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Impact of Mechanized Harvesting on the Cultivated and Total Operational Land Area of Rice Farmers in Bangladesh

K. K Hossain^{1*}, M. A. Hossain², T. Islam³, M. Rana⁴ and M. I. Jewel⁵

¹Department of Economics, Gopalganj Science & Technology University, Bangladesh

²Sociology, Directorate of Secondary and Higher Education (DSHE), Ministry of Education, Bangladesh

³Department of Fisheries and Marine Bioscience, Gopalganj Science & Technology University, Bangladesh

⁴Department of Agricultural Marketing, Ministry of Agriculture, Dhaka, Bangladesh

⁵Department of Economics, Government Prafulla Chandra College, Bangladesh

Abstract

In Bangladesh, crop harvesting is considered the most labor-intensive and costly phase of farming. The adoption of mechanized harvesting techniques can significantly improve efficiency and minimize losses resulting from shattering, lodging or adverse weather conditions, especially for rice farmers. However, the impact of mechanized harvesting on rice farmers in Bangladesh has not been evaluated. We aimed to examine the impact of mechanized harvesting on rice farmers in Bangladesh on cultivated land, temporary cropped land and the total operated area. This study considered which rice farmers have crop reaping machines, rice threshers or both in the treatment group. To assess the influence of mechanized harvesting on rice farming, we employed propensity score matching and inverse probability weighted regression adjustment, complemented by Rosenbaum sensitivity analysis for robustness. Our findings revealed that harvesting mechanization increased cultivated land by 0.48 acres and expanded temporary cropped land by 0.55 acres, resulting in a total operated area increased by 0.49 acres among rice farmers. This highlights the significant potential for mechanization to improve efficiency across the sector. Additionally, only 22.96% of rice farmers own crop reaping machines or rice threshers, which indicates that the adoption rate is also low. Despite these benefits, widespread

* Corresponding author: khalidju41@gmail.com

adoption of mechanical harvesting faces obstacles such as high startup costs, limited access to financing and a shortage of skilled operators. Addressing these challenges through subsidies, training programs and improved access to funding is essential for advancing mechanized harvesting and promoting sustainable rice production in Bangladesh.

Keywords: Cultivated land, Mechanized harvesting, Rice farmers, Temporary cropped land, Total operated land

Introduction

Bangladesh, located in South Asia along the eastern coast of the Bay of Bengal, shares its borders with India to the north and east and Myanmar to the southeast (World Bank, 2021; Asian Development Bank, 2023). According to the Bangladesh Bureau of Statistics (BBS), the total food grain production in the fiscal year 2022–23 was 40.27 million metric tons (MMT), comprising 2.90 MMT of Aus, 15.43 MMT of Aman, 20.77 MMT of Boro and 1.17 MMT of wheat (BBS, 2023). Rice, produced mainly from the three varieties Aus, Aman and Boro is vital, as it serves as the country's staple food and is essential to food security and rural livelihoods (BBS, 2023). Beyond nutrition, rice farming is deeply embedded in the socio-economic fabric of Bangladesh, providing employment for millions of rural families, contributing significantly to the GDP, and supporting smallholder farmers and agribusinesses. The consistent cultivation of rice varieties like Boro, Aman and Aus ensures a stable supply, making rice production a cornerstone of both food security and the rural economy.

The global mechanization of agricultural practices has significantly transformed food production, allowing it to keep pace with rising population levels in most regions, although many less developed countries, particularly in Africa, continue to lag behind in this regard (C, 2009). Within this broader context, Bangladesh remains predominantly an agrarian economy where agriculture serves as a vital sector, contributing 11.55% to the national GDP and paddy cultivation holds a central position, representing nearly 75% of the total cropped area and accounting for 90–95% of the country's cereal output (BBS, 2024). Furthermore, the overall impact of mechanization on agricultural production depends on advancements in farm-level machinery and the efficiency of farming operations. The broader profitability of agriculture highlights the importance of mechanization (Vortia et al., 2019).

Additionally, mechanization is widely recognized as a key driver of agricultural transformation, as in most high and middle-income countries, only a few farm operations continue to be performed manually (Schmitz & Moss, 2015). In regions such as sub-Saharan Africa, parts of Latin America and South Asia, the availability of farm machinery and tractor power remains minimal in relation to the total cultivated land area (Baudron et al., 2015). In Bangladesh, providing agricultural machinery services has become common, but despite having one of the world's

highest rural populations, farming communities face increasing labor shortages as many people migrate in search of seasonal or permanent non-farm jobs (World Bank, 2018; Zhang et al., 2014). This makes the introduction of scale-appropriate technological innovations in small agricultural machinery a promising strategy to address these issues (Gregg et al., 2019).

Harvesting mechanization is crucial for rice farmers in Bangladesh facing significant agricultural challenges. Traditional manual harvesting methods are labor-intensive, slow, increase costs and crop losses, averaging about 3.09% postharvest loss (Nath et al., 2022). Studies show that adopting mechanized harvesting systems significantly saves time, labor and costs, while also reducing postharvest losses (Nath et al., 2022). Furthermore, mechanization enhances technical efficiency, leading to higher productivity and greater profitability for farmers (Vortia et al., 2019). Although many mechanization technologies are now smaller in scale and increasingly affordable, expanding smallholder farmers' access to such machinery remains challenging. However, low-cost rental systems and service providers create opportunities for smallholders to use machines without bearing the full costs of purchase, ownership, and maintenance (Mottaleb et al., 2016; Diao et al., 2018). These arrangements often involve higher transaction costs that need to be offset and carefully incorporated into sustainable business models (Laxmi et al., 2007). The adoption of mechanized harvesting techniques has the potential to enhance efficiency and reduce losses caused by factors such as shattering, lodging or inclement weather, particularly for rice farmers. Nevertheless, the effects of mechanized harvesting practices on rice farmers in Bangladesh remain underexplored. This study aims to explore whether mechanized harvesting contributes to expanding cultivated land area, temporary cropped land and total operated area among rice farmers in Bangladesh, an aspect that has not been sufficiently addressed in existing literature. While many studies have examined the productivity and profitability impacts of mechanization, fewer have directly linked mechanization to the outcome of land area expansion. Filling this gap will provide insights not only into the economic benefits of mechanization but also into how it can drive agricultural growth and sustainability in a country where rice farming is both a livelihood and a cornerstone of rural development. Given the importance of rice cultivation in Bangladesh's economy and its role in ensuring national food security, understanding the potential for mechanization to influence land area is crucial.

Evaluation of Methodology

Estimating the propensity score (PS) is a crucial initial step in Propensity Score Matching (PSM), aimed at minimizing selection bias between treated and control groups in observational research (Bai, 2013). This method improves the credibility of causal conclusions by balancing observed covariates across groups. While matching estimators are frequently used to assess average treatment effects, their asymptotic properties are still uncertain in many scenarios, as pointed out by Abadie and Imbens

(2005). Nevertheless, they remain a key tool in empirical research because of their straightforward approach and practical usefulness.

This study, within the PSM framework, estimates the Average Treatment Effect on the Treated (ATT), which is the expected difference in outcomes between treated individuals and their hypothetical outcomes had they not been treated (Li, 2013). The treatment effect is precisely expressed using the ATT formula shown in Equation 1 (Hossain et al., 2025; Hossain & Joshi, 2025a).

$$ATT(q) = E[Y_1|T = 1, B = q] - E[Y_0|T = 1, B = q] \dots\dots (1)$$

Vector B represents time-invariant covariates employed in the matching process. The term $E[Y_1|T=1, B=q]$ captures the expected outcome for treated units, while $E[Y_0|T=1, B=q]$ reflects the expected outcome for comparable control units with the same covariate profile (i.e., $B=q$). The treatment indicator T is a binary variable.

The Inverse Probability Weighted Regression Adjustment (IPWRA) method provides a strong alternative for estimating the ATT, especially in situations where PSM might be susceptible to model misspecification (Bari et al., 2024). Using multiple estimation techniques improves the reliability and comprehensiveness of the results. The IPWRA-based estimates were produced using the procedures described in the following section (Hossain et al., 2025; Hossain & Joshi, 2025a).

$$ATT_{IPWRA} = N^{-1} \sum_{i=1}^n [(\alpha_1^* + \beta_1^* X_i) - (\alpha_0^* + \beta_0^* X_i)] \dots\dots\dots (2)$$

The parameters α_1^* and β_1^* were estimated based on the procedure applied to the treated group, whereas α_0^* and β_0^* were obtained for the control group, following the specification provided in the corresponding equations.

Estimating ATT through PSM can be affected by unobserved confounder variables not captured within the model, which may introduce bias and compromise the credibility of the results. Prior research has underscored the significance of these limitations (Rosenbaum & Rubin, 2023; Tagel & Anne, 2015). To ensure that the estimated treatment effect genuinely represents a causal relationship, it is essential to address this potential source of bias. As a final diagnostic step, a sensitivity analysis is employed to evaluate the robustness of PSM estimates against the presence of hidden biases (Li, 2013).

Li (2013) proposed three techniques for conducting sensitivity analysis: altering the equation specification, employing instrumental variables, and implementing the Rosenbaum Bounding (RB) method. In this study, the RB approach is utilized to evaluate the robustness of the estimated treatment effects. The resulting odds ratio can be expressed as follows.

$$\Gamma = \exp(\gamma(w_{1i} - w_{0i})) \dots\dots\dots (3)$$

The parameter Γ (gamma) denotes the odds ratio of receiving the treatment. If the unobserved characteristics w_{1i} and w_0 are identical, it implies that treatment assignment was effectively random. As a result, the ATT estimate remains unbiased,

neither inflated nor deflated, indicating that hidden confounding due to unobserved variables did not distort the findings.

Result and Discussion

Table 1. Variables and their description.

Variables	Description
Gender Dummy	1=Male Headed, 0= Otherwise
Education	Years of education of household head
Fishery Household	Yes=1, Otherwise=0
Agricultural Labor Household	Yes=1, Otherwise=0
Child Labor	Agricultural worker from family (10 to 14 years)
Agricultural worker	Agricultural worker from family (14 years and above)
Wheat Dummy	1= If farmer cultivate wheat, No=0
Maize Dummy	1= If farmer cultivate maize, No=0
Potato Dummy	1= If farmer cultivate potato, No=0
Brinjal Dummy	1= If farmer cultivate brinjal, No=0
Tomato Dummy	1= If farmer cultivate tomato, No=0
Outcome Variables	
Cultivated Land	Acres
Total Operated Area	Acres
Temporary Cropped Land	Acres

For this study, we used 11 covariates to calculate the PS (gender dummy, education, fishery household, agricultural labor household, child labor, agricultural worker, wheat dummy, maize dummy, potato dummy, brinjal dummy, tomato dummy) and three outcome variables, whose descriptions are listed in Table 1. The data for this study comes from the Bangladesh Agricultural Census of 2019. The cultivated land area is the total of temporary crop land, permanent crop land, and land under nursery. Total operated area equals the area owned plus land taken from others, minus the area given to others as their own. Land under temporary crops includes all land where crops are grown with a cycle of less than one year (BBS, 2020).

Table 2. Descriptive statistics

Variables Name	Observations	Mean	Standard Deviation	Minimum value	Maximum value
Gender Dummy	5,20,309	0.95	0.21	0	1
Education	5,20,309	4.77	4.24	0	18
Fishery Household	5,20,309	0.03	0.19	0	1
Agricultural Labor Household	5,20,309	0.38	0.48	0	1
Child Labor	5,20,309	0.04	0.25	0	3
Agricultural worker	5,20,309	0.98	1.12	0	15
Wheat Dummy	5,20,309	0.13	0.34	0	1
Maize Dummy	5,20,309	0.10	0.30	0	1
Potato Dummy	5,20,309	0.16	0.37	0	1
Brinjal Dummy	5,20,309	0.06	0.24	0	1
Tomato Dummy	5,20,309	0.04	0.20	0	1
Outcome Variables					
Crop Cultivated Land	5,20,309	0.80	1.34	0	99.9
Total Operated Area	5,20,309	1.21	2.15	0	196.71
Temporary Cropped Land	5,20,309	0.74	1.08	0	99.9

Table 2 presents the descriptive statistics for matching covariates and the outcome variables. For this study, we have used data from 5,20,910 rice farmers. First, we run the probit regression to estimate the PS. Then we applied the trimming rule to exclude the rice farmers whose $PS < 0.1$ and $PS > 0.9$, as proposed by Crump et al., (2009). We found that 601 farmers have $PS < 0.1$ and $PS > 0.9$. For the final study, we used 5,20,309 rice farmers to estimate a more precise result. Among them, 4,00,846 farmers are in the control group, and 1,19,463 (22.96%) farmers are in the treatment group, who own machinery for mechanized harvesting. This study considered which farmers had crop reaping machines, rice threshers or both in the treatment group to estimate the impact of harvesting mechanization on the cultivated land, temporary cropped land and total operated area of rice farmers in Bangladesh.

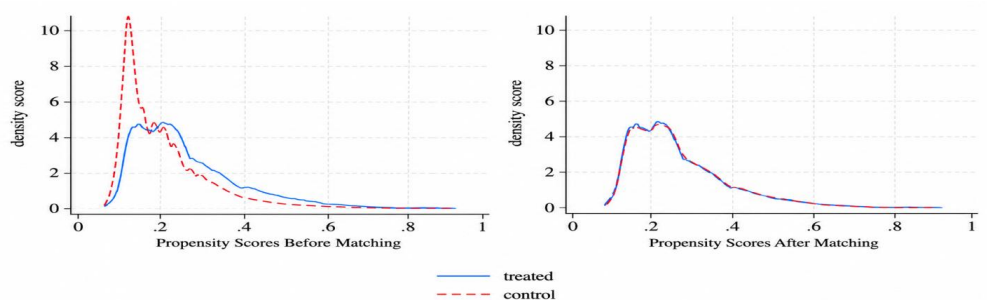


Fig. 1. Overlap of Propensity scores.

Before conducting the PSM, it's essential to have enough overlap in PS between the control and treatment groups to accurately estimate the unbiased ATT. The left side of Figure 1 illustrates that prior to matching; the PS overlap was limited. After the matching process, the overlap improves notably, suggesting that the two groups are more comparable, which enhances the accuracy of the unbiased ATT estimate.

Table 3. Impact of harvesting mechanization on outcome variables for rice farmers

Estimation method	Cultivated land	Temporary cropped land	Total operated area
	ATT	ATT	ATT
PSM	0.48*** (0.20)	0.55* (0.29)	0.49*** (0.16)
NNM	0.48*** (0.20)	0.55* (0.29)	0.49*** (0.16)
IPWRA	0.53*** (0.006)	0.49*** (0.005)	0.65*** (0.007)

* $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 3 reports the estimated effects of mechanized harvesting on rice farmers' land use, based on three different methods: PSM (random draw version), nearest neighbor matching (NNM), and inverse probability weighted regression adjustment (IPWRA). The results consistently showed that mechanized harvesting machinery has a positive and statistically significant impact on cultivated land, temporary cropped land, and total operated land area. Specifically, rice farmers with mechanized harvesting cultivated 0.48 acres more land, increased the temporary cropped land by 0.55 acres, and expanded their total operated area by 0.49 acres compared to farmers without mechanized harvesting. The PSM and NNM one-to-one matching methods yield similar results. Similarly, IPWRA results indicate that farmers with mechanized harvesting experienced an increase of 0.53 acres of cultivated land, 0.49 acres of temporary cropped land, and 0.65 acres in total operated area, which does not differ

significantly from the PSM estimates. These findings robustly suggest that mechanized harvesting contributes to an expansion of rice farming areas.

Table 4. RB sensitivity test for robustness

Gamma (Γ)	Crop cultivated land		Temporary cropped land		Total operated area	
	sig+	sig-	sig+	sig-	sig+	sig-
1.00	0.00	0.00	0.00	0.00	0.00	0.00
1.10	0.00	0.00	0.00	0.00	0.00	0.00
1.20	0.00	0.00	0.00	0.00	0.00	0.00
1.40	0.00	0.00	0.00	0.00	0.00	0.00
1.50	0.00	0.00	0.00	0.00	0.00	0.00

Note: sig+ - level of upper bound significance (H_0 = ATT over estimated)
 sig- - level of lower bound significance (H_0 = ATT under estimated)

This study demonstrates the robustness of its PSM results by conducting the RB sensitivity test for the estimated ATT of the outcome variables. Since PSM can be influenced by unmeasured covariates, the study tested Gamma (Γ) values ranging from 1.00 to 1.50, and the results are shown in Table 4. The results rejected the null hypothesis of over- or underestimation, confirming the finding's reliability and impact.

The results of this study (Table 3) show that the ownership of harvesting machinery is beneficial in increasing the cultivated land, temporarily cropped land, and total operated area of rice farmers. In Bangladesh, harvesting is regarded as the most costly and labor-intensive operation in crop production (Rahman et al., 2021). The use of harvesting machinery significantly boosts farmers' efficiency, enabling them to cover larger areas of land in less time. This advancement is especially vital in Bangladesh, where land resources are limited and a growing population puts a strain on available land.

Mechanization reduces both the time and labor needed for harvesting, empowering farmers to expand their cultivation more effectively (Vortia et al., 2021) which is helpful for increasing the cultivated land and the total operated area for farmers in Bangladesh. This reinforces the long-standing notion that mechanization must be integral to any agricultural development strategy in less developed nations. Furthermore, mechanized harvesting and threshing not only significantly reduce losses and increase yields per hectare but also have a positive socio-economic impact (Castelein et al., 2022). Mechanization in agriculture has the potential to significantly boost farmers' earnings (Peng et al., 2022), which can positively influence the expansion of cultivated land and increase the overall operating area for rice farmers. In addition, the adoption of combine harvesters in Bangladesh for rice farming is a

positive sign, although it needs further care in order to make it sustainable (Rahman et al., 2021).

The harvesting mechanization is also helpful in increasing the temporary cropland for rice farmers in Bangladesh. This aligns with prior research by Ji et al., (2021) which demonstrated that Agricultural technology enhances the frequency of cropping on cultivated land, enabling many crop cycles annually, hence augmenting yields and land output rates. Furthermore, the expansion of temporarily cropped land reflects significant advancements in harvesting efficiency. These innovations facilitate crop rotation and the adoption of diverse cropping systems, thereby substantially enhancing land productivity. Additionally, mechanization accelerates harvest timelines, enabling farmers to maximize their land use for short-season crops and ultimately expanding the total cropped area. This efficiency not only boosts productivity but also mitigates crop losses caused by sudden climate changes, which increasingly threaten rice production (Hossain and Joshi, 2025b). Together, these advantages highlight how mechanization can bolster resilience and sustainability in agriculture.

The total operated area indicates the overall size of farm operations, which is affected by the increased capacity of mechanized equipment (Table 3). As more farmers begin using mechanized harvesters, this will help the total agricultural land in use expand. This will also give an opportunity to increase efficiency and may also help boost incomes for rice farmers, as they can cut costs related to manual labor and produce more.

Despite these positive impacts, adopting mechanization presents challenges. The upfront cost of buying harvesting machinery can be a barrier for small-scale farmers in Bangladesh. However, as access to the technology improves through leasing options or government subsidies, the advantages of mechanization could become more widespread (Bakhtiar et al., 2025; Mottaleb et al., 2016). To enhance the mechanization adoption rate for rice farmers in Bangladesh, the government put forward a plan to go for all-out mechanization of the farming sector, starting with the introduction of harvesters at a subsidized rate up to 70% (DAE, 2021). Therefore, access to credit and subsidized options should be made easy, but monitoring of such credit must be strengthened in order to stop the money from going out of the farming sector (Rahman et al., 2021). Consequently, Policymakers need to consider farmers' financial limitations and implement measures to make mechanization more affordable, such as low-interest loans or subsidies. Furthermore, training and capacity-building programs are crucial to ensure farmers can effectively operate and maintain harvesting equipment.

Conclusion

The findings of this study emphasize the significant role of harvesting mechanization in enhancing the cultivated land and operational capacity of rice farming in

Bangladesh. It underscores how adopting modern harvesting technology can transform the region by increasing cultivated and operated land areas. This efficiency enables rice farmers to expand their farms, manage larger areas more effectively and optimize cropping patterns, contributing to higher yields and enhanced food security.

Mechanized rice harvesting significantly reduces labor dependency, addressing critical challenges such as labor shortages and harvest delays. This technological advancement ensures timely operations, thereby minimizing post-harvest losses and elevating overall productivity. The capacity to manage larger cultivated areas and facilitate rapid crop rotations not only enhances the economic sustainability of rice farming but also fortifies the agricultural economy by optimizing land use. In essence, the adoption of mechanization is pivotal to the modernization of rice agriculture in Bangladesh, yielding substantial benefits for farmers and the broader sector. To fully realize these gains, a coordinated effort involving both governmental and non-governmental organizations is imperative to overcome adoption barriers and foster sustainable growth. Such collaborative initiatives are crucial for enhancing food security, improving farmers' livelihoods and promoting the long-term agricultural development of Bangladesh.

This study has certain limitations to consider. The treatment was not randomly assigned. Additionally, due to data constraints from the 2019 Agricultural Census, the study lacks information on rice farmers' production, costs and profits.

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