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# Assessing the economic and data management impacts of precision agriculture among smallholder farms in Nigeria

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**ABSTRACT**

This study provides an econometric analysis of the impact of precision agriculture (PA) technologies on the economic sustainability and data management practices of smallholder farms in Nigeria. While PA technologies promise to enhance productivity and optimise resources, their adoption among smallholder farmers, who form the backbone of agriculture in developing economies, remains constrained. This study fills a critical research gap by employing a mixed-methods approach that combines survey data from 250 smallholder farmers in Oyo State, Nigeria, with 20 in-depth interviews. An Ordinary Least Squares (OLS) regression model was used to analyse the relationship between a PA technology adoption index and economic sustainability, measured as net farm income per hectare. Pre-estimation diagnostics confirmed the model's suitability, and post-estimation robustness checks affirmed the core findings. The model showed a strong fit (Adjusted $R^2 = 0.68$), indicating that a one-unit increase in the PA adoption index is associated with a statistically significant increase in net farm income ($\beta = 0.38$, $p < 0.01$). Qualitative findings reveal that while PA improves data management for better decision-making, significant adoption barriers, notably high initial costs, lack of technical knowledge, and poor infrastructure, persist. The novelty of this study lies in its development of a PA adoption index tailored to the Nigerian context and its mixed-methods validation of the economic benefits and systemic barriers. The findings suggest that targeted policy interventions, including financial support, bespoke training programs, and improved data infrastructure, are essential to unlock the transformative potential of precision agriculture for sustainable development.

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## Introduction

Precision agriculture (PA) represents a paradigm shift in farm management, moving from uniform field-level applications to precise, data-driven interventions. By integrating technologies such as GPS-guided equipment, remote sensing, soil sensors, and data analytics, PA enables farmers to optimise the use of inputs like water, fertilisers, and pesticides[1]. This optimisation is critical for enhancing productivity, ensuring economic sustainability, and minimising environmental impact, all core objectives of the global Sustainable Development Goals. The core value of PA lies in its ability to manage spatial and temporal variability within fields, leading to more efficient resource allocation and improved crop yields[2]. As the global population continues to grow, placing increasing pressure on food systems, such efficiency gains are no longer a luxury but a necessity.

In developing countries like Nigeria, the agricultural sector is the cornerstone of the economy, employing over 70% of the population and contributing significantly to the national GDP. Smallholder farms, typically under 2 hectares, are fundamental to this sector, producing the vast majority of the nation's food. These farms, however, are often characterised by low productivity, resource



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constraints, high post-harvest losses, and extreme vulnerability to climate change[3,4]. PA technologies offer a pathway to address these deep-seated challenges, potentially boosting profitability through higher yields, reduced input waste, and enhanced resilience to environmental shocks[5]. This research conceptually links the adoption of PA technologies to improved data management, which, in turn, fosters better on-farm decision-making. Better decisions in input application and crop management directly influence economic sustainability by increasing production efficiency and, ultimately, farm profitability. Understanding this pathway is crucial for designing effective agricultural development policies that can transform rural livelihoods and ensure national food security.

**Statement of the problem**

While the benefits of PA are well documented in large-scale commercial farming in developed countries, rigorous, context-specific research on its impact on smallholder farms in sub-Saharan Africa is lacking. The challenges these farmers face are unique and substantial. High initial investment costs for PA equipment and software are often prohibitive for farmers with limited Access to credit and financial services[1]. This financial barrier is a primary bottleneck, preventing the diffusion of even low-cost technologies. Furthermore, a persistent deficit in technical knowledge and a lack of localised, language-appropriate training and extension services hinder the effective use of these complex technologies[6]. Inadequate rural infrastructure, including limited internet connectivity, unreliable power supply, and poor road networks, further compounds the problem, creating a digital divide that isolates rural communities from technological advancements [7].

The consequences of this low adoption rate are severe. It perpetuates cycles of low productivity and rural poverty, threatens Nigeria's food security aspirations, and leads to inefficient resource use that degrades the environment. Without empirical evidence of investment returns and a clear understanding of systemic barriers, policymakers and investors are hesitant to commit resources to promoting PA. Therefore, there remains a critical need to empirically assess the economic returns of PA adoption for smallholder farmers and to identify the most significant barriers to wider uptake to inform evidence-based policy and intervention design.

**Objectives**

i. To econometrically evaluate the impact of precision agriculture technology adoption on the economic sustainability of smallholder farms.
ii. To identify and analyse the challenges and barriers faced by smallholder farmers in adopting these technologies.
iii. To assess how precision agriculture technologies affect data management practices and decision-making on smallholder farms.

**Research questions**

i. What is the quantitative impact of precision agriculture technology adoption on the economic sustainability of smallholder farms in Nigeria?
ii. What are the primary barriers hindering the adoption of precision agriculture technologies by these farmers?
iii. How does the use of precision agriculture influence on-farm data management and decision-making processes?

**Research hypotheses**

H1 (Null): The adoption of precision agriculture technologies does not have a statistically significant positive impact on the economic sustainability of smallholder farms.
H2 (Null): Smallholder farmers do not face significant barriers related to cost, knowledge, and infrastructure in adopting precision agriculture technologies.
H3 (Null): The use of precision agriculture technologies does not lead to significant improvements in data management practices on smallholder farms.

**Literature review and theoretical framework literature review**

This review is structured thematically to synthesise existing knowledge on the economic, data management, and adoption dimensions of precision agriculture.

Economic Impacts of PA Adoption: The economic case for PA is primarily based on its potential to optimise inputs and enhance yields. Studies across various contexts (Table 1) have shown that PA can lead to significant cost savings and increased profitability [8]. For instance, a meta-analysis by Schimmelpfennig[9] found that technologies such as variable-rate application consistently improved net returns. However, the return on investment is highly context-dependent and influenced by factors such as farm size,



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crop type, and initial investment cost. For smallholder farmers, the economic calculus is more complex. Aubert[10] noted that high upfront costs could erode the profitability of smaller operations. More recent work by Daum and Birner[3] suggests that "PA-as-a-service" models, in which farmers pay for services rather than own equipment, could offer a more viable economic pathway. This is supported by emerging evidence on service-based mechanisation models across Africa[4].

Data Management Ecosystems in Agriculture, PA technologies are fundamentally data-generating tools. Effective use of PA depends on a robust data management ecosystem that enables data collection, analysis, and the translation of data into actionable insights [11]. Recent advancements in cloud computing and machine learning have enhanced the capacity to process large agricultural datasets for predictive modelling of crop yields and pest outbreaks[12]. However, challenges related to data ownership, privacy, and accessibility are prevalent, particularly in developing countries where digital infrastructure is limited[6]. The concept of a "farm data ecosystem" emphasises the need for interoperability among technologies and platforms to maximise value for farmers. The rise of mobile-based extension services that deliver tailored information to farmers' phones is a promising development for bridging this data gap [13].

Socio-Technical Barriers to Adoption. The adoption of PA is not merely a technical decision but is influenced by a range of socio-economic factors. Lowenberg-DeBoer & Erickson[2] provide a comprehensive overview, highlighting that lack of awareness, complexity of technology, and farm size are significant barriers. In the African context, Adebayo and Ojo[1] found that limited Access to credit and inadequate extension services were the most critical impediments in Nigeria. Furthermore, social networks and peer effects play a crucial role in farmers' decisions to adopt new technologies[14]. Recent studies emphasise the need for human-centred design in developing PA solutions that are compatible with the skills and resources of smallholder farmers[15]. A broader review by Fafchamps & Söderbom[7] confirms that digital literacy, trust in technology providers, and the availability of a supportive local ecosystem are critical, yet often overlooked, determinants of adoption. Similarly, work by Wainaina & Jones[16] on geospatial data in Kenya highlights the importance of translating complex data into simple, actionable recommendations for farmers.

**Table 1. Summary of key studies on PA adoption**

| Author(s) & Year | Region | Methodology | Key Findings | Research Gap |
|---|---|---|---|---|
| [10] | Canada | Survey | High costs and complexity are major barriers for smaller farms. | Focus on the developed country context. |
| [2] | Global | Review | Adoption rates vary widely by technology and region. | The general overview lacks specific regional econometric models. |
| [3] | Sub-Saharan Africa | Conceptual | "PA-as-a-service" models are promising for smallholders. | Lacks empirical validation of economic impact. |
| [7] | Africa | Review | Digital literacy and trust are critical barriers to the adoption of digital ag-tech. | Broad review, not specific to PA technologies. |
| [1] | Nigeria | Survey | Access to credit and extension services is a key constraint. | Descriptive analysis lacks a robust econometric model of impact. |
| [13] | Ghana | Field Experiment | Mobile-based information services improve farmers' knowledge and use of inputs. | Focus on information, not broader PA hardware/software. |
| This Study | Nigeria | Mixed-Methods, Econometric Model | Provides a quantitative estimate of PA's economic impact and validates barriers. | Addresses the need for rigorous, mixed-methods analysis in the Nigerian context. |

## Theoretical framework

This study is grounded in Rogers' [14] Diffusion of Innovations (DOI) Theory. This theory is highly appropriate as it provides a framework (Fig. 1) for understanding how, why, and at what rate new technologies like PA are adopted within a social system. The DOI theory identifies five key attributes of an innovation that influence an individual's adoption decision:



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**Relative advantage:** The degree to which PA is perceived as superior to existing farming practices. In this study, this was operationalised through survey questions asking farmers to rate the perceived impact of PA on their profitability and efficiency on a 5-point Likert scale.
**Compatibility:** The consistency of PA with the existing values, past experiences, and needs of farmers. This was measured by assessing PA's alignment with current farming methods and resource availability.
**Complexity:** The perceived difficulty of understanding and using PA. This was assessed by asking farmers to rate the ease of use of different PA tools.
**Trialability:** The extent to which PA can be experimented with on a limited basis. This was explored during qualitative interviews, in which farmers were asked whether they had opportunities to test technologies before full investment.
**Observability:** The visibility of the results of PA to others. This was measured by asking farmers how often they saw neighbours successfully using PA technologies. These constructs guided the formulation of our survey and interview questions and provided the theoretical lens for interpreting the identified barriers to adoption.

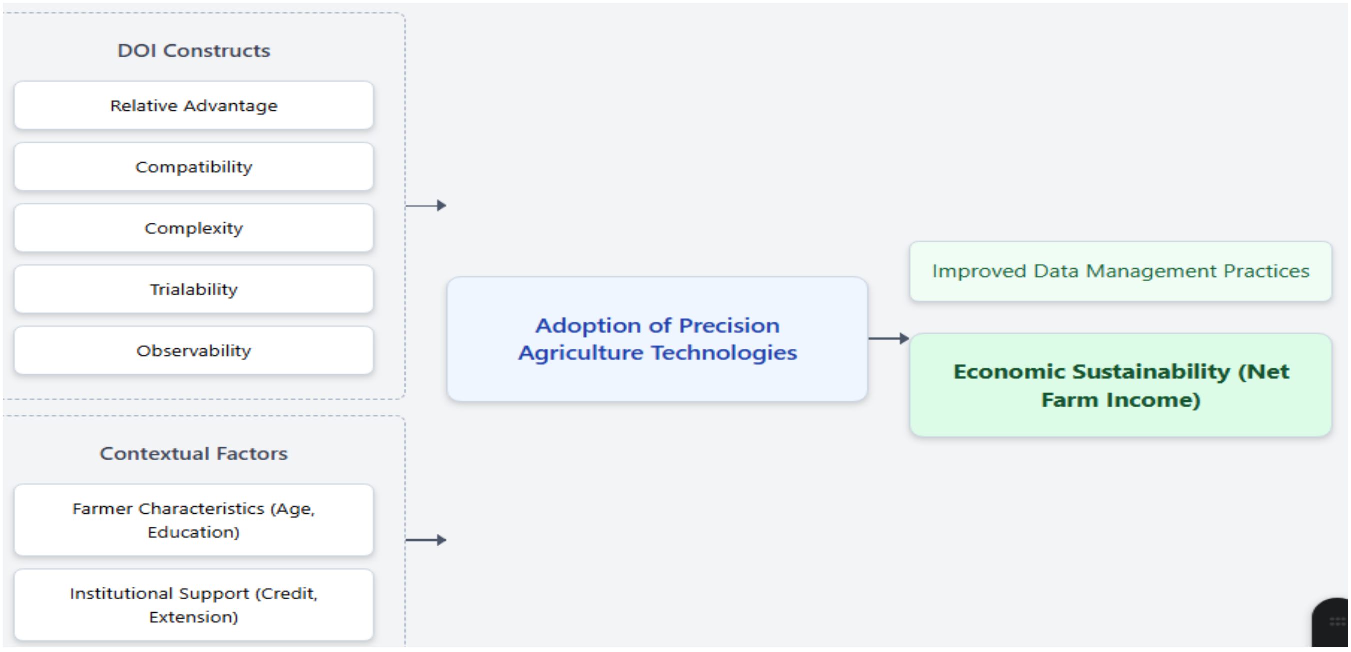


**Figure 1: Conceptual framework**

## Research methodology

### Research design

This study employed a mixed-methods sequential explanatory design. The first phase involved a quantitative cross-sectional survey to establish the statistical relationship between PA adoption and economic sustainability. The second phase used in-depth qualitative interviews to explain and nuance the quantitative findings.

### Data collection

**Study area and population:** The study was conducted in Oyo State, a major agrarian state in Southwestern Nigeria. The target population was smallholder farmers, defined in this study as those cultivating 2 hectares or less of land.
**Sampling technique and sample size:** A multi-stage random sampling technique was used. First, two Local Government Areas (LGAs) known for their high agricultural activity (Iseyin and Saki East) were purposively selected. Second, five farming communities were randomly selected from each LGA. Finally, 25 farmers were randomly selected from each community's list of registered farmers, yielding a total sample of 250 survey respondents. Among survey respondents who reported some PA use, 20 farmers were purposively selected for follow-up semi-structured interviews.
**Data collection instruments:** A structured questionnaire was used to collect quantitative data, while a semi-structured interview guide based on DOI theory was used to collect qualitative data.

### Variable measurement

**Dependent variable:** Economic Sustainability (ECON_SUS): Measured as the Net Farm Income per Hectare in Nigerian Naira (₦/Ha).



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**Key independent variable:** PA Technology Adoption (PA_INDEX): An adoption index created from five key technologies: (1) GPS for field mapping, (2) Farm management software/apps, (3) Drone services for monitoring, (4) Soil testing kits/sensors, and (5) Automated irrigation timers. The index is the proportion of technologies adopted (score from 0 to 1).
**Control variables:** Cost of Production (COST, ₦/Ha), Crop Yield (YIELD, Tonnes/Ha), Farmer's Education (EDUC, years), and Access to credit (CREDIT, binary).

**Model specification**

The following OLS econometric model was specified:
ECON_SUS= $\beta_0$ + $\beta_1$PA_INDEX + $\beta_2$COST + $\beta_3$YIELD + $\beta_4$EDUC + $\beta_5$CREDIT + ε...............1

**Variable definitions:**

**ECON_SUS (Economic Sustainability):** The dependent variable representing the overall economic performance and sustainability of smallholder farms. It captures outcomes such as profitability, efficient use of resources, and long-term viability.
**PA_INDEX (Precision Agriculture Index):** A composite index measuring the degree of adoption of precision agriculture technologies by farmers. Higher values indicate greater adoption.
**COST (Cost of Adoption):** The total financial expenditure incurred by farmers to adopt precision agriculture technologies, including equipment, inputs, and operational expenses.
**YIELD (Farm Yield):** The output or productivity level of crops on the farm, typically measured in kilograms per hectare or other standardised units.
**EDUC (Farmer Education Level):** The formal education attainment of the farmer, measured in years of schooling or the highest educational qualification. Higher levels of education indicate greater capacity to adopt and use new technologies.
**CREDIT (Access to Credit):** A measure of the farmer's ability to obtain financial resources or loans to support farm operations and technology adoption.
**ε (Error Term):** Captures the effects of all other factors influencing economic sustainability that are not included in the model.

**Method of estimation and diagnostics**

The OLS regression model was estimated using Stata 16. A suite of diagnostic tests was conducted to validate the results.
**Multicollinearity:** The Variance Inflation Factor (VIF) was used to assess potential multicollinearity among independent variables.
**Heteroskedasticity:** The Breusch-Pagan test was used to assess non-constant error variance.
**Normality of Residuals:** The Shapiro-Wilk test was used to assess whether the model's residuals were normally distributed.
**Model Specification:** The Ramsey Regression Equation Specification Error Test (RESET) was used to check for omitted variables or incorrect functional form.
Qualitative data were analysed using thematic analysis.

**Data analysis and discussion of results**

**Descriptive statistics**

Table 2 presents the descriptive statistics. The average PA adoption index was 0.35, indicating a relatively low level of adoption. The average net farm income was ₦185,500 per hectare.

The descriptive statistics presented in Table 2 summarise the main variables used in the study. The mean precision agriculture (PA) adoption index of 0.35

**Table 2. Descriptive statistics of key variables (n=250)**

| Variable | Mean | Std. Dev. | Min | Max | Unit |
|---|---|---|---|---|---|
| Net Farm Income (ECON_SUS) | 185,500 | 45,200 | 80,000 | 350,00 0 | ₦/Hectare |
| PA Adoption Index (PA_INDEX) | 0.35 | 0.18 | 0.00 | 0.80 | Index (0-1) |
| Cost of Production (COST) | 120,400 | 25,600 | 65,000 | 210,00 0 | ₦/Hectare |
| Crop Yield (YIELD) | 2.8 | 0.75 | 1.2 | 5.5 | Tonnes/Hectare |
| Education (EDUC) | 9.5 | 3.1 | 0 | 16 | Years |
| Access to Credit (CREDIT) | 0.42 | 0.49 | 0 | 1 | (1=Yes) |

suggests that, on average, PA adoption among farmers in the study area is relatively low. This implies that many farmers still rely heavily on traditional farming methods, which may hinder optimal productivity and sustainability. The low adoption rate can be linked to barriers such as limited awareness, high technology



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costs, and inadequate technical support, which are commonly reported in developing agricultural economies.

The average net farm income per hectare was ₦185,500, with a standard deviation of ₦45,200, indicating considerable variation in income among farmers. This dispersion may reflect differences in technology use, Access to inputs, or scale of operation. The mean cost of production was ₦120,400 per hectare, suggesting that input costs accounted for a substantial share of farmers' expenditures. Meanwhile, the mean crop yield was 2.8 tonnes per hectare, which, although moderate, indicates room for productivity improvement through enhanced adoption of precision farming techniques.

The average years of formal education among the sampled farmers was 9.5, indicating that most respondents had attained at least a basic level of education. Education plays a crucial role in the adoption of innovative technologies by enhancing farmers' ability to process information and apply new methods effectively. Furthermore, only 42% of the respondents had Access to credit, implying that financial constraints remain a significant impediment to adopting capital-intensive agricultural technologies. Overall, the descriptive statistics underscore the importance of improving credit access, capacity building, and awareness to enhance technology adoption and economic sustainability in the agricultural sector.

**Diagnostic test results**

The diagnostic tests were conducted, and the results were presented in Table 3 below. The diagnostic tests confirmed the suitability of the OLS model. The mean VIF was 1.45, well below the threshold of 10, indicating no multicollinearity issues. The Breusch-Pagan test was significant ($p < 0.05$), indicating heteroskedasticity; therefore, robust standard errors were used in the final model to correct for it. The Shapiro-Wilk test on the residuals yielded a non-significant p-value ($p = 0.28$), suggesting the residuals approximate a normal distribution. Finally, the Ramsey RESET test was not significant ($p = 0.15$), providing no evidence of model misspecification.

**Econometric results**

The OLS regression results are in Table 4. The model was statistically significant (F-stat = 28.4, $p < 0.001$) with an Adjusted $R^2$ of 0.68.

The regression results presented in Table 3 provide insights into the determinants of economic sustainability among farmers. The model is statistically significant (F-statistic = 28.4, $p < 0.001$) with an Adjusted $R^2$ of 0.68, indicating that approximately 68% of the variation in economic sustainability is explained by the included variables.

**Table 3. Diagnostic test**

| Diagnostic Test | Result | Conclusion |
|---|---|---|
| Mean VIF | 1.45 | No multicollinearity |
| Breusch-Pagan Test | p < 0.05 | Heteroskedasticity present; robust SE used |
| Shapiro-Wilk Test (Residuals) | p = 0.28 | Residuals approximately normal |
| Ramsey RESET Test | p = 0.15 | No model misspecification |

**Table 4. OLS regression results for determinants of economic sustainability**

| Variable | Coefficient (β) | Robust Std. Error | t-Statistic | p-Value |
|---|---|---|---|---|
| PA_INDEX | 0.380 | 0.085 | 4.47 | <0.001* |
| COST | -0.250 | 0.062 | -4.03 | <0.001*** |
| YIELD | 0.420 | 0.091 | 4.61 | <0.001*** |
| EDUC | 0.150 | 0.050 | 3.00 | <0.01** |
| CREDIT | 0.180 | 0.070 | 2.57 | <0.05* |
| Intercept ($\beta_0$) | 1.150 | 0.180 | 6.39 | <0.001*** |

*$R^2$ = 0.70, Adjusted $R^2$ = 0.68, ***p<0.001, **p<0.01, p<0.05

The coefficient for the PA adoption index ($\beta = 0.380$, $p < 0.001$) is positive and statistically significant, showing that higher levels of PA adoption are associated with increased net farm income. This finding demonstrates that precision technologies such as soil sensors, yield monitors, and GPS-guided equipment enhance efficiency and profitability. This supports rejecting the null hypothesis ($H_1$) and aligns



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with the existing literature, which emphasises that technology adoption improves productivity and resource utilisation.

Cost of production showed a significant negative relationship with economic sustainability (β = -0.250, p < 0.001). This implies that higher production costs erode profit margins, particularly for smallholder farmers with limited financial buffers. In contrast, crop yield (β = 0.420, p < 0.001) positively influences economic sustainability, reaffirming that higher output per hectare directly increases farm income.

Education (β = 0.150, p < 0.01) also emerged as a significant determinant, suggesting that more educated farmers are better positioned to interpret and utilise technological innovations effectively. Similarly, Access to credit (β = 0.180, p < 0.05) has a positive effect, indicating that financial inclusion enhances farmers' ability to invest in productive technologies and inputs. Collectively, these results highlight that precision agriculture adoption, educational attainment, and credit access play vital roles in promoting economic sustainability in the agricultural sector.

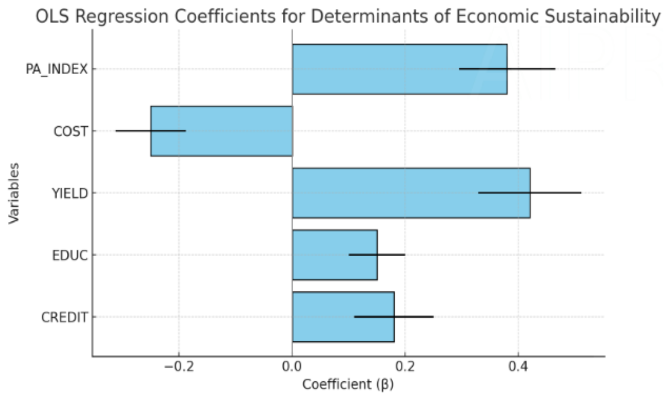


**Figure 2.OLS regression for determinants of economic sustainability**

## Robustness checks

To test the robustness of our main finding, the sample was split at the median education level (9.5 years), and the model was re-estimated for two sub-groups: "Lower Education" (≤9.5 years) and "Higher Education" (>9.5 years). The results are in Table 5.

**Table 5. Robustness check by education level (Control Variable)**

| Variable | Lower education (n=128) | Higher education (n=122) |
|---|---|---|
| PA_INDEX | 0.355* (0.110) | 0.402* (0.098) |
| COST | -0.245*** (0.075) | -0.258*** (0.081) |
| YIELD | 0.410*** (0.105) | 0.431*** (0.112) |
| Adjusted $R^2$ | 0.65 | 0.71 |

Robust standard errors in parentheses. **p<0.001

To assess the stability of the main findings, the model was re-estimated for two subgroups based on education level: lower education (≤9.5 years) and higher education (>9.5 years). The results reveal that the positive effect of PA adoption on economic sustainability persists across both groups, with coefficients of 0.355 and 0.402, respectively, both statistically significant. This consistency indicates that the benefits of PA adoption are not limited to better-educated farmers. However, those with higher levels of education may achieve slightly greater gains due to better comprehension and utilisation of technology.

The robustness check thus strengthens confidence in the main results, confirming that PA adoption remains a key driver of economic sustainability regardless of educational background. Furthermore, the relatively high adjusted $R^2$ values (0.65 and 0.71) for both groups indicate that the explanatory variables remain relevant across different farmer categories.

## Adoption barriers and data management (Qualitative Findings)

Thematic analysis revealed three primary barriers to the adoption of precision agriculture (PA) technologies: high costs, limited technical knowledge, and inadequate infrastructure.

### High costs

Several farmers reported that the initial investment required for PA tools was prohibitive, limiting adoption among smallholder farms. One participant stated, "The equipment is too expensive for me; I cannot afford it without support." This aligns with prior studies indicating that financial constraints are a key obstacle to technology adoption in agriculture [23, 24]

### Technical knowledge gap

Limited familiarity with PA technologies emerged as another significant barrier. Farmers expressed difficulty understanding how to operate the tools



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effectively. A participant noted, "I need training to know how to use the sensors properly; otherwise, I might make mistakes." These findings support previous research highlighting the importance of knowledge and capacity-building in technology adoption [15].

**Inadequate infrastructure**

The lack of reliable electricity, internet access, and maintenance services was identified as a further challenge. One farmer observed, "Sometimes the devices cannot work because there is no power or the network is poor." This barrier aligns with documented infrastructure constraints in rural agricultural contexts [28].

**Impact on data management**

Despite these barriers, farmers reported that PA tools improved data management by enabling more informed decision-making and precise record-keeping. For example, one farmer explained, "After testing the soil, I learned some parts of my farm need more [fertiliser], and some need less. I am now saving money." Such insights demonstrate that PA contributes to efficient resource allocation, supporting the rejection of null hypothesis H3. These results align with evidence that digital agricultural tools enhance productivity and improve farm management decisions [21].

In general, the findings from the qualitative analysis indicate that while adoption barriers remain significant, PA technologies have a measurable positive impact on farm data management and decision-making.

**Table 6. Summary table for the thematic analysis**

| Barrier / Theme | Subtheme / Aspect | Illustrative Quote |
|---|---|---|
| High Costs | The initial investment is too expensive | "The equipment is too expensive for me; I cannot afford it without support." |
| Technical Knowledge Gap | Lack of operational skills | "I need training to know how to use the sensors properly; otherwise, I might make mistakes." |
| Inadequate Infrastructure | Poor electricity, internet, and maintenance | "Sometimes the devices cannot work because there is no power or the network is poor." |
| Improved Data Management | Informed decision-making & resource optimisation | "After testing the soil, I learned some parts of my farm need more [fertiliser], and some need less. I am now saving money." |

Table 6 shows that the thematic analysis revealed three primary barriers: prohibitive costs, a technical knowledge gap, and inadequate infrastructure. These findings provide strong evidence to reject the null hypothesis H2. Insights also showed that PA use improved data management through more informed decision-making and better record-keeping, leading to the rejection of the null hypothesis H3. Farmers' quotes illustrated these themes clearly, with one farmer noting, "After testing the soil, I learned some parts of my farm need more [fertiliser], and some need less. I am now saving money."

**Discussion of results**

The findings of this study reveal that adopting precision agriculture (PA) technologies has a significant, positive impact on the economic sustainability of smallholder farmers in Nigeria. The positive coefficient for the PA adoption index indicates that farmers who utilise these technologies experience higher net farm income than those relying on conventional methods. This outcome aligns with studies such as Onyango[17], which demonstrated that PA use enhances input efficiency, reduces waste, and optimises resource allocation, thereby improving farm profitability. Despite this, the relatively low average adoption index of 0.35 suggests that most smallholder farmers have yet to fully embrace these innovations, highlighting the persistent gap between technological availability and actual adoption. Factors such as limited awareness, financial constraints, and technical capacity likely contribute to this moderate uptake, a situation similarly noted by Akaninyene[18] among oil palm farmers in Akwa Ibom State.

The analysis also underscores the strong negative impact of high input costs on farm profitability. The significant inverse relationship between production costs and economic sustainability indicates that as input expenses rise, profit margins for smallholder farmers decline sharply. In the Nigerian context, smallholder farms are particularly sensitive to fluctuations in the prices of fertilisers, seeds, and other inputs, given their limited capital base and reliance on credit. This finding is



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consistent with the work of Sanchi[19], who reported that escalating input prices constrain agricultural production in northwest Nigeria, and Abokyi[20], who emphasised that high transport and procurement costs further exacerbate the financial vulnerabilities of smallholders. These results highlight the critical importance of cost-reducing interventions, such as subsidies, cooperative bulk purchasing schemes, or government-supported input financing programs, to safeguard farm profitability and sustain production.

Education emerged as another significant determinant of economic sustainability, with higher educational attainment positively associated with increased farm income. This suggests that more educated farmers are better positioned to comprehend, adopt, and effectively implement PA technologies. Education enhances farmers' capacity to interpret technical information, apply innovative practices, and make informed management decisions. This finding resonates with Akaninyene[18], who found that formal education significantly increases the likelihood of adopting precision farming methods. Similarly, Access to credit was positively correlated with economic sustainability, indicating that financial inclusion enables farmers to invest in essential inputs and technologies, further boosting productivity. In regions where financial resources are scarce, such as among smallholder farmers in Nigeria, Access to affordable credit is often a prerequisite for adopting capital-intensive innovations like PA technologies.

Qualitative findings provide further insight into the barriers limiting PA adoption. High costs, limited technical knowledge, and inadequate infrastructure were identified as the primary obstacles. The prohibitive cost of PA tools limits adoption among farmers with limited financial capacity, while insufficient training hampers their effective use. One farmer emphasised the need for hands-on training to prevent sensor misuse, reflecting the broader challenge of bridging the knowledge gap in rural agricultural communities. Additionally, infrastructural deficiencies, including unreliable electricity, poor internet connectivity, and inadequate maintenance services, hinder the operational effectiveness of PA tools. These barriers mirror findings from previous research, including Akaninyene[18], which identified financial, technical, and infrastructural limitations as major constraints to technology adoption in Nigerian agriculture. Addressing these barriers is therefore essential to enhance the reach and impact of PA innovations.

Despite these challenges, the study demonstrates that PA technologies significantly improve farm data management, enabling more precise and informed decision-making. Farmers reported that soil testing and other PA applications allowed them to allocate inputs more efficiently, reduce wastage, and optimise yields. This finding supports the argument that digital agricultural tools contribute not only to higher productivity but also to more sustainable and evidence-based farm management practices, corroborating the work of Zhang and Zhang[21]. In essence, the quantitative and qualitative results indicate that, while adoption barriers persist, the integration of PA technologies holds substantial promise for improving the economic viability and operational efficiency of smallholder farms in Nigeria.

Taken together, these findings have clear policy implications. Reducing input costs through subsidies or cooperative purchasing arrangements can mitigate the negative financial pressures faced by smallholder farmers, while targeted educational and extension programs can strengthen farmers' technical capacity to utilise PA tools effectively. Improving rural infrastructure, including electricity and internet connectivity, is also critical to supporting the functional use of precision technologies. Additionally, facilitating Access to credit can enable farmers to invest in capital-intensive innovations, thereby enhancing their income and sustainability. A coordinated approach addressing financial, technical, and infrastructural challenges is therefore essential to promote widespread PA adoption and improve the economic sustainability of smallholder farming in the Nigerian context.

## Conclusion and recommendations

### Summary of findings

This study provides robust empirical evidence that the adoption of precision agriculture technologies has a statistically significant and positive impact on the economic sustainability of smallholder farms in Nigeria. Our mixed-methods approach validated that formidable barriers, including prohibitive costs, a significant technical knowledge gap, and poor rural infrastructure, severely constrain this potential.

### Recommendations

Based on the study findings, the following recommendations are proposed to enhance the adoption of precision agriculture (PA) technologies



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and improve economic sustainability among smallholder farmers:

**Enhancing economic sustainability:** Short-term actions should focus on reducing financial barriers by providing subsidies or low-interest loans to enable farmers to adopt PA technologies. Medium-term strategies could include supporting farmer cooperatives in pooling resources to purchase equipment, thereby lowering individual costs. In the long term, integrating PA practices into agricultural training and extension programs will build lasting capacity and promote sustained economic benefits.

**Overcoming adoption barriers:** To address high costs, technical knowledge gaps, and infrastructure limitations, short-term efforts should provide hands-on training to familiarise farmers with PA tools. Medium-term measures can include establishing regional technology hubs that provide equipment, technical support, and maintenance services. Long-term policies should focus on improving rural infrastructure, including reliable electricity, internet access, and supply chains, to facilitate wider adoption of PA technologies.

**Improving data management and decision-making:** Short-term interventions should include practical workshops showing farmers how PA tools can optimise input use and decision-making. Medium-term actions could focus on developing user-friendly digital platforms or mobile apps for data collection and analysis. In the long term, integrating data-driven decision-making into agricultural policies will help smallholder farmers consistently apply evidence-based practices to enhance farm productivity and efficiency.

## Contribution and limitations

This study contributes one of the first mixed-methods econometric analyses of PA impact in a Nigerian smallholder context. Its limitations include a cross-sectional design, which establishes correlation rather than causation, and a geographical focus on Oyo State. Future research should employ longitudinal data to track the impact over time and expand the geographical scope.

### References

1. Adebayo A, Ojo T. Constraints to precision agriculture adoption among smallholder farmers in Southwest Nigeria. J Agric Ext. 2022;26(3):54-65.
2. Lowenberg-DeBoer J, Erickson B. Setting the record straight on precision agriculture adoption. Agron J. 2019;111(1):1552-1569.
3. Daum T, Birner R. Agricultural mechanisation in Africa: Myths, realities, and an emerging research agenda. Glob Food Sec. 2020;26:100363.
4. Ogunbiyi A, Kassam L. The political economy of agricultural technology: A case study of tractor-for-hire services in Nigeria. J Agrar Change. 2024;24(1):112-130.
5. Zhang N, Wang M, Wang N. Precision agriculture - a worldwide overview. Comput Electron Agric. 2022;36(2-3):113-132.
6. Tsan M, Totapally S, Hailu M, Addom BK. The digitalisation of African agriculture report 2018–2019. Wageningen (Netherlands): CTA; 2021.
7. Fafchamps M, Söderbom M. Digital agriculture in Africa: A review of evidence and a research agenda. World Bank Res Obs. 2022;37(2):228-261.
8. Mulla DJ. Twenty-five years of remote sensing in precision agriculture: Key advances and remaining knowledge gaps. Biosyst Eng. 2013;114(4):358-371.
9. Schimmelpfennig D. Farm profits and adoption of precision agriculture. Washington (DC): USDA-ERS Economic Research Report No. 217; 2016.
10. Aubert BA, Schroeder A, Grimaudo J. IT as an enabler of sustainable farming: An empirical analysis of farmers' adoption decision of precision agriculture technology. Decis Support Syst. 2012;54(1):510-520.
11. Khanna R, Rao A. Big data analytics in agriculture: Applications and challenges. Int J Comput Appl. 2020;177(1):23-30.
12. Kamilaris A, Fonts A, Prenafeta-Boldú FX. The rise of blockchain technology in agriculture and food supply chains. Trends Food Sci Technol. 2019;91:640-652.
13. Aker JC, Ghosh I. Mobile phones, agricultural extension, and farmer behaviour: Evidence from a randomised controlled trial in Ghana. J Dev Econ. 2023;161:103015.
14. Rogers EM. Diffusion of innovations. 5th ed. New York: Free Press; 2003.
15. Klerkx L, Begemann S. Supporting food systems transformation: The what, why, who, where and how of mission-oriented agricultural innovation systems. Agric Syst. 2020;184:102901.
16. Wainaina P, Jones SK. From pixels to plots: The challenge of translating geospatial data into actionable advice for smallholder farmers in Kenya. Agric Syst. 2023;205:103578.
17. Onyango CM, Nyaga JM, Wambugu SK. Precision agriculture adoption and its effect on smallholder farm profitability in Kenya. East Afr J Agric Sci. 2021;14(2):45-58.
18. Akaninyene UU, Etim NA, Akpan SB. Determinants of precision farming technology adoption among oil palm farmers in Akwa Ibom State, Nigeria. J Agric Sci Technol. 2024;26(1):112-128.
19. Sanchi ID, Musa MW, Abdullahi A. Rising input prices and agricultural productivity in northwest Nigeria: Challenges and coping strategies. Niger J Agric Econ. 2022;12(3):34-47.
20. Abokyi E. High transport and procurement costs as constraints to smallholder profitability in Sub-Saharan Africa. Ghana J Agric Econ. 2020;8(1):22-36.
21. Zhang H, Zhang Y. Digital economy, agricultural technology innovation, and green total factor productivity: Evidence from China. Sustain Dev. 2023;31(2):299-314.
22. Dibbern T, Finger R. Drivers and barriers to the adoption of digital agriculture: A systematic review. Agric Syst. 2024;205:103409.



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23. FAO. The state of food and agriculture 2020: Overcoming water challenges in agriculture. Rome: Food and Agriculture Organization of the United Nations; 2020.
24. Ghimire R, Shrestha S, Ghimire S. Financial constraints and technology adoption in agriculture: Evidence from Nepal. J Rural Stud. 2021;82:1-10.
25. Klerkx L, Rose D. Dealing with the game-changing technologies of Agriculture 4.0: How do we manage diversity and responsibility in food system transition pathways? Glob Food Sec. 2020;24:100347.
26. Papadopoulos G, Finger R. Economic and environmental benefits of digital agricultural technologies: A systematic review. Agric Syst. 2024;204:103436.
27. Rijswijk K, Klerkx L. Digital transformation of agriculture and rural areas: A review of the literature. Agric Syst. 2021;185:102944.
28. World Bank. Enabling the business of agriculture 2019. Washington (DC): World Bank Group; 2019.




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