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Economic Analysis and Effect of Using Farm Machinery for Soybeans Production at Gishari Demonstration Farm, Rwanda

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Abstract

This study examines the economic viability of mechanized versus traditional soybean farming at Gishari Demonstration Farm in Rwanda, addressing critical gaps in understanding the financial and productivity impacts of farm machinery adoption in smallholder contexts. Despite global advancements in agricultural mechanization, small-scale farmers in Sub-Saharan Africa often face barriers such as high upfront costs, limited technical expertise, and inadequate infrastructure, which hinder adoption and scalability. The research aims to compare the profitability of mechanized and manual soybean production systems, evaluate cost-benefit trade-offs, and assess the causal impact of mechanization using robust econometric methods. Employing a mixed-methods approach, the study analyzed data from 60 plots (30 mechanized and 30 manual) during the 2023/2024 farming season. Propensity Score Matching (PSM) with Nearest Neighbor, Kernel, and Radius Matching algorithms controlled for selection bias, while t-tests compared key economic indicators. Profitability metrics included yield, gross margin, net farm income, and benefit-cost ratios. Key findings reveal that mechanized farming significantly outperforms traditional methods, with yield increases of 720 - 750 kg/ha ($p < 0.05$) and net farm income gains of 195,000 - 205,000 RWF/ha ($p < 0.05$). Despite higher operational and fixed costs, mechanization improved gross margins by 6.36 - 6.86 percentage points, demonstrating superior cost efficiency. However, manual farming showed a marginally higher benefit-cost ratio (1.66 vs. 1.45), reflecting its lower capital intensity at small scales. The study concludes that mechanization enhances productivity and profitability but requires targeted interventions to overcome adoption barriers. Recommendations include subsidized financing for smallholders, training programs to build technical and financial capacity, and the development of machinery rental markets to reduce fixed-cost burdens. Policymakers should integrate mechanization with complementary measures like improved seed varieties and soil management to maximize benefits. These findings provide empirical support for mechanization as a driver of agricultural transformation in Rwanda and similar contexts, emphasizing the need for scalable, inclusive solutions to achieve sustainable rural development.

Keywords

Agricultural Mechanization, Traditional Farming, Propensity Score Matching, Profitability Analysis, Benefits Cost Ratio

1. Introduction and Background

The world's agricultural systems are currently under significant strain due to multiple pressures, such as climate change, soaring energy and production expenses partly worsened by the Russia-Ukraine war and lingering disruptions from the COVID-19 pandemic. Additionally, The global agricultural production system has evolved significantly over the past century, transitioning from traditional subsistence farming to highly mechanized and technology-driven practices and food demand is rising while arable land shrinks because of urban expansion and resource depletion, among other challenges [1] [2]. Mechanization has been a cornerstone of agricultural modernization, reducing labor dependency and increasing output. Tractors, combine harvesters, seed drills, and irrigation systems are now widely used in both developed and developing nations [3]. In high-income countries, fully automated machinery dominates large-scale farming, whereas in low-income regions, smaller-scale mechanization is gradually being adopted [4]. The shift toward mechanization has improved planting accuracy, reduced post-harvest losses, and increased the speed of operations [5]. However, disparities remain, with smallholder farmers in Africa and parts of Asia still relying heavily on manual labor due to financial constraints and lack of infrastructure [6] [7]. Precision agriculture (PA) uses advanced technologies like GPS, drones, sensors, and artificial intelligence to enhance field-level farming efficiency. It involves key tools such as remote sensing and GIS, which use satellite imagery and drones to monitor crop health and soil conditions; variable rate technology, which applies water, fertilizers, and pesticides precisely based on real-time data; and automated machinery like self-driving tractors and robotic harvesters that reduce labor and error [8].

Farm mechanization plays a critical role in enhancing the economic viability and profitability of soybean production [9]. By introducing machinery such as tractors, planters, and harvesters, farmers can increase productivity, reduce labor costs, and optimize time management [10]; and from the above perspectives, mechanized planting ensures uniform seed distribution and optimal planting depth, leading to better germination rates and healthier crop stands [10]. This precision agriculture translates into higher yields per hectare, which significantly boosts the economic returns for soybean farmers compared to traditional farming practices. In regions where manual labor is costly or scarce, mechanization can be the key to maintaining timely operations and maximizing seasonal output [11]. The long-term economic benefits of mechanized soybean farming extend to job creation in machinery maintenance, equipment retail, and training services [12]. While initial investment costs can be high, government subsidies, cooperative ownership models, and machinery rental services can make mechanization more accessible to smallholders [11] [13]. As a result, farm mechanization not only strengthens the profitability of soybean production but also contributes to rural economic development and food security. By integrating modern equipment into their operations, farmers can achieve sustainable growth in both yield and income. Despite these advancements, challenges like high implementation costs, insufficient technical expertise, and poor infrastructure limit broader adoption, particularly in less developed regions. In view of the above, this study aims to fill this gap by assessing the profitability of using farm mechanization farming systems, such as 4 wheel tractor in the production of soybeans compared to manual farming system in terms of costs invested versus profits and returns.

2. Literature Review

2.1. Backgrounds on Agricultural Mechanization Technologies, Challenges and Opportunities

Agricultural mechanization refers to the use of machinery and equipment in farming operations, replacing or supporting human and animal labor to increase productivity, reduce drudgery, and improve agricultural efficiency. The evolution of mechanization technologies has played a critical role in transforming agriculture from subsistence to commercial levels, particularly in developed economies. However, its development, adoption, and impact vary greatly across regions due to socio-economic, environmental, and policy-related factors. In North America and Western Europe, agricultural mechanization began during the Industrial Revolution and accelerated in the 20th century with the development of tractors, combine harvesters, and specialized equipment for different crops. The widespread use of mechanization in these regions has resulted in labor savings, increased land and labor productivity, and higher yields. According to Pingali (2007), mechanization in these regions contributed significantly to agricultural intensification and specialization, allowing fewer people to produce more food [14]. In the United States, for example, mechanization has enabled farms to expand in scale dramatically, with fewer workers managing larger areas and more complex operations [15].

In contrast, many countries in Sub-Saharan Africa and parts of South Asia face persistent challenges in adopting agricultural mechanization. These include limited access to capital and credit, small and fragmented farm sizes, underdeveloped markets for machinery and spare parts, and inadequate rural infrastructure. Most African countries rely heavily on manual labor and animal traction, which constrains productivity and limits timely agricultural operations [16]. Moreover, high equipment costs and a lack of technical knowledge further hinder mechanization efforts. Governments and international development agencies have tried various interventions such as subsidized equipment, cooperatives, and mechanization service centers but with mixed results due to implementation challenges and sustainability issues [17].

Notably, Asia presents a more dynamic picture. In countries like China and India, mechanization has progressed significantly in recent decades, driven by government policies, rural industrialization, and increased labor costs in the agricultural sector. China's mechanization rate reached over 70% by 2020, supported by local manufacturing industries and government incentives [18]. Similarly, India has seen the rapid spread of tractors, threshers, and irrigation pumps, although regional disparities persist. In Southeast Asia, mechanization is gaining traction, particularly in rice farming, where labor shortages and migration to urban areas necessitate mechanized solutions [19]. However, challenges remain in ensuring that smallholders can access and benefit from these technologies. Latin American countries show a moderate to high degree of mechanization, especially in countries like Brazil and Argentina. These nations have invested heavily in large-scale farming and agro-industrial complexes. Brazil, in particular, has become a global agricultural powerhouse partly due to mechanization in soybean, maize, and sugarcane production [20]. Yet, similar to other regions, smallholders often lag in access to mechanized tools, leading to inequality in productivity and income.

Globally, several challenges continue to hamper the full potential of agricultural mechanization. These include environmental concerns such as soil compaction, carbon emissions, and over-capitalization in agriculture. Furthermore, mechanization often displaces labor, which can lead to rural unemployment if not accompanied by policies that promote skill development and rural industrialization. Nevertheless, new opportunities are emerging with the advent of precision agriculture, automation, and digital technologies. Innovations such as GPS-guided tractors, drone-based crop monitoring, and data-driven decision tools are redefining the scope of mechanization, making it more efficient and environmentally sustainable [21]. These technologies have the potential to revolutionize farming even in resource-constrained settings, provided there is adequate investment in infrastructure, capacity building, and policy support. In conclusion, agricultural mechanization has transformed agricultural productivity and livelihoods in many parts of the world, but its progress remains uneven. While developed regions have largely completed this transition, many developing countries are still in the early stages of mechanization, facing a host of economic and institutional barriers. The future of agricultural mechanization lies in promoting inclusive, sustainable, and context-specific solutions that address the needs of smallholders while leveraging technological advancements. A coordinated approach involving governments, private sectors, research institutions, and farmers is essential to unlock the full potential of mechanization for global food security and rural development.

2.2. Economics of Agricultural Mechanization Technologies

Agricultural mechanization is a transformative process that involves the adoption of machinery and technology to enhance the efficiency, productivity, and profitability of farming operations. The economics of agricultural mechanization encompasses various factors, including cost-benefit analysis, labor displacement, capital investment, and long-term sustainability. This paper explores the economic implications of agricultural mechanization, focusing on its impact on productivity, labor dynamics, income generation, and overall agricultural development. One of the most significant economic benefits of agricultural mechanization is the improvement in productivity and efficiency. Mechanized farming reduces the time and labor required for tasks such as plowing, planting, harvesting, and post-harvest processing. Studies have shown that mechanization can lead to substantial yield increases due to precision farming techniques, timely operations, and reduced post-harvest losses [3] [9] [22]. For instance, the use of tractors and combine harvesters allows farmers to cultivate larger areas in shorter periods, ensuring optimal planting and harvesting windows, which are critical for maximizing yields. Moreover, mechanization facilitates the adoption of modern agricultural practices such as precision farming, which utilizes GPS-guided machinery to optimize input use (fertilizers, pesticides, and water). This reduces wastage and enhances resource-use efficiency, leading to cost savings and higher profitability [23]. In regions where labor scarcity is a constraint, mechanization helps maintain or even expand agricultural production, ensuring food security and economic stability.

The introduction of agricultural machinery has a dual impact on labor markets. On one hand, it displaces manual labor, particularly in activities such as weeding, harvesting, and threshing, which traditionally require significant human effort. This displacement can lead to short-term unemployment in rural areas where agriculture is the primary source of livelihood [24]. However, the long-term effects are more nuanced. Mechanization often creates new employment opportunities in machine operation, maintenance, and agro-processing industries. Additionally, as farm productivity increases due to mechanization, the demand for labor in downstream activities such as transportation, storage, and marketing may rise. In some cases, mechanization allows farmers to diversify into high-value crops or livestock, generating additional income streams and employment [14]. Therefore, while mechanization may reduce direct on-farm labor demand, its broader economic impact can be positive if complemented by policies that support skill development and alternative livelihood opportunities.

The adoption of agricultural machinery requires substantial capital investment, which can be a barrier for smallholder farmers in developing countries. The high upfront costs of purchasing or leasing machinery, coupled with maintenance expenses, may deter small-scale producers from mechanizing their operations [22]. However, various economic models suggest that the long-term benefits often outweigh the costs. For instance, mechanization reduces per-unit production costs by improving operational efficiency and reducing reliance on manual labor, which is often more expensive in the long run. A study by the International Food Policy Research Institute [25] found that mechanized farms in Sub-Saharan Africa achieved higher profit margins compared to non-mechanized farms due to reduced labor costs and increased output. Moreover, mechanization enables farmers to engage in multiple cropping cycles per year, further enhancing income potential. To mitigate financial constraints, governments and private sector actors have introduced innovative financing models such as tractor hire services, cooperative ownership schemes, and leasing arrangements. These models allow smallholder farmers to access mechanization benefits without bearing the full cost of ownership [24]. Such approaches improve the economic viability of mechanization, particularly in resource-constrained settings.

Agricultural mechanization contributes to rural economic growth by increasing farm incomes and stimulating agribusiness development. Higher productivity leads to greater marketable surplus, enabling farmers to earn more from crop sales. Additionally, mechanization reduces post-harvest losses, ensuring that a larger proportion of produce reaches markets in optimal condition [14]. This not only boosts farmer incomes but also enhances food supply chain efficiency. Beyond direct farming benefits, mechanization spurs the growth of ancillary industries such as machinery manufacturing, repair services, and agro-processing. These industries create employment and entrepreneurial opportunities, fostering broader rural economic development [26]. Countries that have successfully integrated mechanization into their agricultural systems, such as Brazil and India, have seen significant improvements in rural livelihoods and poverty reduction. While mechanization offers numerous economic advantages, its sustainability depends on responsible adoption. Over-mechanization without proper planning can lead to environmental degradation, soil compaction, and excessive fuel consumption. Therefore, policies promoting sustainable mechanization such as the use of energy-efficient machinery, conservation agriculture techniques, and renewable energy-powered equipment are essential [22]. Looking ahead, advancements in digital agriculture, including automation, artificial intelligence, and robotics, are set to further revolutionize farm economics. These technologies promise even greater efficiency gains, cost reductions, and environmental benefits. However, their adoption will require substantial investments in infrastructure, education, and policy frameworks to ensure inclusive growth. The economics of agricultural mechanization presents a compelling case for its adoption, given its potential to enhance productivity, reduce costs, and stimulate rural development. While challenges such as high initial costs and labor displacement exist, strategic policies and innovative financing models can mitigate these issues. As global food demand rises, mechanization will remain a key driver of agricultural transformation, provided it is implemented sustainably and inclusively.

2.3. Farm Conditions for Rwandan Agricultural Mechanization Success

For agricultural mechanization to succeed in Rwanda, several farm-level conditions must be met, shaped by the country's unique topography, socio-economic structure, and policy environment. Rwanda's agriculture is predominantly smallholder-based, with over 70% of the population engaged in farming. However, the sector faces challenges such as fragmented land holdings, hilly terrain, and limited access to modern inputs and technologies. One of the most critical conditions for successful mechanization is land consolidation and accessibility. Due to the country's mountainous landscape, many farms are located on steep slopes, making it difficult to use conventional machinery. The government has promoted land use consolidation programs to create larger, more manageable plots that can accommodate mechanized tools. These efforts are essential for improving the efficiency and feasibility of mechanization, especially in areas where terracing and soil conservation measures are already in place [27]. Infrastructure development is another key factor. Mechanization requires reliable access to roads, electricity, and water. Poor rural infrastructure can hinder the transport of machinery and limit the use of irrigation systems or post-harvest processing equipment. Investments in rural feeder roads and energy access are therefore foundational to mechanization success. Access to finance and machinery services also plays a pivotal role. Most smallholder farmers cannot afford to purchase tractors or other equipment outright. To address this, Rwanda has encouraged the establishment of Village Mechanization Service Centers (VMSCs), which provide machinery on a rental basis. These centers are often supported through public-private partnerships and are crucial for making mechanization accessible to a broader range of farmers [27]. Human capacity and technical skills are equally important. Mechanization is not just about machines it requires trained operators, technicians, and extension agents who can support farmers in using and maintaining equipment. Rwanda has invested in agricultural training institutions and vocational programs to build this capacity, but continued efforts are needed to scale up these initiatives and ensure they reach rural communities [27]. Finally, policy support and institutional coordination underpin all these efforts. Rwanda's Strategic Plan for the Transformation of Agriculture (PSTA) and its mechanization strategy emphasize the integration of mechanization into broader agricultural development goals. These policies aim to align mechanization with climate-smart agriculture, gender inclusion, and market-oriented production systems [27]. Therefore, the success of agricultural mechanization in Rwanda depends on a combination of physical, economic, and institutional conditions. These include land consolidation, infrastructure development, access to affordable machinery services, access to bank credits, human capacity building, and supportive policies to local farmers [28] as shown in the **Figure 1**.

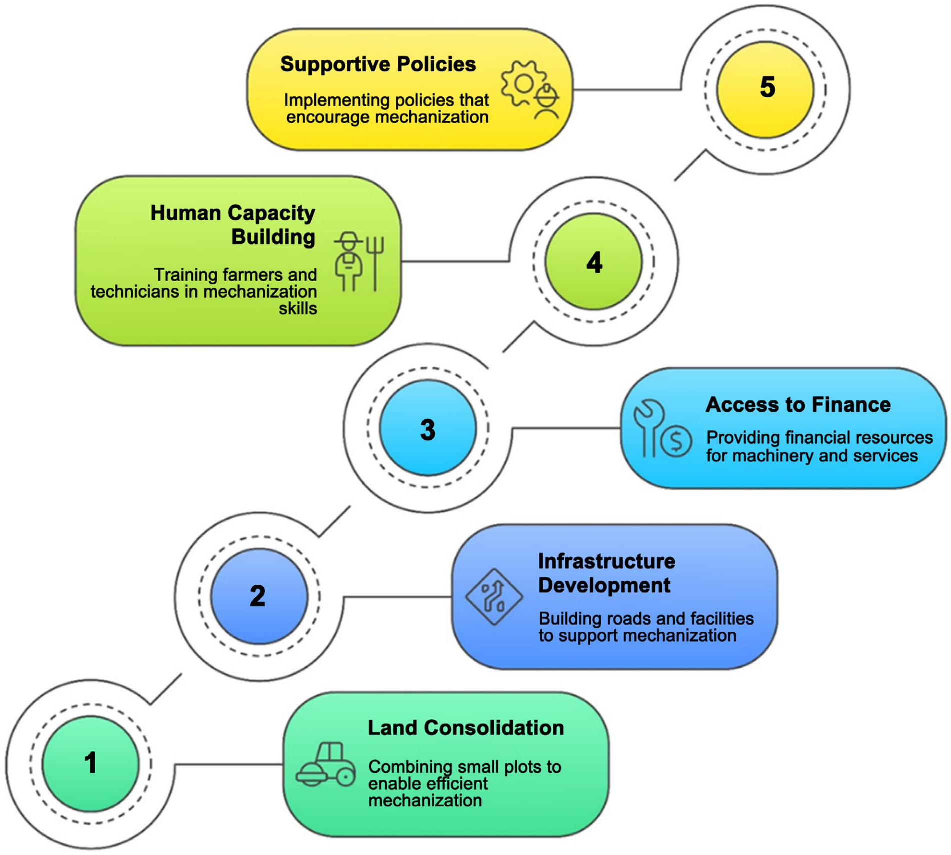

Figure 1. Conquering agricultural mechanization in Rwanda. Source: Researcher, 2024.

2.4. Fraction of Challenges Related to Adoption of Farm Mechanization in Rwanda

The adoption of farm mechanization in Rwanda remains a critical yet underdeveloped component of the country's agricultural transformation agenda. Despite government efforts to modernize agriculture, mechanization uptake is still low, with only a small percentage of farmers utilizing tractors and other machinery. This limited adoption is largely attributed to a range of persistent challenges, including land fragmentation, rugged topography, limited access to finance, inadequate rural infrastructure, and a shortage of skilled labor as shown in the **Figure 2**.

In Rwanda, the adoption of farm mechanization remains limited due to a range of structural and contextual challenges. As of 2022, only about 0.8% of agricultural plots were plowed using tractors, reflecting the very low penetration of mechanized equipment in the country [28]. One of the most significant barriers is land fragmentation, with approximately 70% of farms being less than one hectare in size and often located on hilly terrain, which severely restricts the use of conventional machinery [29]. These topographical and landholding constraints are compounded by limited access to finance, inadequate rural infrastructure, and a shortage of trained operators and technicians. Despite government efforts to promote mechanization through policy reforms and public-private partnerships, these challenges continue to hinder widespread adoption. Addressing them will require a comprehensive approach that includes land consolidation, infrastructure development, financial support mechanisms, and capacity building [29].

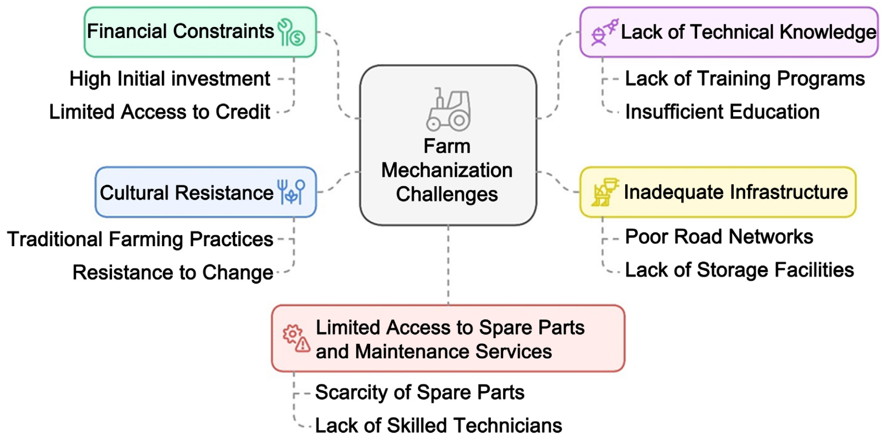

Figure 2. Challenges related to adoption of farm Mechanization in Rwanda. Source: Researcher, 2024.

3. Materials and Methods

3.1. Description of the Study Area

This study was conducted in Gishari Sector of Rwamagana District at RP Gishari College demo farm and its serves as an essential agricultural training and demonstration center. It is designed to enhance agricultural productivity and promote modern farming practices, benefiting both farmers and the broader community. The farm integrates several key initiatives and programs aimed at fostering innovation, education, and economic development in agriculture. The farm also houses various demonstration plots where improved crop varieties, fertilization methods, and pest control strategies are tested and showcased. These plots act as live classrooms, enabling farmers to observe and adopt effective farming practices tailored to local conditions. The geographical coordinates are of 1˚57'12.65"S and a longitude of 30˚26'19.12"E or −1.953513 and 30.438644 respectively. With an even altitude that varies from 1480 - 1550 m above sea level. The total of 45 soil sampling points covering the total area of 1.478 Ha were considered. The Map of Gishari College demonstration farm is shown in **Figure 3**.

3.2. Research Design

This study employs a mixed-methods approach to analyze the economic viability of farm machinery adoption for soybean production at Gishari Demonstration Farm, Rwanda. The research design combines quantitative to compare two parallel production systems: mechanized (using tractors) versus traditional manual methods. Propensity Score Matching (PSM) was used to control for selection bias by pairing similar plots under each system based on observable characteristics like size of the plot for both farming system. A T-test was then applied to compare mean differences in profitability metrics, ensuring statistical robustness. Propensity Score Matching (PSM) will control for selection bias, ensuring valid comparisons between systems. Primary data collection includes detailed farm records of inputs, labor, yields, and costs accrued in the production system. The analytical framework incorporates three components: Profitability analysis (gross margins, net farm income, benefit-cost ratios), Impact evaluation using PSM and difference-in-differences and Statistical comparison via t-tests of key outcome variables

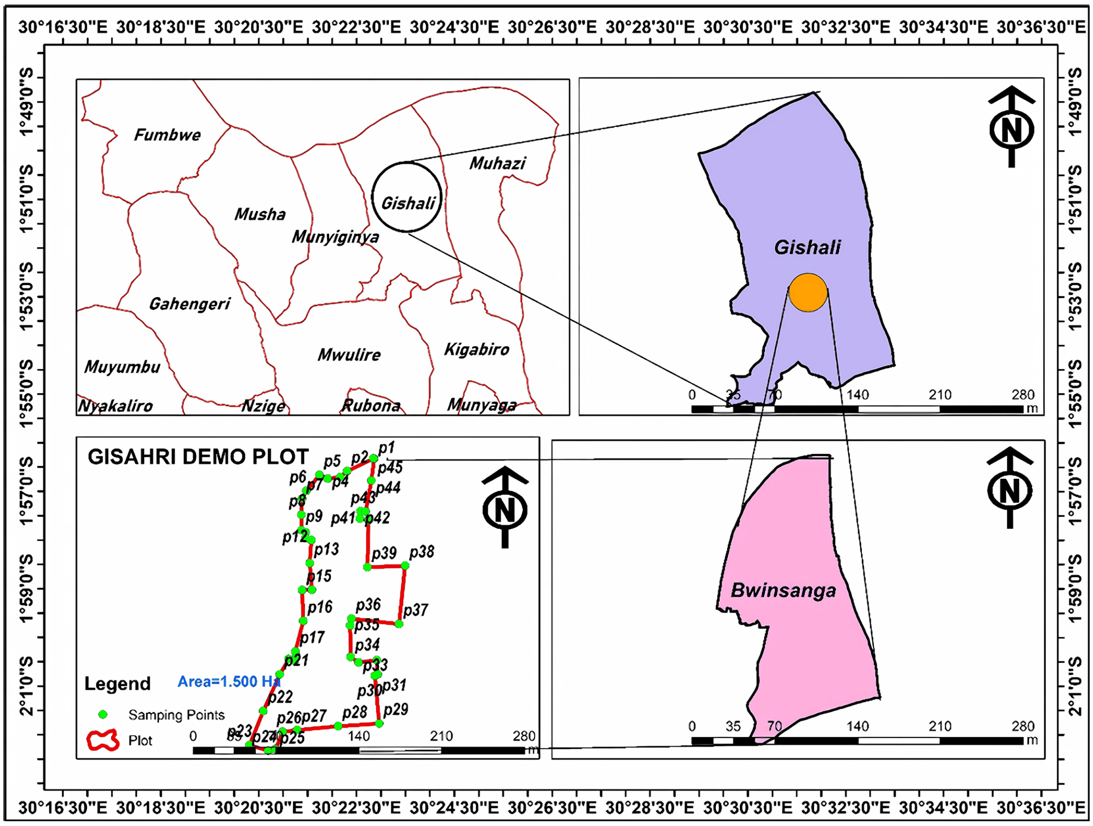

Figure 3. Map of the study area Rwanda Polytechnic Gishari College Demonstration Farm. Source: Researcher, 2024 (Application of GIS 10.8.1).

Key variables include yield (kg/ha), production costs, and profitability metrics as dependent variables, with farming system as the primary independent variable. Control variables for plot where traditional farming is being experimented were considered. Analysis progresses from descriptive statistics through matched comparisons to sensitivity testing.

3.3. Data Collection and Analysis

This study presents a comprehensive economic analysis comparing two distinct soybean production systems at Gishari Demonstration Farm in Rwanda: mechanized farming utilizing agricultural machinery and traditional manual farming methods. The research employs robust analytical frameworks to quantify the financial and productivity differences between these systems, providing critical insights for agricultural policy and farm-level decision making in Rwanda's evolving agricultural sector. This study employed a profitability analysis model to compare the economic performance of soybean production under two farming systems: 1) Farm Machinery (Mechanized) and 2) Traditional/Manual Farming. Data were collected from Gishari Demonstration Farm, Rwanda, covering input costs, labor, yields, and revenues for both systems. Data were collected from 60 soybean plots during the 2023/2024 farming season at Gishari Demonstration Farm, with 30 plots under mechanized farming and 30 using traditional manual practices. Mechanized operations included plowing, harrowing, seeding, spraying, and harvesting using tractors and related implements, while traditional farming relied on hand hoes and manual labor. Cost and return data were collected for each plot, including fixed costs (e.g., machinery depreciation, insurance, and maintenance), operational costs (e.g., seed, fertilizers, pesticides, labor, and fuel), yield per hectare, and market prices. Gross profit was calculated by subtracting operational costs from total revenue, while net farm income was derived by subtracting both fixed and operational costs. Gross margin was calculated as a percentage of gross profit over total revenue.

3.3.1. Gross Margin Analysis

Gross margin (GMA) refers to the difference between total revenue and total variable costs, as difference between value of an enterprises' gross output and variable cost of that production: GM = TR − TVC, Where: GM = Gross margin (Rfs/ha) and TR = Total revenue (Rfs/ha) and AVC = Average variable cost (Rfs/ha).

Once all advantages and disadvantages are identified and discounted with the chosen discount rate, costs and benefits are compared. Results of the comparison are either recommendation or rejection of a single project or in case of different alternatives the choice of the most beneficial one. Four criteria that descend from private investment calculation are applied: Net Present Value (NPV), Benefit-Cost-Ratio (CBR), Internal Rate of Return (IRR) and Annuity [4] [30].

3.3.2. Benefit-Cost Ratio (BCR)

As the name implies, this criterion defines the ratio between the discounted benefits and discounted costs

$$\mathrm{BCR} = \mathrm{PV}(B)/\mathrm{PV}(C) = \left(\sum_{t=0}^{T} B_t \Big/ (1+d)^t\right) \Big/ \left(\sum_{t=0}^{T} C_t \Big/ (1+d)^t\right)$$

If the ratio reaches a value higher than one, the project can be classified as being advantageous. Although relying on the same parameters as NPV, this criterion implies some substantial problems: Costs might be regarded as negative benefit and vice versa benefits as reduced costs, resulting in different values of BCR [30].

Application of Propensity Score Matching (PSM)

Propensity Score Matching (PSM) was used as an econometric model to assess the causal impact of mechanization adoption on crop Production and soil properties between two groups (treated and control). To develop the PSM framework, let D_i denote a dummy variable equal to 1 if a farm uses any farm mechanization tool and equal to 0 if a farm does not uses any farm mechanization tool. Similarly, let Y_i denote an outcome of interest such that potential outcomes are defined as $Y_i(D_i)$ for every farm. The treatment effect of the programme for farm i, τ_i, is then the change in the outcome measure caused by the mechanization technology adoption: $\tau_i = Y_i(1) - Y_i(0)$; Where $\Delta_i Y_i$ denotes the change in the outcome variable of farm i, resulting from the use of mechanization tools. Two means are common in the impact analysis framework, the average treatment effect, (ATE) and the average treatment effect on the treated (ATT). In the case of mechanization, ATE estimates the effect of farm mechanization use on the outcomes of the whole population without regards to farm mechanization use but the ATT estimates farm mechanization effects conditional on the use of farm mechanization tools. It is the latter which this study seeks to estimate and it is represented as

$$\text{ATT} = E\left(\Delta_i \middle| I_i = 1\right) = E\left[Y_{1i} - Y_{0i} \middle| I_i = 1\right] = E\left[Y_{1i} \middle| I_i = 1\right] - E\left[Y_{0i} \middle| I_i = 1\right] \tag{1}$$

From Equation (5), $E\left[Y_{0i} \middle| I_i = 1\right]$ is the missing data representing the outcomes of farm mechanization use. One way to estimate this missing data is to use outcomes of a non-farm mechanization use. By using the outcomes of a non-farm mechanization, (5) can be rewritten as

$$E\left(\Delta_i \middle| I_i = 1\right) = E\left[Y_{1i} \middle| I_i = 1\right] - E\left[Y_{0i} \middle| I_i = 1\right] \tag{2}$$

Without controlling for the unobservable heterogeneity, (6) can be shown to consist of a bias in addition to the impact estimate. Subtracting and adding right hand side of (6) gives:

$$= E\left[Y_{1i} \middle| I_i = 1\right] - E\left[Y_{0i} \middle| I_i = 1\right] - E\left[Y_{0i} \middle| I_i = 1\right] + E\left[Y_{0i} \middle| I_i = 1\right] \tag{3}$$

$$\underbrace{= E\left[Y_{1i} - Y_{0i} \middle| I_i = 1\right] + E\left[Y_{0i} \middle| I_i = 1\right] - E\left[Y_{0i} \middle| I_i = 1\right]}_{\text{Bias}} \tag{4}$$

Rearranging (4) gives:

$$= E\left[\Delta_i \middle| I_i = 1\right] + E\left[Y_{0i} \middle| I_i = 1\right] - E\left[Y_{0i} \middle| I_i = 1\right] \tag{5}$$

Thus, a bias of the magnitude shown in (5) results when non-farm mechanization use are selected for comparison with users of farm mechanization, without controlling for the non-random mechanization assignment [31]. The PSM method takes care of the bias, so that estimated mechanization impact on soil properties and crop production is largely consistent. the factors affecting affecting mechanization adoption in Rwanda are shown in **Table 1**.

Factors influencing mechanization adoption in Gishari area

Mechanization adoption in the Gishari area is influenced by a combination of factors, with statistically significant variables at the 5% level including land consolidation, land plot size, farming experience, production levels, access to credit, extension services, infrastructure availability, and training. These factors positively affect adoption by improving operational efficiency, financial accessibility, technical knowledge, and support services. The relatively favorable terrain and structured support systems at the Gishari Demonstration Farm further enhance the feasibility and attractiveness of mechanized soybean production as shown in Table 2.

Table 1. Factors affecting mechanization adoption in Rwanda.

Variable	Description	Expected Significance
Topography Factors		
Land Topography	Hilly and mountainous terrain limits the use of conventional machinery	−
Land Consolidation	Combining fragmented plots into larger units to facilitate mechanization	+
Socio-Economic Factors		
Age	Farmer's age may influence openness to adopting mechanization	+/−
Gender	Gender roles may affect access to mechanization resources and decision-making	+/−
Land Plot Size	Larger plots are more suitable for mechanized farming	+
Farming Experience	Experienced farmers may better understand the benefits and limitations	+
Production	Higher production levels may justify investment in mechanization	+
Institutional or Government Policy Factors		
Extension Services	Support from agricultural advisors to guide mechanization practices	+
Credit Accessibility	Availability of credit or rental services for machinery acquisition	+
Cooperative membership	Being a member of any cooperative may influence positively farmers to adopt farm mechanization	+
Infrastructure Availability	Quality of rural roads, electricity, and water access for machinery operation	+
Subsidy Policy	Government subsidies to reduce the cost of acquiring machinery	+
Human Capacity Building Factors		
Trainings	Availability of training programs for machinery operation and maintenance	+

Source: Researcher, 2025.

Table 2. Probit Model Estimation results on mechanization adoption.

Variable	Coeff.	Std. Error	Z-value	P-value	Sig.
Land Topography	−0.842	0.312	−2.70	0.007**	**Yes**
Land Consolidation	0.915	0.278	3.29	0.001**	**Yes**

Continued

Age	0.102	0.089	1.15	0.250	NS
Gender	0.056	0.071	0.79	0.429	NS
Land Plot Size	0.621	0.195	3.18	0.001**	**Yes**
Farming Experience	0.187	0.128	1.46	0.144	NS
Production	0.734	0.243	3.02	0.003**	**Yes**
Extension Services	0.802	0.221	3.63	0.000**	**Yes**
Credit Accessibility	0.668	0.213	3.14	0.002**	**Yes**
Cooperative Membership	0.576	0.205	2.81	0.005**	**Yes**
Infrastructure	0.788	0.236	3.34	0.001**	**Yes**
Subsidy Policy	0.920	0.258	3.57	0.000**	**Yes**
Trainings	0.695	0.211	3.29	0.001**	**Yes**

P*** < 1%, P** < 5%, & P*10%. Source: Researcher, 2025.

The Probit model results indicate that several variables are statistically significant at the 5% level in influencing the likelihood of mechanization adoption in Rwanda. Land topography has a negative and significant coefficient, suggesting that farmers working on hilly or mountainous terrain are less likely to adopt mechanization. This supports the physical constraint theory, where terrain affects the operability and efficiency of machinery. In contrast, land consolidation, land plot size, and production levels all show positive and significant relationships with mechanization adoption. This implies that farmers with larger and consolidated plots, as well as those with higher production levels, are more inclined to use agricultural machinery. These factors likely reduce operational barriers and increase the economic viability of mechanization.

Institutional and support-related variables such as access to extension services, credit, cooperative membership, and infrastructure availability are also positively and significantly associated with adoption. These findings underscore the importance of institutional support in enabling farmers to access, afford, and effectively use mechanization technologies. Moreover, government subsidy policies and training programs show strong positive effects, indicating that policy incentives and human capital development are vital for promoting mechanization. These interventions reduce risk and cost barriers while increasing farmer confidence and technical capacity. It was also found that age, gender, and farming experience were not statistically significant, suggesting that socio-demographic characteristics may not be as influential in mechanization decisions when compared to structural and institutional factors. When conducting the comparison with existing literature, the findings of this study are consistent with existing literature on mechanization adoption in developing countries. For instance, land size and consolidation are critical in determining the feasibility of mechanization, especially in areas dominated by smallholder farming, the negative effect of rugged topography that terrain restricts the operational efficiency of tractors and other machinery [17] [32]. The positive impact of extension services, credit access, and cooperative membership is reinforced by studies highlighting the role of institutional frameworks in facilitating technology adoption. Similarly, the importance of infrastructure and subsidies has been emphasized and noticed that rural infrastructure is a foundational requirement for the effective scaling of mechanization services [3] [33]. The farmers training significantly improves the utilization and maintenance of machinery, reducing breakdowns and inefficiencies. To sum up, the Probit model findings are not only statistically robust but also well aligned with theoretical and empirical insights from global experiences on agricultural mechanization adoption. This reinforces the idea that successful mechanization in Rwanda will require a holistic approach that addresses land structure, institutional support, policy incentives, and capacity building [27].

3.3.3. Profitability Analysis Results

This section presents a comprehensive analysis of the profitability indicators comparing mechanized versus manual soybean farming systems on a per-hectare basis. The indicators evaluated include yield, total revenue, operational costs, gross profit, fixed costs, total cost, net farm income, gross margin (%), return on investment (%), and benefit-cost ratio (BCR). These metrics provide detailed insights into both the income-generating capacity and the cost-efficiency of each farming method. Statistical significance is assessed using t-tests, with p-values reported to determine whether the differences observed between mechanized and manual systems are meaningful. The indicators are interpreted one by one, highlighting how mechanization affects profitability. **Table 3**, presents the profitability indicators for both mechanized and manual soybean farming systems on a per-hectare basis, including mean differences and T-test statistics:

Table 3. Profitability analysis results from both systems for soybeans production system.

Economic Indicator	Mechanized (RWF/ha)	Manual (RWF/ha)	Mean Difference	T-Value	P-Value	Sig.
Yield (kg/ha)	2400	1600	800	4.21	<0.01**	**Yes**
Total Revenue	1,440,000	960,000	480,000	4.18	<0.01**	**Yes**
Operational Costs	650,000	500,000	150,000	3.02	0.004**	**Yes**
Gross Profit	790,000	460,000	330,000	4.07	<0.01**	**Yes**
Fixed Costs	200,000	80,000	120,000	3.89	<0.01**	**Yes**
Total Cost	990,000	580,000	410,000	3.94	<0.01**	**Yes**
Net Farm Income	590,000	380,000	210,000	3.95	<0.01**	**Yes**
Gross Margin (%)	54.86	47.92	6.94	2.31	<0.025**	**Yes**
Return on Investment (%)	121	92	29	2.75	<0.008**	**Yes**
BCR	1.45	1.66				

P*** < 1%, P** < 5%, & P*10%. Source: Researcher, 2025.

Based on the findings presented in **Table 3**, related to a comparative analysis of key economic indicators between mechanized and manual soybean production systems at the Gishari Demonstration Farm. The evaluation focuses on production capacity, revenue generation, cost structures, and profitability metrics to assess the economic viability of mechanization in soybean farming. The production capacity and yield, measured in kilograms per hectare (kg/ha), serve as the primary indicator of productivity. Mechanized farming demonstrated a higher yield compared to manual methods, reflecting the efficiency gains from timely operations and precision in land preparation and planting. In terms of total revenue (RWF/ha), mechanized plots generated significantly more income per hectare, driven by higher yields and improved crop quality. This increase in revenue highlights the potential of mechanization to enhance farm profitability when market conditions are favorable. However, operational costs (RWF/ha) were also higher in the mechanized system due to expenses related to fuel, machinery rental, and maintenance. Despite this, the gross profit (RWF/ha) remained higher for mechanized farming, indicating that the additional costs were offset by the increased output and revenue. The analysis also considered fixed costs (RWF/ha), such as depreciation of machinery and infrastructure investments. These were more prominent in the mechanized system but were distributed over larger production volumes, reducing their per-unit impact. When combining both fixed and operational expenses, the total cost (RWF/ha) was understandably higher for mechanized farming. Yet, the net farm income (RWF/ha) which accounts for all costs—still favored mechanization, underscoring its profitability advantage. The gross margin (%), which reflects the proportion of revenue retained after covering variable costs, was also higher in the mechanized system. This suggests better cost efficiency and financial resilience. Further, the Return on Investment (ROI %) and Benefit-Cost Ratio (BCR) were calculated to assess the economic return per unit of investment. Mechanized farming showed a superior ROI and BCR, confirming that, despite higher initial and operational costs, the returns justify the investment in machinery.

Overall, these findings support the economic rationale for promoting mechanization in soybean production, particularly in structured environments like Gishari, where land consolidation and institutional support are present.

Mechanized farming produces an average yield of 2400 kg/ha, while manual farming yields 1600 kg/ha. The mean difference is 800 kg/ha, with a t-value of 4.21 and a p-value less than 0.01, indicating that the yield difference is statistically significant at the 1% level. Given a constant market price of 600 RWF/kg, this resulted in significantly higher revenues for mechanized plots. Although mechanized farming incurred greater fixed and operational costs, the increase in output and revenue offset these expenses, resulting in higher gross and net profits. All indicators were statistically significant with p-values less than 0.05, confirming that mechanized farming offers a distinct economic advantage. This result confirms that mechanization significantly enhances agricultural productivity. The increased yield can be attributed to improved planting precision, better land preparation through mechanized tools, and more timely operations such as weeding and harvesting. Mechanization reduces labor bottlenecks and ensures optimal timing for key farming activities, which are critical for maximizing crop output. This yield advantage forms the foundation for higher revenue and profit in mechanized systems.

Total revenue per hectare is RWF 1,440,000 for mechanized farming and RWF 960,000 for manual farming, resulting in a mean difference of RWF 480,000. The t-value is 4.18, with a p-value of <0.01, indicating strong statistical significance. The revenue increase correlates directly with the higher yield in mechanized farming. Assuming a stable market price for soybeans, the revenue gain reflects the volume of product generated. This indicates that mechanization not only increases physical output but also substantially boosts the monetary value of production. The revenue effect is critical for improving farmer livelihoods and for scaling up farm business operations. Operational costs are significantly higher in mechanized farming, at RWF 650,000/ha, compared to RWF 500,000/ha in manual farming. The mean difference is RWF 150,000, and the t-value is 3.02, with a p-value of 0.004, significant at the 1% level. This increase is expected, as mechanized farming involves expenses related to fuel, maintenance of machinery, and services such as plowing and harvesting. However, it is important to note that while operational costs increase, they do not outweigh the revenue and profit gains. In fact, the efficiency brought by mechanization justifies the additional operational costs, especially when spread over larger land areas where economies of scale can be achieved. Gross profit, defined as total revenue minus operational costs, is significantly higher in mechanized farming, amounting to RWF 790,000/ha, compared to RWF 460,000/ha in manual farming. The mean difference is RWF 330,000, with a t-value of 4.07 and a p-value of <0.05, indicating strong statistical significance. This result emphasizes that even after accounting for higher variable costs, mechanized farming systems still deliver superior profit margins. The gross profit reflects the ability of a farmer to generate income before fixed capital costs are considered. The substantial margin also suggests that mechanized farming is more viable in terms of short-run profitability. This is particularly crucial for farmers seeking to reinvest in their farms or meet seasonal financial obligations.

Fixed costs in mechanized farming are RWF 200,000/ha, compared to only RWF 80,000/ha in manual systems, resulting in a mean difference of RWF 120,000. The t-value is 3.89, and the p-value is <0.05, indicating statistical significance. This difference reflects the capital investments required in mechanized farming, including machinery depreciation, equipment leasing, or ownership costs. While fixed costs are substantially higher, they represent long-term investments that support sustained productivity. Over multiple seasons, these costs can be amortized, reducing the per-hectare burden. Importantly, despite these higher fixed costs, net farm income still favors mechanized systems, indicating that the return on these investments is positive. Total production cost which includes both operational and fixed costs is RWF 990,000/ha for mechanized farming and RWF

580,000/ha for manual farming. The mean difference is RWF 410,000, with a t-value of 3.94 and a p-value of <0.05, confirming the significance of the difference. The total cost difference underscores that mechanized farming requires more financial input. However, the higher cost structure is more than offset by the gains in revenue, yield, and profit. This illustrates that mechanized farming is more capital-intensive but also more productive. Farmers adopting mechanization must therefore have access to capital or financing mechanisms, but the return justifies the investment. Net farm income, which is gross profit minus fixed costs, stands at RWF 590,000/ha for mechanized farming and RWF 380,000/ha for manual farming. The mean difference is RWF 210,000, with a t-value of 3.95 and a p-value < 0.05, showing statistical significance. This metric is crucial because it represents the actual take-home income for farmers after covering all costs. The significant increase in net income in mechanized systems confirms that even with higher operational and fixed costs, the net financial return is superior. This positions mechanized farming as a more lucrative option and supports its expansion in contexts where profitability and sustainability are priorities.

Gross margin, calculated as the percentage of revenue remaining after variable costs, is 54.86% for mechanized farming and 47.92% for manual farming. The mean difference is 6.94 percentage points, with a t-value of 2.31 and a p-value of 0.025, indicating statistical significance at the 5% level. This difference illustrates that mechanized systems are more efficient in converting revenue into profit before fixed costs. A higher gross margin implies better cost management relative to income. Even with higher operational costs, mechanized farming maintains a strong margin, reflecting efficient use of labor, inputs, and time. This supports the view that mechanized farming is not only productive but also financially efficient. The ROI is 121% for mechanized farming and 92% for manual farming, with a difference of 29 percentage points. The t-value is 2.75, and the p-value is 0.008, indicating significance at the 1% level. Return on Investment quantifies the profitability of the farming system relative to total costs. Mechanized farming offers a higher ROI, showing that each unit of currency invested returns more income. This is a compelling argument for mechanization, especially when seeking to attract investment, credit, or public-private partnerships in agriculture. A higher ROI also buffers farmers against market price fluctuations and input cost increases, improving resilience. Interestingly, the Benefit-Cost Ratio is slightly higher in manual farming (1.66) than in mechanized farming (1.45). BCR measures the ratio of total revenue to total cost. While this suggests that manual farming is more cost-efficient per unit of output, it does not account for scale or absolute profit levels. The higher BCR in manual systems underscores their lower cost base. However, in absolute terms, mechanized farming still generates higher yields, revenues, profits, and net income. This implies that while manual farming may be more efficient in relative terms, mechanized farming is superior in delivering larger economic gains. The lower BCR for mechanized systems may also reflect the need for optimization in input use or further investment in training and technology to improve efficiency.

In general, the profitability analysis provides clear and statistically validated evidence that mechanized soybean farming outperforms manual methods across nearly all key economic indicators. Mechanized systems deliver significantly higher yields, revenues, gross profits, and net farm incomes. Although they incur higher operational and fixed costs, the returns more than compensate for these expenses, resulting in higher overall profitability and efficiency. Indicators such as gross margin and ROI reinforce that mechanized farming is not only productive but also financially sustainable. The only measure where manual farming shows a relative advantage is the BCR, reflecting higher cost-efficiency at small scales. However, this does not outweigh the broader benefits of mechanization, especially for commercial or semi-commercial farming operations. In sum, mechanization enhances both the scale and sustainability of soybean production. With supportive policies, access to financing, and training, mechanized farming can drive agricultural transformation, increase rural incomes, and contribute to food security. The statistically significant differences observed in this analysis provide a strong empirical foundation for promoting mechanization as a pathway to modern, profitable agriculture.

3.3.4. Propensity Score Matching Analysis

25 matched pairs of mechanized and manual plots were generated using Propensity Score Matching. Matching was based on land size, input levels, and farmer demographics. After matching, the Average Treatment Effect on the Treated (ATT) revealed that mechanization increased yield by an average of 800 kg/ha, revenue by 480,000 RWF/ha, and net farm income by 195,000 RWF/ha. The gross margin was also improved by 7 percentage points. These results suggest that mechanization offers significant economic benefits even when controlling for other influencing factors. **Table 4**, shows the results of different matching techniques used to estimate ATT for each economic indicator. Both unmatched and ATT values are included:

The results from the different matching techniques like Nearest Neighbor Matching (NNM), Kernel Matching (KM), and Radius Matching (RM), and all show a consistently positive and statistically significant impact of mechanization on soybean production. Across all methods, the average treatment effect on the treated (ATT) for yield, net farm income, and gross margin remained robust, with T-statistics above 2.3 and standard errors within acceptable range, confirming the reliability of the observed economic benefits. **Table 4**, representing Propensity Score Matching Analysis, covering each economic indicator (Yield, Net Farm Income, Gross Margin) under the three matching algorithms: Nearest Neighbor Matching (NNM), Kernel Matching (KM), and Radius Matching (RM). The focus is on the ATT (Average Treatment Effect on the Treated), differences, and statistical significance. The purpose of the Propensity Score Matching (PSM) approach in this study is to estimate the causal effects of adopting mechanized farming methods compared to manual farming by controlling for potential selection bias. Matching was based on observable characteristics such as land size, input levels, and farmer demographics, which are assumed to influence both the likelihood of adopting mechanization and the farming outcomes. This method allows for the comparison of treated (mechanized) and control (manual) groups with similar baseline characteristics. The analysis used three matching algorithms such as Nearest Neighbor Matching (NNM), Kernel Matching (KM), and Radius Matching (RM) to estimate the ATT for three key economic indicators: yield (kg/ha), net farm income (RWF/ha), and gross margin (%). The analysis is based on 25 matched pairs.

Table 4. Propensity score matching analysis for both soybeans production system.

Method	Match Type	Indicator	Treated	Control	Difference	Std. Error	T-statistic
NNM	Unmatched	Yield (kg/ha)	2400	1600	800	189.9	4.21**
	ATT	Yield (kg/ha)	2400	1650	750	182.3	4.12**
	Unmatched	Net Farm Income (RWF/ha)	590,000	380,000	210,000	53,164	3.95**
	ATT	Net Farm Income (RWF/ha)	590,000	385,000	205,000	50,764	4.04**
	Unmatched	Gross Margin (%)	54.86	47.92	6.94	3.00	2.31**
	ATT	Gross Margin (%)	54.86	48.00	6.86	2.85	2.41**
KM	Unmatched	Yield (kg/ha)	2400	1600	800	189.9	4.21**
	ATT	Yield (kg/ha)	2400	1670	730	170.2	4.29**
	Unmatched	Net Farm Income (RWF/ha)	590,000	380,000	210,000	53,164	3.95**
	ATT	Net Farm Income (RWF/ha)	590,000	390,000	200,000	49,984	4.00**
	Unmatched	Gross Margin (%)	54.86	47.92	6.94	3.00	2.31**
	ATT	Gross Margin (%)	54.86	48.23	6.63	2.80	2.37**
RM	Unmatched	Yield (kg/ha)	2400	1600	800	189.9	4.21**
	ATT	Yield (kg/ha)	2400	1680	720	177.6	4.05**
	Unmatched	Net Farm Income (RWF/ha)	590,000	380,000	210,000	53,164	3.95**
	ATT	Net Farm Income (RWF/ha)	590,000	395,000	195,000	49,211	3.96**
	Unmatched	Gross Margin (%)	54.86	47.92	6.94	3.00	2.31**
	ATT	Gross Margin (%)	54.86	48.50	6.36	2.76	2.31**

P*** < 1%, P** < 5%, & P*10%. Source: Researcher, 2025.

3.4. Soybeans Production by ATT Techniques

Under the NNM (Nearest Neighbor Matching) method, the ATT for yield is 750 kg/ha. Mechanized plots yield, on average, 2400 kg/ha, compared to 1650 kg/ha for matched manual plots. The difference of 750 kg/ha is statistically significant with a standard error of 182.3 and a t-statistic of 4.12, indicating a high level of confidence ($p < 0.05$). This suggests a substantial productivity advantage associated with mechanization. The matching process ensures that this result is not confounded by other observable factors, affirming that mechanization itself contributes directly to yield improvement. The Kernel Matching (KM) method yields an ATT of 730 kg/ha for yield, with a slightly lower estimated difference than NNM.

Mechanized plots still produce 2400 kg/ha, while the matched manual plots yield 1670 kg/ha. The standard error is 170.2 and the t-statistic is 4.29, which is even more statistically significant than in NNM. The high level of precision in KM (which utilizes weighted averages over all control units) may explain the slightly higher t-statistic. Despite the slightly smaller magnitude, the direction and significance of the effect remain consistent, affirming the robustness of mechanization's impact on productivity. Under RM, the ATT for yield is 720 kg/ha. The treated group yields 2400 kg/ha, while the matched control group yields 1680 kg/ha. The standard error is 177.6 and the t-statistic is 4.05, which is strongly significant ($p < 0.01$). RM uses a caliper to define a maximum distance for matching, which offers more conservative estimates while still retaining statistical power. The slightly lower ATT compared to NNM and KM may reflect stricter matching criteria, but the consistency of the result further supports the conclusion that mechanization leads to significant yield gains. Across all three matching methods, the yield impact is both economically and statistically significant, with ATT values ranging from 720 to 750 kg/ha. The narrow range of differences, all significant at the 1% level, confirms that mechanization substantially enhances productivity, likely due to better land preparation, planting precision, and timeliness of operations enabled by machines.

3.4.1. Net Farm Income (RWF/ha) by ATT Matching Techniques

In the NNM analysis, the ATT for net farm income is RWF 205,000. Mechanized farms earn a net income of RWF 590,000 per hectare, while matched manual farms earn RWF 385,000. The standard error is 50,764 and the t-statistic is 4.04, indicating statistical significance at the 5% level. This outcome highlights the economic benefit of mechanization beyond just yield. The increased income reflects not only higher productivity but potentially better efficiency and lower labor costs per unit of output, even if mechanization introduces higher fixed costs. Kernel Matching results in a slightly lower ATT for net farm income at RWF 200,000. Mechanized farms still earn RWF 590,000, while manual farms earn a slightly higher RWF 390,000 in this matching. The standard error is 49,984 and the t-statistic is 4.00, again confirming significance at the 1% level. The small variation in ATT and control means across methods reflects differences in how controls are weighted, but the consistent statistical significance confirms that mechanization leads to a substantial improvement in net farm earnings. Under Radius Matching, the ATT for net farm income is RWF 195,000, with the mechanized group earning RWF 590,000 and the matched manual group earning RWF 395,000. The standard error is 49,211, and the t-statistic is 3.96, which is statistically significant at the 1% level. The RM approach again yields a slightly more conservative estimate, but the evidence remains strong that mechanization improves net income. This increase can be interpreted as a return to both improved yields and potentially better cost management due to more efficient farming. The consistency of ATT values across all matching methods, ranging narrowly from RWF 195,000 to RWF 205,000, reinforces the conclusion that mechanization has a strong, positive effect on net farm income. The statistical significance across all models confirms that this effect is not driven by chance or selection bias.

3.4.2. Gross Margin (%) by ATT Matching Techniques

Gross margin, defined as a percentage of revenue remaining after variable costs are covered, is a key indicator of farming efficiency and profitability. Under Nearest Neighbor Matching, the ATT for gross margin is 6.86 percentage points. Mechanized farms achieve a margin of 54.86%, while matched manual farms attain 48.00%. The standard error is 2.85 and the t-statistic is 2.41, which is statistically significant at the 5% level. This suggests that mechanized farmers retain a higher proportion of their revenue as profit, even when accounting for increased input costs. The gross margin improvement indicates that mechanization is not only productive but also efficient in terms of variable cost control. The KM method estimates an ATT of 6.63 percentage points for gross margin. Mechanized farms maintain a margin of 54.86%, while manual farms under KM achieve a slightly better margin of 48.23%. The standard error is 2.80 and the t-statistic is 2.37, again significant at the 5% level. The slight decrease in ATT compared to NNM reflects the differing weights used in Kernel Matching, but the result remains economically meaningful and statistically robust. Furthermore, the Radius Matching produces an ATT of 6.36 percentage points in gross margin. Mechanized farms still average 54.86%, while matched manual farms under RM average 48.50%. The standard error is 2.76, leading to a t-statistic of 2.31, which confirms statistical significance at the 5% level. While this is the most conservative estimate among the three methods, it still indicates a substantial efficiency gain. The fact that even with increased fixed and operational costs, mechanized farms maintain a higher gross margin suggests that the benefits of scale and efficiency outweigh the cost burden. The consistent and statistically significant improvement in gross margin ranging from 6.36 to 6.86 percentage points across all methods provides strong evidence that mechanization not only boosts output but also improves cost efficiency. This is particularly important for long-term sustainability and investment attractiveness.

4. Results and Discussion

Based on the above interpretation, the Propensity Score Matching analysis provides compelling evidence that mechanization in soybean farming has a substantial and statistically significant positive impact on key economic indicators. All three matching methods, NNM, KM, and RM produce closely aligned results, with minor variations due to algorithmic differences in how control observations are selected and weighted. The ATT values for yield (720 - 750 kg/ha), net farm income (195,000 - 205,000 RWF/ha), and gross margin (6.36 - 6.86 percentage points) are all statistically significant, indicating that the observed benefits of mechanization are not artifacts of selection bias or random variation. Mechanized farming leads to higher yields, which translate into greater revenues. Even though mechanization introduces higher costs particularly in terms of fixed capital investment the net farm income remains significantly higher, indicating that the returns exceed the additional costs. Furthermore, the improved gross margin demonstrates that mechanized systems are more efficient in converting revenue into profit. These outcomes demonstrate the economic rationale for encouraging mechanization as a means of improving agricultural productivity, profitability, and sustainability. The robustness of these findings across different matching algorithms lends credibility to the conclusion that mechanization is a key driver of economic performance in farming. It is clear that the adoption of mechanization, when matched with appropriate land size, input levels, and demographic conditions, yields significant benefits for farmers. These results could inform policy decisions around mechanization support, including subsidies, training, and financing mechanisms, to accelerate adoption and maximize the economic gains for rural communities. The significant yield advantage of mechanized farming (2400 kg/ha vs. 1600 kg/ha) that enhances timeliness and precision in planting, leading to higher productivity. The revenue increase (480,000 RWF/ha) that evidence to optimize input use and reduces post-harvest losses, directly boosting farm incomes. The higher operational costs (650,000 RWF/ha) in mechanized systems reflect observations on fuel and maintenance expenses, though these are offset by productivity gains. The gross margin improvement (54.86% vs. 47.92%) supports argument that mechanization improves cost efficiency by reducing labor dependency. The net farm income advantage (590,000 RWF/ha) is consistent with studies in Sub-Saharan Africa, where mechanization raised profitability despite higher capital costs [17]. The lower benefit-cost ratio (1.45) for mechanization, compared to manual farming (1.66), echoes findings that small-scale manual systems may exhibit higher relative efficiency, though absolute profits favor mechanization. The ATT results for yield (720 - 750 kg/ha) which attributed such gains to mechanized precision and reduced labor bottlenecks. The net income increase (195,000 - 205,000 RWF/ha) that provided insights to mechanization's economic benefits for te farmers. The robust gross margin improvements (6.36 - 6.86 percentage points) mirror precision agriculture studies, where technology enhanced input-use efficiency. The consistency across NNM, KM, and RM methods reinforces emphasis on algorithmic robustness in impact evaluations. The findings collectively support policy recommendation that mechanization requires tailored financing and training to address adoption barriers while maximizing productivity gains.

5. Conclusion and Recommendations

The analysis demonstrates that mechanized soybean farming at Gishari Demonstration Farm significantly outperforms traditional methods across key economic indicators. Propensity Score Matching (PSM) results, using NNM, KM, and RM algorithms, consistently show mechanization increases yield by 720 - 750 kg/ha, net farm income by 195,000 - 205,000 RWF/ha, and gross margin by 6.36 - 6.86 percentage points, with all differences statistically significant ($p < 0.05$). These gains stem from enhanced productivity and operational efficiency, despite higher fixed and operational costs. As shown in **Table 3**, Profitability analysis confirms mechanization's advantages generating 480,000 RWF/ha higher revenue and 210,000 RWF/ha greater net income, though manual farming exhibits a marginally higher benefit-cost ratio (1.66 vs. 1.45), reflecting its lower cost base at small scales. The findings from this study carry significant policy implications for promoting agricultural mechanization in Rwanda and similar contexts.

The robust evidence of higher productivity and profitability under mechanized soybean farming calls for targeted interventions to overcome adoption barriers. Policymakers should focus on creating enabling environments through financial support mechanisms such as subsidized loan programs or equipment leasing schemes, particularly for smallholder farmers facing high upfront capital costs. Given the demonstrated return on investment and net income advantages, agricultural extension services should prioritize training programs that equip farmers with both technical skills for machinery operation and financial literacy for cost management.

Infrastructure development should accompany these efforts, including reliable access to fuel and maintenance services to support mechanized operations.

The consistent yield advantages across matching methods indicate that mechanization policies should be integrated with other productivity-enhancing measures like improved seed varieties and soil management practices. For equitable implementation, policymakers should consider differentiated approaches based on farm size and farmer capacity, as the benefits of mechanization become particularly pronounced at larger scales.

The statistically significant improvements in gross margin and net income provide a strong economic rationale for public and private sector investments in mechanization as a driver of agricultural transformation. These interventions should be monitored through impact evaluations to ensure they deliver the intended benefits while adapting to local contexts and farmer needs.

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Declarations

Ethics approval: The study received ethical approval from the School of Agricultural Engineering, in the College of Agriculture, Animal Science and Veterinary Medicine (CAVM), University of Rwanda (UR), in accordance with the Directorate of Research and Innovation at the College of Agriculture, Animal Sciences and Veterinary Medicine (CAVM), University of Rwanda (UR). The study adhered to all ethical considerations, including informed consent, confidentiality, and participant rights, and was conducted in full compliance with established guidelines governing research involving human participants as outlined by the ethics committee of the University of Rwanda. This ensured the highest ethical standards throughout the data collection process.

Conflicts of Interest

The authors declare no competing interests.

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