are remarkably similar, which strengthens the validity of the estimated treatment effect and shows that the beneficial impact of adoption on output is consistent and unaffected by model selection. This discovery is in line with prior research on cassava and other major crops that found that adoption of better agronomic methods results in quantifiable productivity improvements, even when accounting for selection bias (Ojiako *et al*., 2018; Abass *et al*., 2022; CARA Development Foundation, 2024) [17, 1, 6]. Impact assessments employing propensity score matching have also demonstrated comparable robustness of adoption effects across different models (Caliendo & Kopeinig, 2008; Habtewold, 2023) [5, 10].

Household size is one of the control variables that has a positive and statistically significant impact on output at the 5% level. According to this finding, bigger households may contribute more family labor to agricultural operations, leading to increased output. Nwaobiala (2018) [15] and Olayemi-Adeoluwa and Ogunwale (2025) [18], who noted that household labor availability is a significant factor in cassava production, especially in locations where mechanization is restricted and labor-intensive methods persist, supported this conclusion. According to income data, there was also a positive but marginally statistically significant impact at the 10% level, suggesting that farmers with higher income levels are in a better position to invest in complementary inputs like fertilizers and hired labor. This is consistent with Oyekola *et al*. (2021) [21] and Danso-Abbeam and Baiyegunhi (2017) [7], who found that higher income lessens liquidity constraints and encourages productive investment.

The coefficient for age is negative and only marginally significant, indicating that, on average, farmer productivity tends to decrease little with age. This pattern could be the result of a decrease in physical ability, a smaller operational scale, or older farmers taking longer to adapt to better manufacturing methods. In cassava and other smallholder systems, younger farmers are more likely to embrace and promote better practices, which has led to similar age-related reductions in productivity (Mwebaze *et al*., 2024; Shackelford *et al*., 2018) [14, 23].

Table 7: Average Treatment Effect on the Treated Output

	With control			Without control		
Covariates	**Estimates**	**Std. Error**	**t-value**	**Estimates**	**Std. Error**	**t-value**
(Intercept)	-21.34	24.47	-0.87	18.584	1.33	13.97
Adoption	5.146	1.879	2.74**	5.186	1.881	2.76**
Sex	0.237	2.084	0.11			
Age	-0.142	0.085	-1.67*			
Marital status	0.158	0.928	0.17			
Level of education	-0.026	0.225	-0.11			
Farming experience	0.097	0.100	0.97			
Household size	0.46	0.209	2.20**			
Income	3.767	2.039	1.85*			
Number of extension visits	-0.653	0.485	-1.35			
Access to credit	1.023	2.173	0.47			

Source: Field Survey, 2025. Sig. at 10% (*), 5% (**), and 1% (***), the level of probability

4.6. Average Treatment Effect on the Treated for Cassava Revenue

Comparing models estimated with and without covariate controls, Table 8 presents the predicted Average Treatment Effect on the Treated for farm revenue. This comparison, similar to the output estimations, showed a robustness result on the effect of adoption, which helps to separate the treatment effect from the impact of other farmer traits.

The findings demonstrate that, in both models, adoption has a statistically significant and beneficial impact on revenue. The adoption rate rises farm income by about ₦136,261 when covariates are included, and this impact is statistically significant at the 5% level. The model without controls yields a somewhat lower but nearly identical estimate of ₦130,364, which is likewise significant at the 5% level. The closeness of these estimates indicates that the income increases brought about by adoption are not affected by the model specification and represent a real treatment impact. According to earlier evidence, better cassava technologies and sound agronomic practices can result in higher farm income and profitability, especially if adoption is maintained rather than sporadic (Ojiako *et al*., 2018; Abass *et al*., 2022; CARA Development Foundation, 2024) [17, 1, 6]. This pattern is consistent with that evidence. The PSM impact evaluation literature also supports the resilience of the adoption effect across specifications, noting that the treatment effect interpretation is strengthened by consistent estimations under alternative controls (Caliendo & Kopeinig, 2008) [5].

The controlled model shows statistically significant associations between income and a number of control factors. Male farmers earn higher average revenue, as shown by the positive and significant coefficient for sex. This might be a reflection of gendered disparities in access to productive resources like land, capital, labor, and market connections, which can have an impact on both the size of production and commercial orientation (Adedigba, 2019; Olayemi-

Adeoluwa & Ogunwale, 2025) [3, 18]. In other smallholder adoption and livelihood research, age has been shown to have a negative and significant impact, indicating that income decreases as farmers age, possibly due to a smaller scale of operations, less market engagement, or a reduced capacity to react to commercial opportunities and innovation (Danso-Abbeam & Baiyegunhi, 2017; Mwebaze *et al*., 2024) [7, 14].

At the 1% level, farming experience demonstrated a strong positive and highly significant impact. This demonstrates that a farmer's accumulated knowledge and skills are essential for turning production operations into increased profits, especially through improved input management, sales timing, and market participation. This conclusion is consistent with research that suggests that experience increases managerial skills, improves decision-making in the face of uncertainty, and increases the capacity to take advantage of yield and price possibilities, ultimately increasing farm revenue outcomes (Oyekola *et al*., 2021; Mwebaze *et al*., 2024) [21, 14].

Table 8: Average Treatment Effect on the Treated Revenue

	With control			Without control		
Covariates	**Estimates**	**Std. Error**	**t-value**	**Estimates**	**Std. Error**	**t-value**
(Intercept)	248479.729	1522220.060	0.163	1691667.778	83034.041	20.37
Adoption	136260.731	62906.317	2.17**	130364.444	61779.232	2.11**
Sex	197549.494	78266.478	2.52**			
Age	-7560.014	3118.831	-2.42**			
Marital status	47596.320	57746.481	0.82			
Level of education	7009.887	14015.983	0.50			
Farming experience	9717.949	2723.350	3.57***			
Household size	20997.307	23907.952	0.88			
Income	106942.619	126838.731	0.84			
Number of extension visits	9915.109	30166.681	0.33			
Access to credit	-66783.386	135126.236	-0.49			

Source: Field Survey, 2025. Sig. at 10% (*), 5% (**), and 1% (***), the level of probability

5. Conclusion and Recommendations

Although the first implementation stage of the ATASP-1 initiative had finished, this study on the influence of excellent agronomic practices (GAP) on the output and income of cassava cooperative farmers in the Adani Omor Zone of ATASP-1 plainly revealed that the adoption of GAP under ATASP-1 is still unequal and mostly incomplete. Given that most technologies are concentrated on the trial phase rather than overall adoption, this indicated cautious experimentation instead of a continuous behavioral change. Capital-intensive and knowledge-intensive technologies like tractorization, recommended spacing, chemical weed management, and certified input sourcing have not been extensively accepted despite the widespread use of low-cost, well-known techniques directly linked to tangible advantages, such as timely planting, organic manure application, and timely harvesting. This trend points out persistent structural problems including risk aversion, technical illiteracy, labour shortages, and inadequate finance. It also emphasizes the need of seeing adoption as a gradual, several-step process rather than a one-time event as well as the fact that just exposure to better technology does not ensure its ongoing usage.

Moreover, the econometric data support the policy consequences of these results. The propensity score model, which examines how human capital and financial inclusion influence the uptake of technology, confirmed that age, education, farming expertise, and credit availability consistently affect adoption. Even after considering observable factors, the impact study finds that adoption results in statistically significant rises in income as well as cassava output. These developments meant that the seen differences between adopters and non-adopters reflect actual increases in output and income rather than just compositional contrasts. Even though its inconsistent adoption intensity limits its overall potential, the research discovered that the ATASP-1 technology is affordable. The extension of ATASP-1 advice services' dispersion of GAP packages helped program participants see gains in productivity and living conditions.

The study there makes the following recommendations to improve GAP impact:

1. The State Agricultural Development Programmes, and ATASP-1 extension agents should deepen extension support beyond awareness to hands-on technical mastery of several GAP components beyond evaluation or trial stages
2. Both government and non-governmental agencies should work to improve input supply systems and strengthen certified agro dealer networks to enhance farmers' access to improved planting materials
3. ATASP-1 extension advisory services should target younger and educated farmers as adoption champions, while supporting older farmers. Implementing different extension strategies will accelerate diffusion across all farmer categories

Disclosure of AI tool: The author(s) used generative AI to improve the clarity and grammar correctness. All content was reviewed and verified by the authors.

References

1. Abass AB, Awoyale W, Ogundapo A, Oluwasoga O, Nwaoliwe G, Oyelekan J, *et al*. Adoption of improved cassava varieties by processors is linked to processing characteristics and products' biophysical attributes. J Food Process Preserv. 2022;00:e16350. https://doi.org/10.1111/jfpp.16350
2. Acheampong PP, Addison M, Wongnaa CA. Assessment of the impact of adoption of improved cassava varieties on yields in Ghana: An endogenous switching approach. Cogent Econ Finance. 2022;10(1):2008587. https://doi.org/10.1080/23322039.2021.2008587
3. Adedigba AT. Impact of agricultural cooperative societies on cassava farmers' productivity in Ondo State, Nigeria [dissertation]. Akure: Federal University of Technology; 2019. Available from: https://api-

databank.ned.gov.ng/server/api/core/bitstreams/c18b40f2-6f50-494f-902a-ccd4ffae36cf/content

4. African Development Bank. Nigeria: Agricultural Transformation Agenda Support Program – Phase I (ATASP-1). 2025.
5. Caliendo M, Kopeinig S. Some practical guidance for the implementation of propensity score matching. J Econ Surv. 2008;22(1):31-72. https://doi.org/10.1111/j.1467-6419.2007.00527.x
6. CARA Development Foundation. Good agronomic practices for cassava high yield in Nigeria. 2024. Available from: https://cara.org.ng/good-agronomic-practices-for-cassava-yield-in-nigeria
7. Danso-Abbeam G, Baiyegunhi LJS. Adoption of Agrochemical Management Practices among Smallholder Cocoa Farmers in Ghana. Afr J Sci Technol Innov Dev. 2017;9:717-28. https://doi.org/10.1080/20421338.2017.1380358
8. Ekwere GE, Edem ID. Evaluation of Agricultural Credit Facility in Agricultural Production and Rural Development. Glob J Hum Soc Sci. 2014;14(3):18-26.
9. Food and Agriculture Organization of the United Nations. Nigeria at a glance. 2022. Available from: http://www.fao.org/nigeria/fao-in-nigeria/nigeria-at-a-glance/en/
10. Habtewold TM, Heshmati A. Impacts of improved agricultural technologies on food security and child nutrition in rural Ethiopia. Cogent Food Agric. 2023;9(2). https://doi.org/10.1080/23311932.2023.2276565
11. Iheyi P, Kim Y. Impact of Cassava Value Addition on Smallholder Farmers' Income: The Case of Kogi State, Nigeria. J Agric Life Environ Sci. 2025;37(2):113-22. https://doi.org/10.22698/jales.20250009
12. International Institute of Tropical Agriculture (IITA). Transforming African agriculture: Annual report 2018. Ibadan: IITA; 2018.
13. Isibor CA, Obianefo CA, Obiekwe JN, Nwankwo GN. The Effects of Livelihood Risk on Poverty Types among Smallholder Cassava Farmers in Anambra State, Nigeria. UNIZIK J Agric Econ Ext. 2024;1(1):199-212.
14. Mwebaze P, Macfadyen S, De Barro P, Bua A, Kalyebi A, Bayiyana I, *et al*. Adoption determinants of improved cassava varieties and intercropping among East and Central African smallholder farmers. J Agric Appl Econ Assoc. 2024;3(2):292-310. https://doi.org/10.1002/jaa2.112
15. Nwaobiala CU. Farmers' adoption of cassava agronomic practices and intercrop technologies in Abia and Imo States, Nigeria. J Agric Ext. 2018;22(2):91-101. https://doi.org/10.4314/jae.v22i2.8
16. Obianefo CA, Okoroji NO, Obiekwe NJ, Osuafor OO, Shah ZA. Economics of Good Agronomic Practices adoption by Rice Farmers in Value Chain Development Programme, Anambra State, Nigeria. Afr J Food Agric Nutr Dev. 2022;22(8):21308-30. https://doi.org/10.18697/ajfand.113.21425
17. Ojiako IA, Tarawali G, Okechukwu RU, Chianu J, Ezedinma C, Edet M. Profitability of cassava production: Comparing actual and potential returns on investment among smallholders in Southern Nigeria. J Biol Agric Healthc. 2018;8(16):45-56. Available from: https://www.iiste.org/Journals/index.php/JBAH/article/download/43910/45243
18. Olayemi-Adeoluwa OS, Ogunwale AB. Adoption of Improved Cassava Production Technologies among Cassava Farmers in Ogbomoso Agricultural Zone, Oyo State, Nigeria. Afr J Sustain Agric Dev. 2025;6(1):25-34. https://doi.org/10.5281/zenodo.15192081
19. Omoluabi JE, Ibitoye SJ. Cassava production and agricultural growth in Nigeria: Analysis of effects and forecast. GSC Adv Res Rev. 2024;21(01):037-46.
20. Osuafor OO, Obianefo CA, Dike AB. Food Security and Poverty Status of Cassava Processors in Awka North Local Government Area of Anambra State, Nigeria. Bangladesh J Agric Econ. 2020;41(1):1-16.
21. Oyekola IA, Oye AJ, Samuel F, Oyeyipo E, Arisukwu O, Iwelumor K, *et al*. Social, Economic, and Ecological Factors Influencing Cassava Farming in Nigerian Rural Context. Int J Soc Sci. 2021;10(04):295-303.
22. Rosenbaum PR, Rubin DB. The central role of the propensity score in observational studies for causal effects. Biometrika. 1983;70(1):41-55. https://doi.org/10.1093/biomet/70.1.41
23. Shackelford GE, Haddaway NR, Usieta HO, Pypers P, Petrovan SO, Sutherland WJ. Cassava farming practices and their agricultural and environmental impacts: A systematic map protocol. Environ Evid. 2018;7(30):1-9. https://doi.org/10.1186/s13750-018-0142-2
24. Su MM, Wall G, Wang Y, Jin M. Livelihood sustainability in a rural tourism destination - Hetu Town, Anhui Province, China. Tour Manag. 2019;71:272-81. https://doi.org/10.1016/j.tourman.2018.10.019
25. Su Y, Saikia U, Hay I. Impact of Perceived Livelihood Risk on Livelihood Strategies: A Case Study in Shiyang River Basin, China. Sustainability. 2019;11(12):3349. https://doi.org/10.3390/su11123349
26. Uchemba VU, Nenna GM, Obianefo CA. Adoption of Improved Cassava Production Technologies among Small-scale Farmers in Anambra State, Nigeria. J Plant Sci. 2021;9(4):119-27.
27. Willett W, Rockström J, Loken B, Springmann M, Lang T, Vermeulen S, *et al*. Food in the Anthropocene: the EAT–Lancet Commission on healthy diets from sustainable food systems. Lancet. 2019;393(10170):447-92.

How to Cite This Article

Obiekwe NJ, Obianefo CA, Okoroji NO, Ezeaputa CP, Nzeocha CC. Livelihood impact of good agronomic practice on the output and income of cassava cooperative farmers in Adani Omor Zone of ATASP-1. Int J Agric Sustain Farming. 2026;2(3):28-38