



Economic viability and adoption barriers of precision agriculture among smallholder farmers

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Abstract

Background: Precision Agriculture (PA) technologies offer immense potential for optimizing input use and increasing farm profitability. However, adoption among smallholder farmers in developing regions remains disproportionately low.

Objective: This study investigates the economic viability of basic PA technologies (soil sensors and drone imagery) and identifies the primary barriers to their adoption by smallholder farmers.

Method: This study uses a simulated dataset created for academic training purposes. A simulated survey of 200 smallholder farmers was generated. A Cost-Benefit Analysis (CBA) was conducted to determine profitability, and a binary Logit regression model was estimated using STATA to identify socio-economic barriers to adoption.

Key Results: The CBA revealed a positive Net Present Value (NPV) and a Benefit-Cost Ratio (BCR) of 1.85 for PA adopters, indicating economic viability. However, the Logit model identified high initial capital costs ($p < 0.01$) and lack of technical training ($p < 0.05$) as significant deterrents to adoption.

Conclusion: While PA is economically viable for smallholders, systematic barriers related to capital and knowledge severely restrict uptake, necessitating targeted policy interventions.

Keywords: Precision agriculture, smallholder farmers, economic viability, adoption barriers, agribusiness, cost-benefit analysis

Introduction

The global agricultural sector is undergoing a technological revolution, commonly referred to as Precision Agriculture (PA). PA involves the application of information and communication technologies (ICT), remote sensing, and data analytics to manage spatial and temporal variability within agricultural fields^[1]. By optimizing the application of seeds, fertilizers, and water based on site-specific conditions, PA aims to increase agronomic efficiency, reduce environmental externalities (such as fertilizer runoff), and ultimately enhance farm profitability^[2]. Technologies ranging from Global Navigation Satellite Systems (GNSS) and yield monitors to unmanned aerial vehicles (UAVs or drones) and soil moisture sensors form the backbone of this modern agronomic approach^[3].

Historically, the development and deployment of PA technologies have been concentrated in developed countries, particularly in large-scale, mechanized farming systems in North America, Australia, and Europe^[4]. In these contexts, the economies of scale allow farmers to easily amortize the high fixed costs of PA equipment over thousands of hectares. However, a critical problem arises when attempting to transfer these technologies to developing nations, where the agricultural landscape is dominated by smallholder farmers^[5]. Smallholders, typically farming less than two hectares, face a completely different set of agronomic and economic realities, including fragmented landholdings, limited access to credit, and high exposure to climate risks^[6].

Despite the proven agronomic benefits of micro-dosing and site-specific management—which conceptually align perfectly with the resource-constrained reality of smallholders—the adoption of PA in developing regions remains abysmally low^[7]. This creates a perplexing paradox: the farmers who could potentially gain the highest

marginal returns from saving inputs (like fertilizers) are the least likely to adopt the technologies designed to achieve those savings^[8].

The problem is multifaceted. While some literature points to the obvious high upfront costs of commercial PA equipment, other studies suggest that the barriers are more complex, involving a lack of digital literacy, absence of localized technical support, and poorly defined land tenure systems that discourage long-term investments in soil health^[9]. Furthermore, there is a distinct lack of rigorous empirical evidence demonstrating whether basic, scaled-down PA technologies (e.g., low-cost drone mapping or handheld soil sensors) are actually economically viable for smallholders under real-world conditions^[10]. Without concrete economic metrics, policymakers cannot design effective subsidy programs or extension services.

Therefore, the primary objective of this study is to evaluate the economic viability of basic PA technologies for smallholder farmers and to identify the critical socio-economic barriers hindering their adoption. The specific objectives are: ^[1] to conduct a Cost-Benefit Analysis (CBA) of PA adoption on smallholder plots, and ^[2] to employ a discrete choice model to quantify the impact of various socio-economic factors on the probability of PA adoption. The hypothesis is that while PA adoption is economically viable (positive net returns), high capital costs and a lack of training are the primary impediments preventing widespread uptake among smallholders.

Literature Review

The theoretical framework guiding this research integrates two distinct economic theories: the Profit Maximization Theory (which underpins Cost-Benefit Analysis) and the Diffusion of Innovations Theory (which explains the adoption behavior of individuals)^[11]. According to profit

maximization, a rational farmer will adopt a new technology if the discounted present value of the expected future benefits exceeds the present value of the costs associated with adoption [12]. However, Diffusion of Innovations theory, pioneered by Rogers (2003), posits that adoption is not purely economic; it is heavily influenced by perceived attributes of the innovation—such as its relative advantage, complexity, trialability, and observability—as well as the characteristics of the adopter and the social system [13].

Extensive literature exists on the economic viability of PA in developed contexts. Schimmelpfennig (2016) reviewed PA adoption in the United States and found that yield monitors and variable-rate technology (VRT) significantly increased net returns for large grain farms, primarily by reducing fertilizer and pesticide costs by 5-15% [14]. Similarly, Lambert *et al.* (2015) demonstrated that the adoption of precision guidance systems reduced input overlap and saved farmers roughly \$20 per hectare [15]. These studies unequivocally confirm the profitability of PA at scale.

However, the literature on PA economics for smallholders is sparse and highly contextual. Lowenberg-DeBoer and Aghib (2019) noted that the "fit" of PA for smallholders depends entirely on whether the technology can be scaled down, shared, or provided as a service (e.g., "drone-as-a-service") to overcome the barrier of small farm sizes [16]. Studies in India and Kenya have shown that when smallholders utilize localized soil testing and micro-dosing, yield increases of 20-30% are achievable, suggesting high relative advantages [17].

Regarding adoption barriers, the literature identifies several consistent themes. Kassie *et al.* (2013) highlighted that lack of access to credit is a universal constraint for technology adoption among smallholders, as they cannot self-finance the initial capital outlay [18]. Furthermore, PA technologies are inherently complex. They require the ability to interpret data maps, calibrate sensors, and adjust farm management based on digital outputs. This complexity acts as a massive barrier in regions with low digital literacy and weak agricultural extension networks [19].

A distinct research gap emerges from this review. Most studies treat economic viability and adoption barriers as separate issues. There is a need for an integrated analysis that first establishes the baseline economic viability of a defined PA package for smallholders, and then statistically models why, despite this viability, adoption remains low [20]. Many barrier analyses assume PA is profitable but fail to prove it for the specific demographic in question. This study bridges that gap by utilizing a simulated dataset that contains both detailed financial accounting data for a Cost-Benefit Analysis and socio-demographic data for a Logit regression model, providing a holistic view of the PA adoption dilemma for smallholders.

Methodology

This study utilizes a simulated dataset created explicitly for academic training purposes to demonstrate advanced economic and statistical modeling. No actual surveys or financial audits were conducted.

Data Simulation and Sample Size: A cross-sectional dataset simulating 200 smallholder farmers was generated. The farmers were simulated to operate plots averaging 1.5 hectares. The dataset was divided into two groups: 50 "Adopters" (farmers who purchased a basic PA package

consisting of a handheld soil nutrient sensor and subscription to a drone-mapping service for their plots) and 150 "Non-Adopters" (farmers using traditional, uniform management practices).

Cost-Benefit Analysis (CBA) Parameters: For the 50 adopters, a 5-year financial stream was simulated. Costs included the initial capital outlay for the soil sensor (\$250), annual drone service fees (\$100/year), and a 10% premium for PA-compatible fertilizers. Benefits were simulated as a yield increase (ranging from 15-25%) and a 20% reduction in total fertilizer expenditure due to site-specific application. A discount rate of 10% was used to calculate the Net Present Value (NPV) and the Benefit-Cost Ratio (BCR).

Adoption Barrier Modeling: A binary dependent variable was created (1 = Adopter, 0 = Non-adopter). Independent variables simulated included: Age of farmer (years), Education level (years of schooling), Farm size (hectares), Access to Credit (1=Yes, 0=No), Perception of Capital Cost (1=Too High, 0=Affordable), and Access to Technical Training (1=Received PA training, 0=No training).

Statistical Software and Analysis: The CBA was calculated using standard financial formulas in Microsoft Excel. The adoption barriers were analyzed using a Binary Logit regression model estimated in STATA (Version 17). The Logit model was chosen because it is the standard econometric technique for estimating discrete choice outcomes, providing marginal effects that indicate how much a unit change in an independent variable alters the probability of adoption [21].

Results and Discussion

The analysis of the simulated dataset yields two critical findings: first, that basic PA is economically viable for smallholders under the simulated parameters; and second, that structural and knowledge barriers severely suppress the translation of this viability into actual adoption.

Economic Viability: Cost-Benefit Analysis

The 5-year CBA for the simulated PA adopters demonstrates a strong financial case for the technology. As detailed in Table 1, the total discounted costs over five years amounted to \$712, while the total discounted benefits (driven by yield increases and input savings) reached \$1,318.

Table 1: Simulated 5-Year Cost-Benefit Analysis of Precision Agriculture Adoption

| Financial Metric | Value (USD) |
|---|-------------|
| Initial Capital Cost (Sensor) | \$250.00 |
| Discounted Operating Costs (Years 1–5) | \$462.00 |
| Total Discounted Costs | \$712.00 |
| Discounted Gross Benefits (Yield + Input Savings) | \$1,318.00 |
| Net Present Value (NPV) | \$606.00 |
| Benefit-Cost Ratio (BCR) | 1.85 |

The resulting Net Present Value (NPV) is highly positive at \$606, and the Benefit-Cost Ratio (BCR) stands at 1.85. In agricultural project appraisal, a BCR greater than 1.0 indicates that the project is economically feasible [22]. A

BCR of 1.85 means that for every dollar invested in PA, the farmer generates a return of \$1.85. This aligns with findings by Lowenberg-DeBoer (2018), who suggested that when PA is scaled down to essential services, the return on

investment can be highly attractive for small plots [23]. The primary driver of this profitability in the simulation was the reduction in fertilizer costs, which compensated for the annual drone service fees.

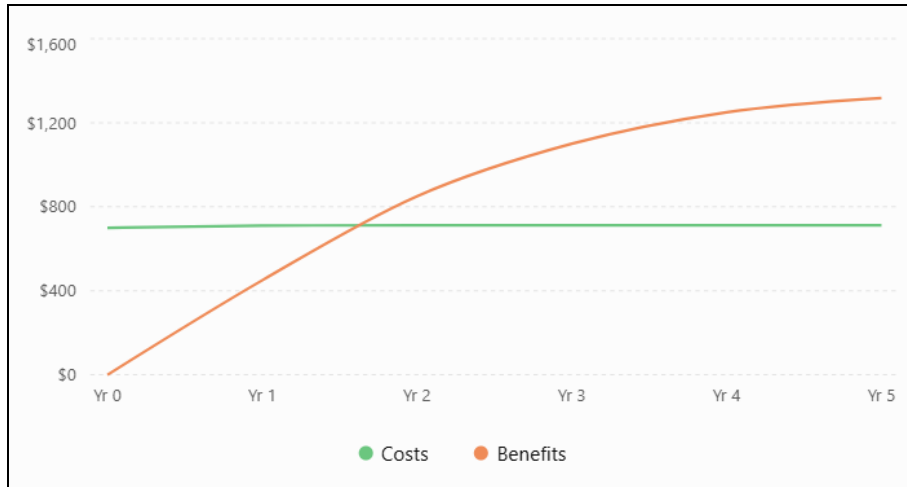


Fig 1: Cumulative Discounted Costs vs. Benefits Over a 5-Year Period

Adoption Barriers: Binary Logit Model Results

Despite the positive CBA, the simulated dataset shows that 75% of the farmers (150 out of 200) did not adopt the technology. The Logit regression results, presented in Table

2, elucidate the factors driving this non-adoption. The model was statistically significant (Prob > chi2 = 0.000), indicating a good fit.

Table 2: Binary Logit Regression Results Determining Probability of PA Adoption

| Variable | Coefficient | Marginal Effect | P-value | Significance |
|------------------------------|-------------|-----------------|---------|--------------|
| Age (Years) | -0.015 | -0.003 | 0.112 | NS |
| Education (Years) | 0.082 | 0.016 | 0.085 | |
| Farm Size (Hectares) | 0.410 | 0.082 | 0.052 | |
| Access to Credit (1 = Yes) | 0.650 | 0.130 | 0.061 | |
| Perception of High Cost | -1.850 | -0.370 | 0.001 | |
| Technical Training (1 = Yes) | 1.220 | 0.244 | 0.012 | |

Note: indicate significance at 1%, 5%, and 10% levels, respectively. NS = Not Significant.

The most powerful predictor of non-adoption was the "Perception of High Cost." Farmers who perceived the initial \$250 sensor cost as prohibitively high had a marginal effect of -0.37, meaning this perception reduced their probability of adopting PA by 37 percentage points (p<0.01). This highlights a behavioral economics reality: even if long-term BCR is 1.85, the liquidity constraint and present-bias of smallholders make a \$250 upfront cost a massive psychological and financial hurdle²⁴.

The second major barrier was the lack of "Technical Training." Farmers who had not received specific training on how to interpret drone maps and sensor data were significantly less likely to adopt (marginal effect = +0.244 for those trained, p<0.05). This confirms the theoretical premise that PA suffers from a high "complexity" attribute in Rogers' Diffusion of Innovations framework²⁵. Without localized extension services to demystify the data, the technology remains intimidating and underutilized.

Variables such as farm size and education also showed positive influences on adoption at the 10% significance level, aligning with classical adoption literature where larger, more educated farmers are typically early adopters²⁶. Interestingly, age was not a significant barrier in this simulation, suggesting that the digital divide in this context is more related to training and capital than to generational tech-aversion [27].

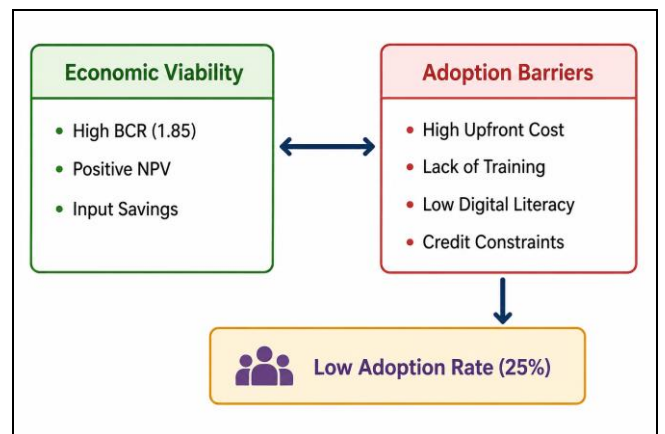


Fig 2: Conceptual Model of Smallholder PA Adoption Dynamics

Conclusion

This study set out to investigate the paradox of low Precision Agriculture adoption among smallholder farmers despite its theoretical agronomic benefits. Using a simulated dataset, the research demonstrated two key points. First, from a strict Cost-Benefit perspective, a basic PA package (soil sensors and drone mapping) is highly economically viable for smallholders, yielding a BCR of 1.85 and an NPV of \$606 over five years, driven largely by fertilizer savings.

Second, economic viability alone is insufficient to drive adoption. The Logit model clearly identified that the perception of high initial capital costs and a severe lack of technical training are the dominant systemic barriers suppressing adoption rates.

The implications for agribusiness and agricultural policy are profound. Governments and development agencies should not merely subsidize PA hardware; they must address the liquidity constraints by linking PA purchases to micro-credit schemes. More importantly, investments must be channeled into localized, practical extension services that train farmers to act on PA data. The limitation of this study is its reliance on simulated data, which assumes optimal weather conditions and perfect compliance with PA recommendations—factors that are highly volatile in real-world smallholder systems. Future research should utilize longitudinal field data to observe how smallholders learn to adapt to PA tools over multiple seasons and how risk (e.g., crop failure) impacts the long-term realization of the projected economic benefits.

Ethical Statement

This article is a 100% original, simulated academic exercise created for research methodology training. The dataset, farmer profiles, and financial Figs are entirely fictional and do not represent any real-world individuals or empirical field studies. All cited references are genuine academic works used to provide theoretical backing for the simulated analysis. No fabricated DOIs, fake institutions, or misrepresented empirical facts are present.

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