Impact of Pump Electrification on Crop Diversification in Bangladesh: Evidence from the Bangladesh Integrated Household Survey

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Abstract

Bangladesh's agricultural sector, crucial to its economy, has undergone a significant transformation in recent years, largely due to the shift from diesel to electric irrigation pumps. This study investigates the impact of this energy transition on crop diversification. While there is extensive literature on crop diversification, the effects of changing energy sources have remained underexplored. Leveraging the substantial increase in pump electrification over the past decade, we utilize data from the Bangladesh Integrated Household Survey (BIHS) for 2011, 2015, and 2018 to examine this shift. Our hypothesis posits that the transition to electric pumps influences cropping patterns by lowering irrigation costs. Using difference-in-differences (DID) and fixed effect model, we find that pump electrification significantly alters cropping patterns. Specifically, we observe a 5.5 percentage point increase in paddy cultivation and a 4.9 percentage point decrease in non-paddy crops. Notably, the rise in the overall paddy proportion is primarily driven by an increase in boro paddy cultivation, while the decline in non-paddy crops is attributed to a reduction in wheat cultivation. These findings highlight the effects of cheaper irrigation through electric pumps, which may disproportionately favor water-intensive paddy cultivation. Policymakers should consider these insights when designing strategies to promote more diverse and nutritionally beneficial cropping patterns.

Keywords: Boro Paddy, Crop Diversification, Irrigation, Electrification, Bangladesh

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1.0 Introduction

Bangladesh's agricultural sector, a cornerstone of its economy and rural livelihoods, has undergone significant transformations in recent years (Mukherji *et al.,* 2021, Krupnik *et al.,* 2017). Among these changes, the transition from diesel-powered to electric irrigation pumps marks a shift in the energy landscape of agriculture. The number of electric pumps in use has increased significantly by 27.6% from the 2010s to the 2020s, reflecting a notable shift (BADC,2020). Recent policy initiatives have sought to transition Bangladesh's irrigation sector from diesel to electricity. This energy transition carries implications for irrigation practices, production costs, and agricultural systems, offering a unique opportunity to analyze its broader impact. Since irrigation accounts for 43% of total agricultural expenses, this shift is crucial for reducing economic burdens and promoting sustainable farming practices (Asian Development Bank, 2023).

The shift to electric irrigation systems can transform rural communities by enhancing food security, livelihoods, and economic resilience (Buisson *et al.,* 2021, Mukherji 2007). Improved irrigation access also plays a critical role in climate change adaptation by ensuring water availability during periods of scarcity (Woznicki *et al.,* 2015). Electric energy systems offer a more cost-effective and sustainable alternative to diesel pumps. Therefore, while diesel pumps remain highly prevalent, their higher operational costs and lower efficiency compared to electric pumps make the latter increasingly attractive (Varshney *et al.,* 2022). Lower irrigation costs reduce the economic constraints on farmers, enabling them to irrigate larger areas or adopt crops with higher water requirements, such as paddy or fruits and vegetables. However, this shift may also discourage the cultivation of high-value or diverse crops, leading to a preference for water-intensive staple crops due to their relatively stable yields and market demand (see Sarkar & Das, 2014; Buisson et al., 2021). As a result, while these energy transitions alleviate financial pressures on farmers, they may inadvertently contribute to the long-term sustainability and resilience of agricultural systems.

Despite extensive literature on the determinants and benefits of crop diversification (See Birthal et al., 2015; De Pinto et al.,2019; Anuja et al., 2020; Nandi et al., 2023), the specific role of energy transitions—such as pump electrification—in influencing crop diversification remains underexplored. This research gap warrants attention for several reasons. First, there is a lack of empirical evidence on the impact of electric pump adoption on crop diversification in Bangladesh. However, studies from other South Asian regions provide valuable insights. In some cases, electrification might reinforce specialization in intensive cropping systems, such as the paddy-wheat system in Punjab (Sarkar & Das, 2014). Conversely, electrification can enable smallholders to shift from subsistence farming to market-oriented production, supporting multiple cropping seasons and increasing land use efficiency (Hussain & Hanjra, 2003). In other contexts, electrification may promote diversification (Birthal et al., 2015), allowing farmers to transition to more profitable or less water-intensive crops, thereby reducing risks, maximizing income, and improving dietary diversity with better nutritional outcomes (Mustafa et al., 2019; Pingali 2015). Second, exploring its impact is critical for understanding the interplay between energy, agriculture, and sustainability.

The adoption of high-yielding paddy varieties and widespread use of groundwater irrigation transformed Bangladesh from a nation plagued by food scarcity in the 1970s to one achieving self-sufficiency by the late 1990s (Mukherji et al., 2021). However, this success came at a cost, including the overexploitation of natural resources and growing reliance on imported diesel for operating shallow tube wells, which have increased both environmental and economic vulnerabilities (Dey et al., 2006; Mitra et al., 2021). Insights gained from this research are essential for formulating energy strategies to roll out similar programs, ensuring that agricultural productivity gains are aligned with the sustainable management of groundwater resources.

One key pathway through which this transition impacts cropping patterns is the reduction in irrigation costs. Another significant pathway lies in the temporal and spatial reallocation of resources driven by the energy transition. Electrification can encourage a shift in cropping seasons, as farmers gain access to reliable irrigation (Mukherji, 2007). For example, this may lead to an increase in the cultivation of specific seasonal crops, such as Boro paddy, which relies on the groundwater irrigation rather than the rainfed irrigation. Moreover, regions with improved access to affordable energy may experience intensified land use, which could exert additional pressure on groundwater resources. Farmers can reduce their dependence on single-crop systems by integrating a wider variety of crops, which are more resilient to adverse weather, pests, and market fluctuations. Literature suggests that diversification towards more remunerative crops can significantly enhance farmers' income security and sustainability. For instance, studies have shown that diversification into high-value commodities improves the livelihoods of small-scale farmers in developing countries (Anuja et al., 2023; Birthal et al., 2015).

Against this backdrop, this research aims to: analyze changes in cropping patterns over time, evaluate trends in irrigation electrification, and assess the impact of this transition on crop diversification. By leveraging data from the Bangladesh Integrated Household Survey (BIHS) and national agricultural statistics, the study employs robust econometric techniques, including the difference-in-differences matching (DIDM) and fixed effects model, to rigorously identify the effects of electric pump adoption.

This research contributes to the literature in several ways. While there is a substantial body of work on crop diversification in South Asia, the specific role of energy transitions, such as the adoption of electric irrigation pumps, in influencing crop diversification, in the context of Bangladesh is missing (Rahman, 2009; Rahman et al., 2015; Assefa et al., 2021). Second, the study enhances understanding of how energy access can reshape agricultural practices at the micro-level and its implications for water resources (Mukherji, 2007; Sadeque et al., 2014; Amin et al., 2022; Das et al., 2024). Finally, it offers insights into the economic impacts of irrigation electrification, particularly how reduced irrigation costs affect farmers' crop choices and land use decisions (Khandekar et al., Bernier et al., 2016; 2009; Buisoon et al., 2021).

The remainder of the paper is organized as follows. The second section outlines the data. Third section discusses empirical framework used in the analysis. The fourth section presents the results of the study. The fifth section discusses the implications of the results, and the paper concludes with final remarks in the sixth section.

2.0. The Data

Data for this study were compiled from multiple sources. For the descriptive analysis, we utilized the Census of Agriculture, the *Statistical Yearbook of Bangladesh*, Agricultural Statistics from the Bangladesh Bureau of Statistics, the Bangladesh Rural Electrification Board (BREB), and the Bangladesh Power Development Board (BPDP). These datasets provided insights into cropping patterns and the adoption of electrified irrigation systems in Bangladesh over the past two decades i.e. 1996 to 2019.

To conduct the impact analysis, we use a panel dataset derived from three rounds of the Bangladesh Integrated Household Survey (BIHS) conducted in 2011, 2015, and 2018. This nationally representative dataset provides detailed information on agricultural production, cropping patterns, and household demographic characteristics. The survey employed a two-stage stratified sampling approach. In the first stage, seven administrative divisions (Barisal, Chittagong, Dhaka, Khulna, Rajshahi, Rangpur, and Sylhet) were included, along with the Feed the Future (FTF) Zone of Influence (ZOI). Primary Sampling Units (PSUs), defined as villages, were selected from each stratum using probability proportional to size (PPS), giving larger villages a higher probability of selection. In the second stage, a complete household census was conducted within each selected PSU, and 20 households were randomly chosen for participation.

The Difference-in-Differences Matching (DIDM) analysis was conducted using data from three survey rounds (2011, 2015, and 2018) to examine the impact of electric pump adoption on cropping patterns(see Appendix Table(3)). The initial sample of 3,409 farming households in 2011 was reduced to 1,916 through a series of adjustments, including the exclusion of households with zero cropped area and those with access to electric pumps in either 2011 or 2015.[1] This resulted in a balanced panel dataset comprising households with no access to electric pumps in both 2011 and 2015. Among this cohort, households that adopted electric pumps by 2018 served as the treatment group, while those that did not adopt electric pumps served as the control group. Comparing cropping patterns across these two groups—adopters and non-adopters—over the period 2015 and 2018, enables the estimation of the effect of electrification on cropping decisions in a DID framework.

Owing to the significant level of attrition, we compared household and demographic characteristics of households that included in the balanced panel with those excluded due to attrition. The comparison revealed that the two groups were broadly similar, with one notable distinction: households retained in the balanced panel operated larger areas of agricultural land compared to those excluded.

Table 2 presents the demographic and households characteristics of the analysis sample (N=1916). 95% being male headed. Household heads have an average of 3.13 years of education, though this varies significantly (SD = 3.87 years). Most households identify as Muslim (88%). Economically, 93% of households rely on agriculture, 5% on labour-based income, and 26% engage in non-agricultural activities. In terms of wealth, the overall asset index averages 2.58, with a focus on agricultural assets at 1.86. Households manage an average of 7.70 plots and operate on approximately 193.06 decimal land units. Access to services varies, with households located 1.88 units from weekly bazaars, 1.60 units from agriculture offices, and 1.50 units from financial services, while the average distance to the end of sale for harvests is 0.29 units.

Additionally, we constructed a panel using data exclusively for the 2015 and 2018 survey rounds, resulting in a balanced panel of 4,901 households for each survey year. We then conducted a fixed-effects analysis on this panel and compared the results with those obtained from the DIDM estimates.

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[1] In 2011, there were 3,409 households, forming the initial dataset. To construct the balanced panel across all three years, we focused on households consistently present across three years, resulting in a panel of 1,916 households. For the fixed effects estimates, the original 3,409 cases were excluded, leaving 12,041 households in the dataset. From this, a balanced panel of 4,901 households was created for analysis.

3.0 Empirical strategy

We leverage both spatial and temporal variations to evaluate the impact of electrification on crop choices, employing two distinct methods. First, we apply a difference-in-differences (DID) approach combined with matching. The DID method exploits variations in electrification adoption over time between treated and untreated groups, controlling for confounding trends common to both groups. By incorporating matching, we ensure comparability between treated and control units, thereby strengthening causal inference. Together, these approaches provide a robust framework to assess the effects of irrigation electrification on crop diversification and choice.

Second, a fixed-effects panel specification is utilized to account for unobserved heterogeneity across households or regions that remains constant over time, thereby isolating the impact of electrification on cropping decisions. This method ensures that time-invariant factors, such as soil quality or long-standing cultural practices, do not bias the results.

3.1. Difference in Difference with kernel matching

To assess the impact of electrification, we use a method proposed by Villa (2016), which combines kernel matching with the basic Difference-in-Differences (DID) approach. The DID method helps us evaluate the effects of an access to electric pumps by comparing changes over time between a treatment group (those who accessed electric pumps) and a control group (those who did not), while accounting for any factors that remain constant over time and might affect the results (such as unobserved differences between the two groups).

Kernel Matching is then applied to create a counterfactual outcome for each treated unit (household with access to electricity) by using a weighted combination of control units (households without access). This method matches treated units with control units with similar characteristics, helping eliminate any pre-existing differences between the two groups and providing a more accurate estimate of the intervention's effect. Kernel Matching improves the estimation by balancing the groups based on their propensity scores, which are probabilities of receiving the treatment based on observable characteristics. This indeed holds for our dataset. Table (4) compares household and demographic characteristics between the treatment and control groups before and after matching. Before matching, significant differences were observed in variables such as non-agricultural income, religion, and distances to agricultural offices, weekly markets, and financial services. However, these differences are no longer statistically significant after applying the matching procedure. This indicates that the matching process effectively balances the covariates between the treatment and control groups, ensuring that we compare like with like and enabling a more robust estimation of the treatment effect.

We estimate the following specifications to identify the effects of electrification on crop diversification (eq 1).

$$Y_{it} = \alpha_1 + \alpha_2 TREAT_i + \alpha_3 TIME_t + \alpha_4 TREAT_i * TIME_t + \varepsilon_{it}$$

Where i is farmer, and Y(it) is represented by cropped area, paddy area, non-paddy area, paddy proportion, and non-paddy proportion. TREAT takes value 1 if household have access to electric pumps and 0 otherwise, in 2018. TIME takes value 1 for 2018 and 0 for 2015. α_4 is the coefficient of interest and it captures the changes in crop choice over the period 2015 and 2018, across treatment and control group. ε is an error term. This specification has been applied to a panel dataset consisting of 1,916 households in each year, allowing for a focused examination of how access to electric pumps influences agricultural decisions over time.

There has been growing literature on the Difference-in-Differences (DID) method that argues testing pre-intervention trends is neither a necessary nor sufficient condition for validating the identifying assumption of DID (Khan-Lang and Lang, 2020). While we have employed a robust DID Matching (DIDM) method that reduces the likelihood of violating the DID identifying assumption, we still present a pre-intervention trend as a robustness check. As noted earlier, for the period between 2011 and 2015, none of the farming households in our dataset were exposed to the treatment (electric pump adoption). By examining the pre-intervention trends during this period, we aim to further confirm our impact estimates' validity.

3.2 Panel Fixed Effect Method

We estimate the following specification (eq 2).

$$Y_{it} = \beta_1 + \beta_2 TIME_t + \beta_3 TREAT_{it} * TIME_t + G_i + \varepsilon_{it}$$

In this model, i represents the farmer, and Y_{it} is the outcome variable, which includes measures such as cropped area, paddy area, non-paddy area, paddy proportion (paddy area/gross cropped area), and non-paddy proportion (non-paddy area/gross cropped area). The variable $TREAT_{it}$ takes the value 1 if the household has access to electric pumps in time-period t, and 0 otherwise. The variable $TIME_t$takes the value 1 for 2018 and 0 for 2015. G_i represents the household fixed effects, which control for unobserved time-invariant factors at the household level. ε_{it} is the error term, which is assumed to be uncorrelated with other covariates.

The coefficient of interest is β_3, which captures the effect of electric pump access on agricultural outcomes. This specification has been applied to the panel of 4,901 households constructed for the 2015 and 2018 survey years.

3.3. Limitations

Despite the methods' robustness, several limitations are associated with both the Difference-in-Differences (DID) approach with kernel matching and the fixed-effects panel specification. One key limitation of the DID method, even with kernel matching, is the reliance on the parallel trends assumption, which posits that the treated and control groups would have followed similar trends over time in the absence of treatment. Furthermore, although kernel matching improves comparability by balancing covariates between treated and control groups, it is not immune to challenges related to finding sufficiently close matches for all treated units, especially when there are significant differences in observed characteristics. Another limitation is that the fixed-effects specification, while helpful in controlling time-invariant heterogeneity, cannot account for unobserved time-varying factors that might influence both treatment assignment and the outcome variable. Additionally, panel data inherently assumes that the treatment effect is homogeneous across all units, which may not always hold, as different households may experience varying degrees of impact from electrification. Lastly, while we present pre-intervention trends as a robustness check, the DID method does not guarantee perfect identification of causal effects, as external factors or events not captured in the model may still influence cropping patterns.

Another limitation of our methods is related to attrition, which occurs when some households drop out of the panel over time. As discussed earlier, the households that dropped from the analysis were broadly similar; however, a notable distinction was observed: households retained in the balanced panel tended to operate larger areas of agricultural land compared to those excluded. This difference could potentially introduce bias in our estimates, as households with larger landholdings may respond differently to electrification than smaller households. Although we controlled for this potential bias in our analysis, attrition remains a concern as it can affect the generalizability of the results, especially if the reasons for attrition are correlated with the treatment effect or outcome of interest.

3.0 Results

3.1 Cropping and Irrigation Trends

Between 1996 and 2019, Bangladesh's agriculture experienced significant transformation, marked by changes in cropping patterns and irrigation practices. Table 1 illustrates the intensification and diversification of agriculture, with a 22.37% increase in paddy cultivation, driven by an 80.30% rise in water-intensive Boro paddy, facilitated by improved irrigation. At the same time, non-paddy crops like vegetables (98.62%) and cash crops (96.09%) also expanded, indicating a shift towards high-value agriculture. However, declines in pulses and oilseeds raise concerns about nutritional and agroecological sustainability. These changes coincided with a 45.63% growth in gross irrigated area, underscoring the critical role of irrigation.

Figure 1 further highlights a transition in irrigation practices between 2009-10 and 2018-19, showing a 27.6% increase in electric pumps and a 7.4% decline in diesel pump usage. This shift reflects a growing preference for electric irrigation methods, influenced by rural electrification, cost factors, and policy initiatives promoting sustainable irrigation practices. Supporting this trend, the electrification of shallow tube wells rose from 5% in 2004 to 21% by 2019, demonstrating the impact of a forward-looking policy framework promoting sustainable water management and efficient irrigation.

These interconnected trends in cropping patterns and irrigation practices suggest a strong association between the adoption of electric pumps and shifts in agricultural choices. The subsequent section will examine the effects of electrification on cropping patterns, offering deeper insights into this relationship.

3.2 Econometric analysis

3.2.1 Impact Estimates -DID with Matching

(a) Gross cropped area : Paddy and Non-Paddy Crops

Table 5(a) presents the DIDM impact estimates based on 2015 and 2018 panel for the following outcomes : gross cropped area, paddy area, non-paddy area, the proportion of paddy in the total cropped area, and the proportion of non-paddy crops in the total cropped area. In 2015, there were no significant differences between the treatment and control groups in total cropped area, paddy area, or non-paddy area.

Over the period, the coefficients for total cropped area and non-paddy area indicate a negative trend, with a larger magnitude for total cropped area (α_3: -14.5) compared to the non-paddy area (α_3: -7.3). The coefficient of interest (α_4), which captures the differential change in cropped area between treatment and control groups, was significant at the 10% level, indicating a marginal increase in total cropped area of 10.2 decimals. This suggests that access to electric pumps positively influenced the total cropped area.

Notably, the interaction term for paddy area showed a relative increase for the treatment group compared to the control group, although the coefficient was insignificant (α_4: 14.065). Conversely, the interaction term for non-paddy area indicated a relative decline for the treatment group compared to the control group (α_4: -3.615), but this coefficient was also insignificant.

Further analysis examined the proportions of paddy and non-paddy areas. The coefficient of interest for the interaction term on the proportion of paddy was significant at the 5% level (α_4: 0.055), indicating an increase of 5.5 percentage points in the paddy proportion for the treatment group relative to the control group, driven by access to electric pumps. In contrast, the coefficient of interest for the interaction term on the proportion of non-paddy crops was also significant at the 5% level (α_4: -0.049), reflecting a reduction of 4.9 percentage points in the non-paddy proportion for the treatment group relative to the control group.

Table 5(b) presents the DIDM impact estimates for the same outcomes using the 2011–2015 panel (antecedent trends). Notably, by the construction of the dataset, none of the households had access to electric pumps during this period. For this timeframe, the coefficient of interest (α_4) was found to be insignificant across all five outcomes. This indicates the absence of systematic trends between the treatment and control groups during the 2011–2015 period. These findings reinforce the credibility of the estimates presented in Table 5(a).

The results for paddy area, non-paddy area, and the proportions of paddy and non-paddy crops are consistent in terms of direction and sign. Specifically, the findings indicate a decline in the share of non-paddy crops and an increase in the share of paddy crops. By providing reliable and economically efficient irrigation, electric pumps have facilitated an expansion in paddy cultivation, rather than encouraging diversification into other crops.

(b) Season-wise Paddy area

We next examined the DIDM impact estimates based on 2015 and 2018 panel for the areas and proportions of different types of paddy (Table 6(a)). The coefficient of interest α_4 , indicated a reduction of 2.7 decimals in the Aus paddy area for the treatment group relative to the control group; however, this result was statistically insignificant. For Aman paddy, was also insignificant, suggesting no significant differential change between the two groups.

In contrast, the Boro paddy area showed a significant increase of 12.4 decimals for the treatment group compared to the control group, indicating a notable positive shift in Boro paddy cultivation for the treatment group.

When proportional changes were examined, the results for both Aus and Aman paddy mirrored the findings for their respective areas and were statistically insignificant. However, for Boro paddy, the coefficient of interest showed a significant increase (α_4: = 0.071), reflecting a 7.1 percentage point rise in the Boro proportion for the treatment group relative to the control group.

Table 6(b) presents the DIDM impact estimates for the areas and proportions of different types of paddy during the 2011–2015 period (antecedent trends). The coefficient of interest, α_4 , was found to be insignificant for all outcomes. This indicates that there were no systematic trends between the treatment and control groups during this period. These findings reinforce the credibility of the estimates presented in Table 6(a).

While there were no significant changes in the areas of Aus or Aman paddy, the treatment group exhibited a substantial increase in the Boro paddy area. This suggests that the overall increase in the paddy proportion as shown in the previous sub-section is primarily driven by the expansion of Boro paddy. These findings underscore the role of electric pumps in driving the intensification of Boro paddy cultivation.

(c) Non-Paddy Crops

Table 7 presents the DIDM impact estimates for the acreage of non-paddy crops, including wheat, maize, pulses, fiber, oilseeds, spices, fruits, and vegetables. The coefficient of interest (α_4) is insignificant for all crops except wheat. The results indicate that access to electric pumps significantly reduces wheat acreage by 3.71 decimals. These findings suggest that the observed decline in the non-paddy crop proportion, as discussed earlier, is primarily driven by reduced wheat cultivation.

Wheat, a relatively water-intensive crop compared to many other non-paddy crops, has seen a decline in acreage, potentially due to the increased attractiveness of cultivating paddy, particularly Boro paddy, which is more water-intensive than wheat. Electric pumps provide reliable irrigation, enabling farmers to shift towards crops that promise higher returns, even if they require more water. This shift underscores a trade-off where increased reliance on electric pumps for irrigation supports water-intensive paddy cultivation at the expense of other crops like wheat. While this may improve incomes in the short term, it raises concerns about long-term water sustainability, especially in regions already facing groundwater depletion.

3.2.2 Fixed effect estimates

Table (8) presents the fixed-effects estimates using panel data specifically constructed for the years 2015 and 2018. This approach was employed to assess the robustness of the DIDM results, particularly because forming a balanced panel for 2015, and 2018 encountered substantial attrition.

The results (see Table 9) reveal that access to electric pumps significantly increases the total cropped area by 22.69 decimals, driven primarily by a 21.0-decimal rise in paddy cultivation. This growth is accompanied by a notable 15.7 percentage point increase in paddy's share of the cropped area ($p < 0.01$). These findings highlight that the expansion in the total cropped area is predominantly attributable to the rise in paddy cultivation, especially water-intensive varieties like Boro paddy, facilitated by improved access to electric irrigation.

These results are consistent with the DIDM estimates in terms of both sign and statistical significance but exhibit larger magnitudes. This suggests that the DIDM impact estimates may have a downward bias, potentially due to the limitations posed by attrition in the balanced panel or other factors.

4.0 Discussion

While improved irrigation can play a key role in providing buffers to climatic shocks and improve adaptative capacity and climate resilience of agriculture, these benefits can be significantly undermined by the adverse resource impacts and reduced adaptive capacity of monocropping and agricultural intensification. The results from the above analysis show that even though the adoption rate of electricity-based irrigation remains low, at less than 3% (see Appendix Table 3), its effects on cropping pattern is clear and significant. With the electrification of irrigation, there has been a clear shift towards intensifying water-intensive Boro paddy cultivation, and a shift away from wheat indicating a trend towards crop specialization rather than diversification. This shift is largely attributed to increased access to affordable and reliable irrigation, which has expanded the area under Boro paddy and reduced reliance on Aus.

Research from other regions across South Asia provides valuable context for understanding the implications of trends observed in this study. In West Bengal, India, Buisson, Balasubramanya, and Stifel (2021) highlighted that electrification of irrigation led to the intensification of water-intensive crops, particularly rice, rather than fostering diversification. Buisson (2015) also observed that electric pump ownership increased income through a shift towards high-value, water-intensive crops such as

Boro rice, reinforcing existing cropping patterns. In regions like Punjab and Haryana, India, cheap electricity for irrigation has further entrenched monocultural paddy cultivation, exacerbating the pressure on groundwater resources by increasing groundwater demand during dry winter months. These states have seen significant increases in the area under paddy cultivation, driven by the ease and affordability of electric irrigation

Different contexts for electrification of irrigation across different agro-ecologies in South Asia, share a common trend: electrification has tended to reinforce established cropping patterns, often prioritizing water-intensive crops like rice over diversification into high-value, less water-intensive alternatives (See Sarkar & Das, 2014; Buisson et al., 2021). Such findings suggest that, despite technological advancements, energy transitions in irrigation must be carefully managed to avoid reinforcing unsustainable agricultural practices. This reinforces the need to view the impacts of electrification through the lens of the water-energy-food nexus to better understand how shifts in energy sources influence cropping choices and, in turn, the sustainability of groundwater resources.

These findings enhance our understanding of how energy transitions, such as electrification, can reshape agricultural practices at the micro-level and influence broader agricultural trends. Rather than viewing these impacts in isolation, it is crucial to consider them more holistically within the framework of the water-energy-food nexus. The study illustrates that while electrification may offer potential economic benefits, it can inadvertently shape cropping patterns in ways that are not aligned with long-term agricultural sustainability or diversification goals. Given the increasing challenges of water scarcity and environmental degradation in regions like Bangladesh, it is essential to reassess how electrification policies are designed to ensure they contribute to broader goals of agricultural resilience and sustainable water use.

5.0 Conclusion

This study has examined the impacts of transitioning from diesel-powered to electric irrigation systems on crop diversification in Bangladesh, a crucial aspect of understanding how energy transitions intersect with agricultural practices. In Bangladesh, cropping patterns are intricately linked to water availability, with distinct differences between rainfed and irrigated systems, further influenced by seasonal flooding.

The transition to electric irrigation offers both opportunities and challenges. On one hand, it has provided farmers with the potential to increase land use efficiency, grow multiple crops per year, and shift towards more market-oriented production systems. On the other hand, it has raised concerns about the overexploitation of groundwater resources and a possible reduction in the cultivation of high-value, less water-intensive crops. The findings indicate that while electric pump adoption has reduced irrigation costs and improved irrigation efficiency, it has inadvertently reinforced monocultural practices, particularly the cultivation of water-intensive Boro paddy, at the expense of diversifying into wheat.

While electrification improves irrigation efficiency and supports rice production—particularly Boro paddy, a staple crop in Bangladesh—it has entrenched monocultural practices. This trend not only limits the scope for diversifying into more sustainable and high-value crops but also raises concerns about food security, environmental degradation, and the long-term resilience of the agricultural system. To achieve a more sustainable and diversified agricultural system, policymakers must adopt a region-specific and more nuanced approach. Technological interventions, such as electric pumps, should be complemented with targeted policies and incentives that encourage the cultivation of diverse cropping systems. These should promote high-value crops, ensure efficient water management, and enhance agricultural resilience

For example, in India, convergence of agriculture policies like the Solar Irrigation program (PM-KUSUM along with Per Drop more Crop) has begun to address the water-energy-food nexus by integrating solar irrigation systems with sustainable agricultural practices. The program not only promotes the use of renewable energy for irrigation but also encourages water-use efficiency, supporting crop diversification. In regions like Rajasthan and Gujarat in India, solar-powered irrigation has been coupled with crop diversification initiatives, promoting the cultivation of less water-intensive, high-value crops such as fruits, vegetables, and pulses. By addressing water and energy needs holistically, these programs align with the broader goals of improving food security, supporting farmers' livelihoods, and promoting environmental sustainability.

Therefore, a balanced and integrated approach to policy implementation is crucial to aligning the transition to electric irrigation with the broader goals of food security, economic stability, and environmental sustainability in Bangladesh’s agricultural sector.

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Tables and figures

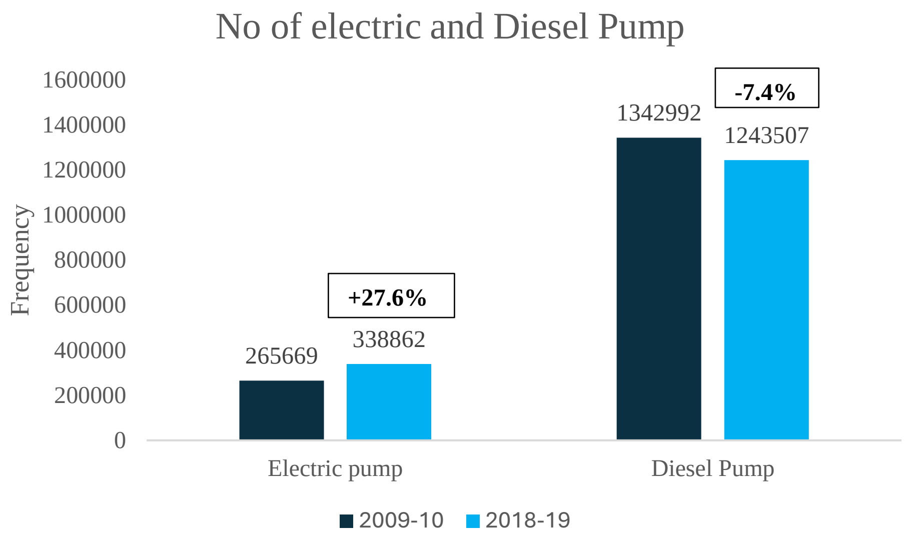
Table (1): Crop acreage of key crops in Bangladesh, 1996-2019.

Crop (000 acres)	**1996 (1)**	**2008 (2)**	**2019 (3)**	**(1996-2008) % change ((2)-(1)/(2))**	**(2008-2019) % change ((3)-(2)/(2))**	**(1996-2019) % change ((3)-(1))/(1))**
Paddy	8586	11846	12504	4.43	17.19	22.37
Paddy (Aus)	4149 (14.50	2515 (8.35)	2459 (7.01)	-39.38	-2.23	-40.73
Paddy (Aman)	10548 (21.45	9261 (30.75)	11971 (34.11)	-12.20	29.26	13.49
Paddy (Boro)	6137 (21.45)	9980 (33.14)	11065 (31.53)	62.62	10.87	80.30
Non-Paddy	5976	6985	7556	16.88	8.17	26.44
Wheat and other minor cereals	1580 (5.52)	1346 (4.47)	1906 (5.43)	-14.81	41.60	20.63
Oilseeds	1185 (4.14)	1249 (4.15)	1053 (3.0)	5.40	-15.69	-11.14
Pulses	1325 (4.63)	1074 (3.57)	873 (2.49)	-18.94	-18.72	-34.11
Cash crops	870 (3.04)	1771 (5.88)	1706 (4.86)	103.56	-3.67	96.09
Vegetables	1016 (3.55)	1545 (5.13)	2018 (5.75)	52.07	30.61	98.62
Gross cropped area	28616	30,114	35098	5.23	16.55	22.65
Gross irrigated area	8586	11846	12504	37.97	5.55	45.63

Note: The values in parentheses indicate the percentage of the gross cropped area.

Source: BBS (2010), BBS (2020)

Figure 1: Number of pumps electric and diesel pumps in Bangladesh



Note: The figure in the box shows the % change in electric and diesel pumps respectively.
Source: BADC (2020)

Table (2) Sample profile

Variable	Mean (1)	S.D. (2)
Head Gender (Male==yes)	0.95	0.22
Years of education of Head	3.13	3.87
Religion (Muslim ==yes)	0.88	0.32
Income (Agriculture ==yes)	0.93	0.26
Income (Labour ==yes)	0.05	0.22
Income (non-agriculture ==yes)	0.26	0.44
Asset index	2.58	1.27
Agriculture asset index	1.86	0.88
No of plots cultivated	7.70	7.02
Operated area (in Decimal)	193.06	194.60
Distance to weekly/periodic bazaar	1.88	1.68
Distance to the agriculture office	1.60	3.96
Distance to financial service)	1.50	2.45
Distance to point of sale of harvest	0.29	0.53
No of Households	1916	

Note: S.D. refers to the standard deviation; Household Asset Index and Farm Asset Index are estimated using Principal Component Analysis. The Household Asset Index includes *Stove Gas burner Electric fan Jewellery gold Jewellery silver Sewing machine Bicycle Rickshaw Van tricycle van Boat Engine boat Motorcycle Mobile phone set Land phone set Dheki Jata Randa Saw Hammer Patkoa Fishing net Spade Kodal Axe Kural Shovel belcha Shabol Daa Horse Mule Donkey Cow Goat Sheep Duck Hen Cash in hand Solar energy panel Electricity Generator IPS Computer Laptop Flash Drive Memory Card Printer Tab*. Agriculture assets include *Winnowing Machine Pesticide sprayer Tractor Power Tiller Trolley Trailers Thresher Fodder cutting machine Spraying machines Reaper Seeder Drills till fert Bed planters Other Heavy Machinery Briquette Urea Appl Inj Briquette Urea Appl Push Combined harvester Rice transplanter* etc.
Source: Authors calculation based on BIHS (IFPRI 2012; IFPRI 2020)

Table (3): Share of crop area for the key crops in Bangladesh,2011

Variable	Overall (1)	Control (2)	Treat (3)	Difference (4)	T statistics (5)
Paddy	0.76	0.75	0.8	-0.0540**	(-2.59)
Wheat	0.014	0.01	0.01	-0.000357	(-0.08)
Maise	0.012	0.01	0.01	-0.000995	(-0.26)
Fiber crop	0.042	0.05	0.03	0.0196*	2.27
Pulses	0.032	0.03	0.01	0.0206**	3.13
Oilseeds	0.031	0.03	0.02	0.0129	1.89
Spices	0.025	0.03	0.03	-0.000488	(-0.07)
Vegetables	0.030	0.03	0.04	-0.0124	(-1.49)
Fruits	0.005	0	0	0.000669	0.18
Other cereals	0.002	0	0	0.00472	1.29
Other crops	0.043	0.06	0.05	0.00972	1.08
Cropped area		194.31	184.14	10.17	0.75
No of Households		1681	235	1916	

Note: The treatment group consists of households identified as having access to electrification for irrigation in 2018, but not in 2011 or 2015. The proportion represents the ratio of the crop group to the gross cropped area. The crops have been grouped into categories based on the categories provided in BIHS[*p < 0.1, **p < 0.05, ***p < 0.01.]

Source: Authors calculation based on BIHS (IFPRI 2012; IFPRI 2020)

Table (4): Sample profile across treatment & control group, (before & after matching) for the year- 2011

Household level Variable	Before matching				After matching			
	Treat (1)	Control (2)	Difference (1)-(2)	p>|t|	Treat (3)	Control (4)	Difference (3)-(4)	p>|t|
Head Gender (Male==yes)	0.96	0.95	0.01	0.57	0.96	0.95	0.00	0.802
Years of education of head	3.18	3.12	0.06	0.81	3.18	3.07	0.12	0.751
Religion (Muslim ==yes)	0.94	0.87	0.06	0.01**	0.94	0.94	-0.01	0.691
Income (Agriculture ==yes)	0.91	0.93	-0.02	0.34	0.91	0.92	-0.01	0.618
Income (Labour ==yes)	0.06	0.05	0.01	0.59	0.06	0.05	0.01	0.78
Income (non-agriculture ==yes)	0.31	0.26	0.05	0.07	0.31	0.27	0.04	0.332
Asset index	2.49	2.59	-0.10	0.24	2.49	2.55	-0.06	0.574
Agriculture asset index	1.89	1.85	0.04	0.54	1.89	1.88	0.01	0.936
No plots cultivated	7.86	7.67	0.19	0.70	7.86	7.68	0.18	0.793
Cropped area	184.14	194.31	-10.17	0.45	184.14	184.12	0.02	0.999
Distance to weekly/periodic bazaar	1.66	1.92	-0.25	0.03*	1.66	1.69	-0.03	0.817
Distance to the agriculture office	2.01	1.54	0.47	0.09	2.01	1.66	0.35	0.37
Distance to financial services	1.82	1.46	0.36	0.03*	1.82	1.52	0.30	0.193
Distance to point of sale of harvest	0.24	0.30	-0.06	0.11	0.24	0.25	-0.01	0.862
No of Households	1681	235	1916		1681	235	1916	

Note: Matching was conducted using Kernel Matching to derive household-level weights. The explanatory variables (listed above) are all measured at the household level. The propensity scores for the control group ranged from [0.032 to 0.35], while for the treatment group, they ranged from [0.047 to 0.32]. [*p < 0.1, **p < 0.05, ***p < 0.01.]

Source: Authors calculation based on BIHS (IFPRI 2012; IFPRI 2020)

Table (5(a)): DID-Kernel Matching: Impact estimates of treatment on Gross Cropped Area Paddy and Non-Paddy Crops

Panel A-Post trends analysis					
Variable	Cropped area (1)	Paddy Area (2)	Non-paddy Area (3)	Paddy Proportion (4)	Non-paddy proportion (5)
Time	-14.536* (8.333)	-7.433 (6.863)	-7.349* (3.86)	0.017 (0.015)	-0.022 (0.014)
Treat	-3.388 (8.333)	2.401 (6.863)	-6.156 (3.86)	0.012 (0.015)	-0.026* (0.014)
Time * Treat	10.204 (11.785)	14.065 (9.705)	-3.615 (5.458)	0.055** (0.022)	-0.049** (0.019)
_cons	186.309*** (5.892)	140.693*** (4.853)	45.984*** (2.729)	0.769*** (0.011)	0.245*** (0.010
No. of Observation	3832	3832	3832	3832	3832

Table (5(b)): DID-Kernel Matching: Pre-intervention estimates on Gross cropped Area, Paddy, and Non-Paddy Crops

Panel B-Pre trends analysis					
Variable	Cropped area (1)	Paddy Area (2)	Non-paddy Area (3)	Paddy Proportion (4)	Non-paddy proportion (5)
Time	-2.48 (8.515)	-2.867 (7.038)	0.662 (3.802)	-0.01 (0.029)	-0.006 (0.014)
Treat	-1.1 (8.515)	8.251 (7.038)	-9.430** (3.802)	0.026 (0.029)	-0.056*** (0.014)
Time * Treat	1.263 (12.043)	-2.635 (9.953)	3.622 (5.377)	-0.013 (0.04)	0.029 (0.02)
_cons	185.239*** (6.021)	140.344*** (4.977)	44.974*** (2.688)	0.777*** (0.02)	0.252*** (0.01)
No. of Observation	3832	3832	3832	3832	3832

Note: For Panel A The variable Time was assigned a value of 1 for 2018 and 0 for 2015, distinguishing the post-intervention period from the pre-intervention period. Panel A presents the results for Post trends analysis i.e. HH which has received electrification from 2015-2018. For Panel B The variable Time was assigned a value of 1 for 2015 and 0 for 2011, distinguishing the post-intervention period from the pre-intervention period. similarly, Panel B presents the pre-trend analysis i.e. for the period 2011-2015. The variable Treat identified households that had access to electricity in 2018 but did not have it during the previous survey iteration. The specification has been provided in the text (ref. equation). The value in the table represents the coefficient and standard errors (in parentheses). [*p < 0.1, **p < 0.05, ***p < 0.01].

Source: Authors calculation based on BIHS (IFPRI 2012; IFPRI 2020)

Table (6(a)): DID-Kernel Matching: Impact estimates of treatment on Paddy crop by major Paddy Seasons.

Panel A: Post trends analysis						
Variable	Aus paddy area (1)	Aman paddy area (2)	Boro paddy area (3)	Aus proportion (4)	Aman Proportion (5)	Boro Proportion (6)
Time	-0.37 (1.17)	-3.898 (3.973)	-3.165 (3.975)	-0.001 (0.005)	0.012 (0.013)	0.005 (0.014)
Treat	-2.699** (1.17)	5.59 (3.973)	-0.49 (3.975)	-0.006 (0.005)	0.018 (0.013)	0 (0.014)
Time * Treat	0.423 (1.655)	1.209 (5.619)	12.433** (5.621)	-0.006 (0.007)	-0.011 (0.019)	0.071*** (0.02)
_cons	6.722*** (0.828)	68.519*** (2.81)	65.452*** (2.811)	0.033*** (0.004)	0.358*** (0.009)	0.378*** (0.01)
No. of Observation	3832	3832	3832	3832	3832	3832

Table (6(b)): DID-Kernel Matching: Pre-intervention estimates of Major Paddy Seasons

Panel B: Pre-Trend Analysis						
Variable	Aus paddy area (1)	Aman paddy area (2)	Boro (3)	Aus proportion (4)	Aman Proportion (5)	Boro Proportion (6)
Time	-4.746*** (1.265)	1.608 (4.123)	0.271 (4.129)	-0.020*** (0.006)	-0.002 (0.028)	0.012 (0.014)
Treat	-4.307*** (1.265)	8.855** (4.123)	3.703 (4.129)	-0.010* (0.006)	0.018 (0.028)	0.018 (0.014)
Time * Treat	1.712 (1.789)	-1.396 (5.831)	-2.95 (5.839)	0.003 (0.008)	0.001 (0.039)	-0.017 (0.02)
Constant	11.364*** (0.895)	65.042*** (2.916)	63.938*** (2.92)	0.053*** (0.004)	0.360*** (0.02)	0.365*** (0.01)
No. of Observation	3832	3832	3832	3832	3832	3832

Note: The variable Time was assigned a value of 1 for 2018 and 0 for 2015, distinguishing the post-intervention period from the pre-intervention period. Panel A presents the results for Post trends analysis i.e. HH which have received electrification during the period 2015-2018. Similarly, the variable Time was assigned a value of 1 for 2015 and 0 for 2011, distinguishing the post-intervention period from the pre-intervention period. similarly, Panel B presents the pre trend analysis i.e. HH for the period 2011-2015. The variable Treat identified households that had access to electricity in 2018 but did not have it during the previous survey iteration. The specification has been provided in the text (ref. equation). The value in the table represents the coefficient and standard errors (in parentheses). [*p < 0.1, **p < 0.05, ***p < 0.01]

Source: Authors calculation based on BIHS (IFPRI 2012; IFPRI 2020)

Table (7): DID-Kernel Matching: Impact estimates of treatment on Major Non-Paddy Crops

Panel A-Post trends analysis				
Variable	Wheat (1)	Maize (2)	Fiber (3)	Pulse (4)
Post	-2.051** (0.865)	-0.769 (0.825)	-0.981 (1.158)	-0.886 (1.094)
Treat	3.263*** (0.865)	0.577 (0.825)	-3.426** (1.158)	-6.095*** (1.094)
Post * Treat	-3.711** (1.224)	0.081 (1.166)	-0.225 (1.638)	0.827 (1.547)
_cons	3.318*** (0.612)	3.093*** (0.583)	8.362*** (0.819)	8.197*** (0.774)
No. of Observation	3832	3832	3832	3832

Panel A-Post trends analysis				
Variable	Oilseeds (6)	Spices (7)	Vegetables (8)	Fruits (9)
Time	-1.919* (1.115)	-0.224 (0.749)	-0.026 (1.178)	0.212 (0.484)
Treat	-2.683** (1.115)	-1.442* (0.749)	3.521** (1.178)	0.206 (0.484)
Time * Treat	0.011 (1.577)	-1.019 (1.06)	-2.035 (1.666)	-0.201 (0.685)
_cons	7.332*** (0.7888)	4.378*** (0.53)	3.608*** (0.8333)	0.931** (0.342)
No. of Observation	3832	3832	3832	3832

Note: The variable Time was assigned a value of 1 for 2018 and 0 for 2015, distinguishing the post-intervention period from the pre-intervention period. The variable Treat identified households that had access to electricity in 2018 but did not have it during the previous survey iteration. The specification has been provided in the text (ref. equation). The value in the table represents the coefficient and standard errors (in parentheses). [*p < 0.1, **p < 0.05, ***p < 0.01.

(Source: Authors calculation based on BIHS (IFPRI 2012; IFPRI 2020)

Table(8)Fixed Effect Estimates: Impact of electrification on cropped, paddy, and Non-paddy area(balanced sample)

	Balanced Panel				
Variable	Cropped area	Paddy Area	Paddy proportion	Non paddy Area	Non paddy Proportion
Treat *Post	22.69*** 4.485	21.01*** 3.83	0.157*** 0.0141	1.68 1.878	-0.00348 0.009
Post	-8.210*** 1.636	-4.236** 1.307	0.00688 0.00641	-3.974*** 0.772	-0.0109* 0.00438
__cons	81.40*** 0.771	61.05*** 0.629	0.379*** 0.00286	20.35*** 0.352	0.134*** 0.00193
No of Observations	9802	9802	9802	9802	9802

Note: Treat takes value when HH has access to electricity for the year 2015 & 2018, post takes value 1 for the year 2018 and 0 for 2015. *p < 0.1, **p < 0.05, ***p < 0.01.
Source: Authors calculation based on BIHS (IFPRI 2012; IFPRI 2020)

Appendix

Table (1) sample distribution

Year	No. of households in BIHS-Panel (A)		Farming Household-Panel (B)		Balanced Household Panel-Panel (C)		Balanced-Household panel data(cropping)-Panel (D)	
	Freq (1)	Pc (2)	Freq (1)	Pc (2)	Freq (3)	Pc (4)	Freq (5)	Pc (6)
2011	6,503	33.82	3,409	22.06	2381	33.33	1,916	33.33
2015	6,715	34.92	6,436	41.66	2381	33.33	1,916	33.33
2018	6,011	31.26	5,605	36.28	2381	33.33	1,916	33.33
N	19,229	100	15,450	100	7143	100	5,748	100

Note: Panel(A): For this study, we include all BIHS and FTF households to ensure a robust panel size, accounting for potential attrition. Farming Household-Panel (B): For this study, we focus exclusively on farming households. Therefore, only households that reported farming activities, as captured in Module H of the BIHS survey, are included in the analysis. This panel encompasses all such households across the three-survey period. Balanced Household Panel-Panel(C): This refers to the subset of households consistently observed across all three survey periods. Balanced Household Panel Data (Cropping)- Panel(D): This subset includes balanced households that have been filtered to ensure the inclusion of those with cropping information.

Source: Authors calculation based on BIHS (IFPRI 2012; IFPRI 2020)

Table(2) Distribution of sample across treatment and control groups

Year	Control (1)	Treatment (2)
2011	No (1916)	No (0)
2015	No (1916)	No (0)
2018	No (1681)	Yes (235)

Note: Control: HH which households that had access to electricity in 2018 but did not have it during the previous survey iteration.
Source: Authors calculation based on BIHS (IFPRI 2012; IFPRI 2020)

Table(3) Comparison of Descriptive Statistics for Households Included in the Panel versus Those Excluded for the Year 2011

Variable	Dropped sample Mean (1)	Dropped sample Sd (2)	Panel sample Mean (3)	Panel sample Sd (4)	Difference (1)-(3)
Head Gender (Male==yes)	0.91	0.29	0.95	0.22	-0.04
Years of education of Head	3.68	4.02	3.13	3.87	0.55
Religion (Muslim ==yes)	0.87	0.33	0.88	0.32	-0.01
Income (Agriculture ==yes)	0.86	0.35	0.93	0.26	-0.07
Income (Labour ==yes)	0.06	0.24	0.05	0.22	0.01
Income (non-agriculture ==yes)	0.33	0.47	0.26	0.44	0.07
Asset index	2.83	1.37	2.58	1.27	0.26
Agriculture asset index	2.28	0.96	1.86	0.88	0.42
No of plots cultivated	5.30	5.17	7.70	7.02	-2.39
Operated area (in Decimal)	130.81	138.04	193.06	194.60	-62.25
Distance to weekly/periodic bazaar	1.72	1.63	1.88	1.68	-0.17
Distance to the agriculture office	1.78	4.47	1.60	3.96	0.18
Distance to financial service)	0.06	0.25	1.50	2.45	-1.44
Distance to point of sale of harvest	0.31	0.59	0.29	0.53	0.02
N	1480		1,916		

Note: Sd represents the standard deviation. There has been a drop in the sample (13 Household information) from the excluded sample due to a lack of data. The comparison period is the year 2011.

Source: Authors calculation based on BIHS (IFPRI 2012; IFPRI 2020)

Table(4)Electric pump adoption rate estimates

Variable	Figures	source
Total agriculture HH	1,68,81,757	Agriculture Census 2019
Total HH	3,55,52,296	Agriculture Census 2019
Total irrigation consumer	398753	Sector-Wise Number of Consumers of Rural Electricity[Source: Bangladesh Rural Electrification Board]
Total electricity consumers in BREB	33642209	Sector-Wise Number of Consumers of Rural Electricity[Source: Bangladesh Rural Electrification Board]
% electricity adoption	2.36%	Authors calculation

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