Does Micro-irrigation Save Energy? An Investigation in Gujarat, India

Piyush Gandhi
UC Santa Cruz

Nick Hagerty
Montana State University

Ariel Zucker *
UC Santa Cruz

June 14, 2026

Abstract

Energy efficiency is a global priority, but investments in energy efficiency do not always deliver the expected benefits. This paper studies micro-irrigation systems (MIS), a technology thought to reduce the energy required for irrigation by as much as 70 percent. We installed individual meters to directly measure the energy consumption of several hundred farmers in Gujarat, India, and linked the meter data with survey data to yield a uniquely comprehensive view into energy use patterns in smallholder agriculture. We document two facts. One, energy use varies widely across farmers, and this variation is unexplained by factors such as farm area or village geography. Two, MIS users in our sample consume 30 to 40 percent more energy than non-users of MIS. This difference does not appear to be fully explained by observable differences across farmers nor by rebound effects, suggesting that the energy efficiency gains of MIS under real-world conditions may be disappointing. Our results highlight a need for increased attention to details of implementation and further research into the actual benefits of resource-conserving technologies.

***Keywords*—** Energy efficiency; Rebound effect; Irrigation; Technology subsidies

*Hagerty: Montana State University, `nicholas.hagerty@montana.edu`. Gandhi: University of California, Santa Cruz, `pigandhi@ucsc.edu`. Zucker: University of California, Santa Cruz, `arzucker@ucsc.edu`. A previous version of this working paper was released as IGC Report E-89483-IND-1 under the same title. We thank Ram Fishman and Xavier Giné for helpful discussion; Mustufa Patel, Gokul Sampath, and Neha Doshi for excellent and tireless project management and research assistance; Isha Fuletra and Aditya Madhusudan for superb assistance; and Suresh Bharda along with many survey enumerators and village para-workers for data collection. Thanks to the Aga Khan Rural Support Programme (India) for a productive partnership. We are grateful for financial support from the International Growth Centre, the Weiss Fund for Research in Development Economics, the Abdul Latif Jameel Water and Food Systems Lab (J-WAFS) at MIT, and a Hellman Fellowship awarded to Ariel Zucker by the Society of Hellman Fellows.

1 Introduction

Energy efficiency is a global priority, as it has the potential to slow carbon emissions and help expand energy access. However, investments in energy efficiency do not always deliver the expected benefits. One reason is that new technologies do not always deliver promised efficiency benefits under real-world conditions. Many technologies require complementary investments or behavioral changes to operate as designed, and users may not always dedicate the needed funds and efforts. Another reason may be the rebound effect, in which efficiency improvements from new technologies can encourage greater energy consumption, which offsets some of the gains. Evidence from the United States suggests that many technological energy efficiency investments deliver less benefit than expected (Fowlie et al., 2018), and also that the rebound effect is relatively small in most situations (Gillingham et al., 2015). However, less evidence is available from low- and middle-income countries, where additional constraints could make suboptimal operation more common and rebound effects larger.

This paper explores the energy efficiency gains from micro-irrigation systems (MIS) in smallholder agriculture in Gujarat, India, by directly measuring individual energy use in a new primary dataset. MIS, referring to both drip and sprinkler irrigation, is a globally significant technology. Many governments across the world heavily subsidize MIS.[1] In the last decade, Gujarat alone disbursed approximately 80 million USD in MIS subsidies annually (Viswanathan et al., 2022). While the justifications for these subsidies often center around groundwater conservation, many MIS subsidy programs explicitly target energy conservation as well,[2] and academic and private-sector observers alike regularly emphasize the potential energy saving co-benefits of MIS adoption (Blog at Jains, 2015; Shah, 2020). Understanding whether, and under what circumstances, energy conservation can help justify the expense of promoting MIS adoption is critical for governments to make informed policy decisions.

MIS is thought to reduce the energy consumption required for irrigation by as much as 70 percent (Jamali et al., 2021; Kumar and Palanisami, 2010; McCarthy et al., 2020; Narayanamoorthy et al., 2018; Qin et al., 2024; Rao et al., 2017) by efficiently delivering water in small doses directly to crop root zones, thereby reducing groundwater pumping. However, if less energy or water is required to irrigate the same crops, farmers may irrigate more land or crop their existing plots more intensively (Dagnino and Ward, 2012; Pfeiffer and Lin, 2014). This behavioral response, an example of a rebound effect, may benefit the farmer but would reduce or even reverse the water and energy savings. Moreover, even if MIS reduces water needs per crop, the potential energy efficiency gains from MIS may not be realized without complementary technology (such as a right-sized pump or surface water storage facility) or ongoing maintenance (National Center for Appropriate Technology, 2023).

Direct measurements of individual-level energy or water consumption are rare in agriculture, limiting the study of technologies like MIS in real-world conditions. To overcome this challenge, we install meters to measure energy use during the growing season for a group of several hundred farmers. We then link this novel dataset of pump-level energy consumption to detailed survey data, producing a uniquely comprehensive window into energy use patterns in smallholder agriculture. Our data is a marked improvement over previous studies that rely on self-reported irrigation intensity or engineering estimates from idealized environments (Fishman et al., 2023; Kumar and Palanisami, 2010; Raman, 2009; Sinha et al., 2017; Surendran et al., 2016). It is also likely more complete than administrative electricity data, since we are able to cover some of the many electricity connections that are unlawful or otherwise unmetered.

These measurements yield two striking facts. First, there is enormous variation in energy use across farmers. This variation covers three orders of magnitude and is not explained by observable factors such as farm area or village geography. Second, MIS users in our sample consume 30 to 40 percent *more* energy than non-users of MIS. This basic fact would seem to counter the common belief that MIS reduces energy needs

[1] Governments providing large MIS subsidies include Australia, Nigeria, Rwanda, and many states in India.

[2] For example, the USDA's Environmental Quality Incentives Program (EQIP) and California's SWEEP program both provide financial support for drip irrigation with a stated aim of reducing greenhouse gas emissions (California Department of Food and Agriculture, 2025; Natural Resources Conservation Service, 2022), while in India the *Pradhan Mantri Krishi Sinchayee Yojana:* Per Drop More Crop initiative also emphasizes the optimal use of energy (National Portal of India, 2018).

per crop. We propose and explore three potential explanations for this fact: selection, rebound effects, and non-efficiency.

We find little evidence that selection into MIS use is the full explanation, at least from observable factors. In the absence of a controlled experiment, we use regression and Mahalanobis distance matching methods to compare MIS users and non-users who are observationally as similar as possible. We find that MIS users consume substantially more energy than non-users even after adjusting for a wide range of farm, socioeconomic, and demographic characteristics. The result persists across all specifications, including multiple linear regression, nearest-neighbor matching, and kernel matching algorithms. Farmers may still select into adoption of MIS based on unobserved factors, but we account for the factors that seem most important.

We find some evidence that rebound effects, in terms of either increased cropping area or increased cropping intensity, can partly explain the increased energy consumption among MIS users. We first investigate rebound effects on cropped area by comparing how MIS affects energy use in two ways: per-hectare per-season (i.e., the direct savings), and in total (i.e., the net energy savings, including any area-wise rebound). This first measure shows the true energy efficiency gains (per area) achieved by micro-irrigation in a real-world setting, while the difference between the two measures reveals the impact of expanded area on energy consumption. We find that MIS users consume 20 to 25 percent more energy on a per-hectare basis. The somewhat smaller coefficients than for total energy suggest that increased cropped area can only partially explain the lack of energy conservation under MIS irrigation. Next, to assess the role of increased intensity, we control for measures of cropping intensity, including number of crops and degree of intercropping. These behavioral channels appear to only partially explain the lack of expected energy savings from MIS.

Evidence for a limited role of selection and rebound effects points toward the presence of a third explanation: non-efficiency. It may indeed be true that MIS users are not more energy-efficient, even per crop, than traditional irrigators. MIS very well may reduce water needs, but it is possible that this is not translating into energy efficiency gains in the typical farmer's installation. This situation could arise if, for example, farmers do not invest in complementary technologies such as downsizing their pumps or installing gravity-based storage tanks. It could also arise if farmers use water with high mineral content or do not perform optimal maintenance, resulting in blockage and over-pressurization. Such a situation would make perfect economic sense in our setting (and in many areas of India), where not only is water unpriced, but so is the energy used for irrigation. For such farmers, there is no economic incentive to realize the potential energy savings from MIS systems.

Our findings do not yield a causal estimate of the impact of MIS use on energy consumption. Absent a natural experiment, we cannot be sure that MIS users and non-users are not systematically different in unobserved ways. Still, given that we see substantially more energy consumption among MIS users than non-users even controlling for a rich set of observable factors, our results suggest that MIS alone is unlikely to yield large energy savings in our setting. This highlights the need for further research on how the implementation of MIS in a real-world setting might impact its resource use. Moreover, our data may be useful in future work given the dearth of direct measurements of energy consumption not only in India, but also more broadly among farmers in developing countries.

The paper proceeds as follows. Section 2 describes the setting and dataset. Section 3 describes basic facts in the data. Section 4 describes the strategy and results to investigate selection, rebound, and non-efficiency in MIS. Section 5 concludes.

2 Sample and Data

Sample. The study sample consists of farming households in the water-scarce region of Saurashtra in Gujarat, India. Gujarat is in western India, the region of the country that experiences the least rainfall. Saurashtra experiences particularly erratic rainfall and has no major surface water resources. Agriculture in Saurashtra traditionally relied on rainfall, which generally falls only during the monsoon (*kharif*) season each year. Improvements in well drilling technology led to a boom in groundwater extraction in the 1970s-

80s, followed by depletion, water shortages, and a movement to promote water conservation and artificial recharge (Patel et al., 2020).

An initial group of farmers were recruited from lists compiled by partner organization, the Agha Khan Rural Support Programme (AKRSP), while implementing two agricultural development initiatives in Saurashtra: Farmer Interest Groups (FIGs) and Drip Pools (DPs).[3] Farmers on the lists had expressed interest or participated in one of the two initiatives. In order to participate in the study, farmers were required to irrigate with groundwater using an electric pump, and had to be willing to install a meter on their groundwater pumpset.[4] This yielded an initial sample of farming households who represent a group of farmers who are broadly interested in micro-irrigation systems and would be likely to voluntarily adopt MIS under the current subsidy regime.

Data. In order to understand how micro-irrigation impacts energy use among this sample, we collect two types of data over the 2018–2019 winter cropping season. First, we directly measure irrigation intensity using hours-of-use meters from the full initial sample. Second, in order to identify plausibly exogenous variation in micro-irrigation adoption, we surveyed a subset of these farmers regarding their MIS use, as well as agricultural, demographic, and socioeconomic characteristics.

We measure energy use for irrigation with hours-of-use meters installed on the electric pump starter of farmers' pumpsets. The meters measure the total hours of irrigation done by the farmer, and offer several advantages over electricity meters and water meters. They are inexpensive, easy to install without pipe modifications, and widely accepted by farmers who are often suspicious of electricity meters that could threaten their subsidized supply. The resulting hours-of-use data can be converted to energy and water consumption using field measurements of pump horsepower. Meters were installed in October and read once per month from November to March by AKRSP field staff using a tablet-based survey. This yields a five-month panel of hours-of-irrigation for each farmer. These data provide a rare view of directly-measured energy use at the level of individual farmers.

We complement the hours-of-irrigation dataset with a survey of 409 of the metered farmers conducted at the conclusion of the growing season.[5] The survey serves four purposes: collecting information to interpret hours-of-use and convert to energy consumption; identifying which farmers use MIS; collecting observable characteristics that may confound MIS impact estimates; and collecting information on potential outcomes of MIS adoption. In particular, the survey data include whether or not a farmer has used MIS as well as fixed characteristics that predict MIS use, such as landholding size and household education levels. We also collect potential behavioral responses to MIS adoption such as area cropped, crops and cropping patterns chosen, and pump type and horsepower. Horsepower of the metered pump is further used to convert hours of use into energy consumption using the formula

$$E = \frac{P}{\eta} t$$

where E is energy consumed, t is duration of pump operation, P is the power rating of the pump's motor, and η is the motor efficiency.

Outcomes. We construct two primary outcomes for measuring the impacts of MIS. First, we measure total impact of MIS on energy consumption using the natural log of monthly kWh consumed. Second, we measure the "mechanical" effect of MIS on energy consumption per cropped area using the natural log of

[3]FIGs are village-level groups formed with AKRSP support and trained in best practices for cotton cultivation and natural resource management. DPs are revolving loan mechanisms for purchasing drip systems administered by AKRSP.

[4]We defined farmers as irrigating using groundwater if they met three criteria: they had irrigated their primary farm the previous winter season, they planned to irrigate their primary farm the next winter season, and they irrigated their primary farm from a groundwater source. Farmers were required to use an electric pump as hours-of-use meters cannot be installed on diesel pumps. When farmers had multiple pumpsets, we selected the well with an electric pump that was used to irrigate their primary farm.

[5]The full survey is available on the corresponding authors' website here.

monthly kWh consumed per hectare cultivated.[6] We use log transformations for all of our main analysis because (1) it allows us to directly estimate proportional differences across farmers, which is appropriate because we are most interested in relative rather than absolute differences between farmers, and (2) it better reflects the central tendency of the data, reduces sensitivity to extreme values, and improves statistical precision for strictly-positive, right-skewed data like energy use.

A set of secondary outcomes measure behavioral mechanisms that might shape the impact of MIS adoption on energy consumption. Specifically, we measure three potential dimensions of rebound effects — cultivated area (defined as the sum of the areas of all crops planted in the season),[7] the fraction of cultivated area inter-cropped, and the number of crops varieties planted over the season — as well pump power, a measure of complementary conservation investment. While these all might be impacted by MIS adoption, they also might drive selection into MIS adoption, and hence we interpret differences in these outcomes between MIS users and non-users only as suggestive of behavioral impacts of MIS.

3 Basic facts

3.1 Summary statistics

Table 1 shows the basic characteristics of the farmers in our sample. They are predominantly smallholder farmers, with a mean area of their primary farm of just 1.45 hectares (the Indian government defines farms under 2 hectares as "small and marginal".)[8] Cultivated area is a bit larger than farm size on average, reflecting that some farmers are able to harvest one crop and grow another on the same land within the year. Nearly all irrigate, about two-thirds used micro-irrigation (MIS), and the vast majority grow cotton (which does not exclude growing other crops). Most farms have one well, but some have two or three,[9] and the average depth of water in these wells was 23 meters. About half of farmers provide water to other farms from their wells, while only one in five receive water from other farms.

Turning to socioeconomic and demographic characteristics, the vast majority of farmers' houses are made of high-quality materials and are electrified, though only about one-third have a private water tap. Nearly all own their land rather than rent; and most earned income from business or work outside the farm.

3.2 Energy consumption varies wildly

We next examine our meter data. Panel (a) of Figure 1 shows the distribution of farmers' pumping time in hours per month on a logarithmic scale. Pumping time varies enormously across farmers: The mode is around 20 hours per month, but many farmers pump more than 100 or fewer than 3 hours per month. Means and standard deviations are listed in Table 2; the mean of pumping time is 33.41 hours per month.

Perhaps surprisingly, this wide variance cannot be explained by cultivated area. Panel (b) of Figure 1 plots the distribution of pumping time per hectare cultivated. This histogram is equally wide, and in fact the variance of this ratio is larger.

Our main outcome of interest, however, is not pumping time but rather energy use. To calculate energy consumption, we use the formula in Section 2 along with survey data on each pump's rated brake horsepower and assuming a 74% motor efficiency.[10] Panels (c) and (d) of Figure 1 plot the distribution of energy consumption, and energy consumption per cultivated area, across farmers. The distribution remains quite

[6]These measures of energy consumption are undefined for the seven farmers who did not irrigate, three of whom were MIS users.

[7]Because cultivated area is defined as the sum of the areas of all crop combinations planted, it can be greater than primary farm size if a farmer harvests a given plot multiple times in the season.

[8]A caveat here is that we only gathered data on each farmer's self-defined primary farm. Some farmers may have multiple non-contiguous farms, for a greater landholding total.

[9]Farmers with more than three wells on their primary farm were excluded from the survey collection. However, such farmers are rare (less than 1%).

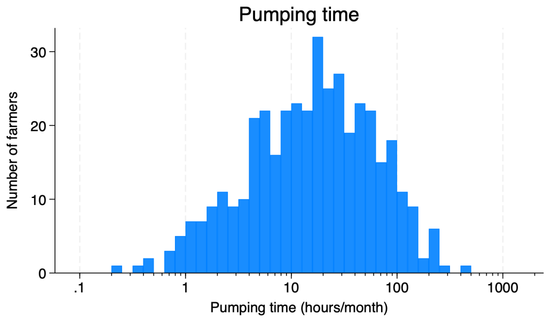
[10]Motor efficiency is unknown without intensive physical testing. Absent this information, we simply assign all pumps a central value from the literature. Because the assumed value is a multiplicative factor, different choices will not affect the results when outcome variables are in logarithms. Results could be biased if actual motor efficiency is correlated with either brake horsepower or pumping time.

	Mean	SD	Min	Max	N
A. Agricultural statistics					
Farm size (ha)	1.45	0.99	0.16	6.80	409
Cultivated area (ha)	1.96	1.51	0.00	10.20	409
Irrigated (share)	0.98	0.13	0.00	1.00	409
Used MIS (share)	0.69	0.46	0.00	1.00	409
Cotton grown (share)	0.91	0.29	0.00	1.00	409
Share cultivated area intercropped	0.16	0.33	0.00	1.00	400
Active wells on primary farm	1.30	0.59	0.00	3.00	409
Groundwater depth (approximate, meters)	23.11	35.60	0.00	213.36	339
Provides water to other farm(s)	0.46	0.50	0.00	1.00	409
Receives water from other farm(s)	0.20	0.40	0.00	1.00	409
B. Socioeconomics					
Pucca floor (share)	0.80	0.40	0.00	1.00	409
Pucca roof (share)	0.95	0.22	0.00	1.00	409
Household electrified (share)	0.95	0.21	0.00	1.00	409
Household has private water tap (share)	0.34	0.47	0.00	1.00	409
Cows or buffalo	3.80	3.59	0.00	35.00	409
Bullocks	0.91	0.89	0.00	4.00	409
Mechanized farm equipment	1.77	1.42	0.00	12.00	409
Earned agricultural income from own land (share)	0.97	0.17	0.00	1.00	409
Earned agricultural income from rented land (share)	0.03	0.18	0.00	1.00	409
Earned sharecropping income (share)	0.15	0.36	0.00	1.00	409
Earned labor income (share)	0.35	0.48	0.00	1.00	409
Earned business income (share)	0.71	0.46	0.00	1.00	409
C. Demographics					
Household size	6.11	2.82	1.00	24.00	408
Religion: Hindu (share)	0.95	0.23	0.00	1.00	409
Religion: Muslim (share)	0.00	0.00	0.00	0.00	409
Caste: SC/ST/OBC (share)	0.81	0.39	0.00	1.00	409
Head of household literate (share)	0.91	0.29	0.00	1.00	409
No education	0.01	0.10	0.00	1.00	409
Primary or secondary education (share)	0.70	0.52	0.00	2.00	409
Post-secondary education (share)	0.31	0.46	0.00	1.00	409

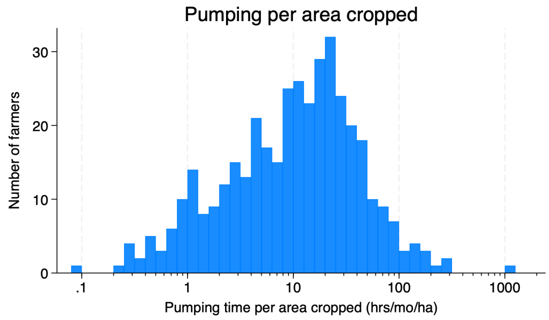
Table 1: Summary statistics.

Note: This table displays summary statistics for the sample of farmers with both baseline data and hours-of-use data.

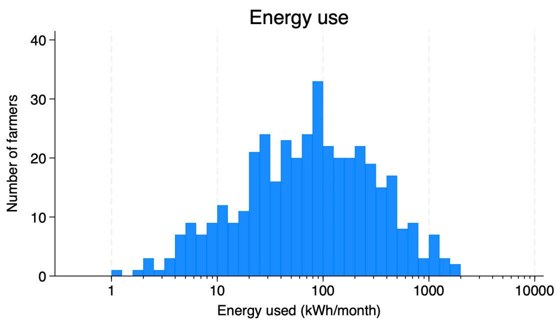
wide and is not explained by cultivated area. As Table 2 shows, the average farmer in our sample uses 173 kilowatt-hours (kWh) of electricity per month.



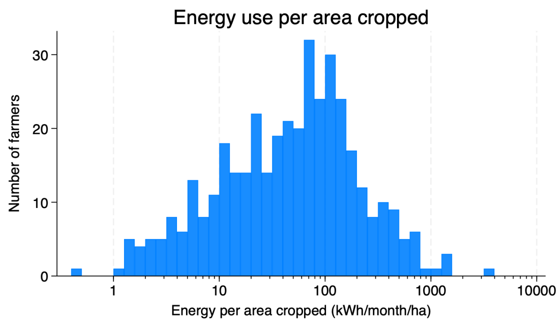
(a) Distribution of pumping hours



(b) Distribution of pumping hours per cultivated area



(c) Distribution of energy consumption



(d) Distribution of energy consumption per cultivated area

Figure 1: Histograms of average energy consumption in the experimental sample.

Note: Figure displays histograms of energy consumption over the winter 2018-19 cropping season. All histograms are shown on a log scale. Panel (a) shows the distribution of average monthly pumping hours, calculated as total hours at the final meter reading divided by the number of months the meter was read. Panel (b) shows the distribution of average monthly pumping hours normalized by the total cultivated area in the winter 2018-19 cropping season. Panel (c) shows the distribution of average monthly energy consumed by the metered pump, and Panel (d) shows the distribution of average monthly energy consumption normalized by cultivated area. The figures show that the distribution of energy consumed for irrigation purposes is very dispersed, even after controlling for the total area cropped.

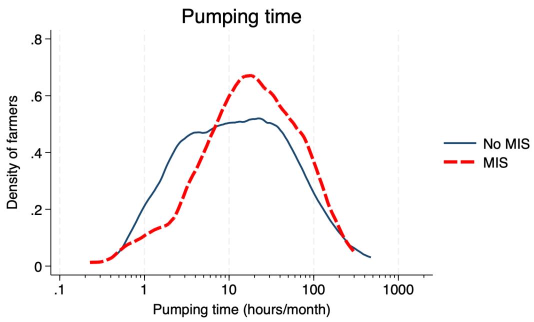
3.3 MIS users consume more energy

Finally, we break down energy consumption by whether farmers use MIS. Panel (a) of Figure 2 plots the kernel density of energy consumption for farmers who use MIS (thick dashed line in red) and those who do not (thin solid line in blue). While both distributions have high variance, the distribution of energy use for MIS users is shifted noticeably to the right, indicating that they consume more energy than non-users of MIS. Table 2 confirms numerically that MIS users consume more energy on average: 178 kWh per month vs. 163 for non-users of MIS. In natural logs, the difference in means is 0.36, which can be interpreted as approximately 36 percent greater energy consumption. A t-test rejects the idea that the log means are the same at a 95 percent confidence level ($p = 0.02$).

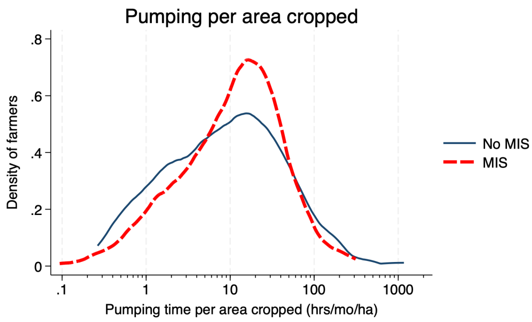
Is this just because MIS users grow on more land, or plant more times per season? Panel (b) of Figure 2 shows the same comparison for energy consumption per area cropped. The distribution of energy consumption for MIS users is still shifted right relative to non-users of MIS, though the difference is not as noticeable. The difference in log means is no longer statistically significant ($p = 0.28$), but remains quantitatively large at 0.19. The raw data suggest that cultivated area might explain some, but not all, of the difference in energy use among MIS users.

	Full Sample		No MIS	Use MIS	Difference=0
	Mean	SD	Mean	Mean	p-value
A. Pumping time					
Pumping time (hours/month)	33.41	47.81	30.92	34.51	0.53
Ln(Pumping time)	2.72	1.38	2.48	2.83	0.02
Pumping time per area cropped (hrs/mo/ha)	24.65	66.98	30.31	22.10	0.41
Ln(Pumping time per area cropped)	2.25	1.46	2.13	2.30	0.30
B. Energy consumption					
Energy used (kWh/month)	172.95	267.11	162.57	177.51	0.63
Ln(Energy used)	4.27	1.45	4.02	4.38	0.02
Energy per area cropped (kWh/month/ha)	119.23	252.04	139.22	110.25	0.41
Ln(Energy per hectare cultivated)	3.80	1.51	3.67	3.86	0.28
Sample size					
Number of individuals	409		125	284	

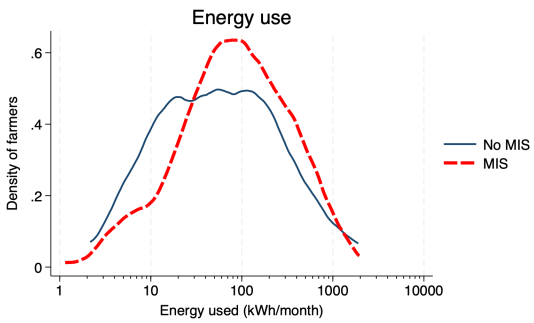
Table 2: Hours of electricity used in full sample, and by MIS-usage.



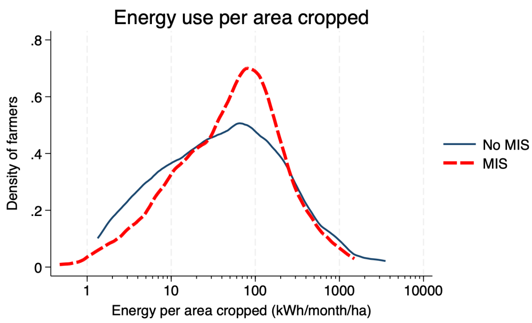
(a) Distribution of pumping hours



(b) Distribution of pumping hours per cultivated area



(c) Distribution of energy consumption



(d) Distribution of energy consumption per cultivated area

Figure 2: Histograms of average energy consumption in the experimental sample.

Note: Figure displays kernel density plots of energy consumption for those with and without micro-irrigation systems (MIS) over the winter 2018-19 cropping season. The x-axes of all plots are drawn on a log scale. Panel (a) shows the distribution of average monthly pumping hours, calculated as total hours at the final meter reading divided by the number of months the meter was read. Panel (b) shows the distribution of average monthly pumping hours normalized by the total cultivated area in the winter 2018-19 cropping season. Panel (c) shows the distribution of average monthly energy consumed by the metered pump, and Panel (d) shows the distribution of average monthly energy consumption normalized by cultivated area. The figures show an overall shift to the right of energy use and energy use per hectare by MIS users.

3.4 Why do MIS users consume more energy?

This basic descriptive fact in our data seems to contradict the conventional wisdom that MIS is resource-conserving. How can this be? We propose three candidate explanations:

1. **Non-efficiency:** Regardless of whether it saves water, MIS actually takes more energy than traditional irrigation to irrigate the same crops under real-world conditions.
2. **Rebound effects:** MIS conserves water and/or energy per crop, allowing its users to irrigate more area or crop more intensively than they otherwise would.
3. **Selection:** MIS users are fundamentally different from non-users in any number of ways – perhaps they use different farming methods or have better access to water – and so comparing their raw data is not useful.

The rest of our analysis attempts to distinguish between these three potential explanations.

4 Effects of MIS via regression and matching

4.1 Empirical Methodology

To learn how MIS affects energy use and whether there are any rebound effects, we construct a group of non-users of MIS that are very similar to the MIS users in all observable ways, so that they form a plausible comparison group.

To control for selection into MIS adoption, we apply regression and matching techniques. These methods can help adjust for observed differences between the groups of MIS users and non-users, either by adjusting for differences (regression) or re-weighting group members in order to construct two groups that are as similar as possible except for the fact that one uses MIS and the other does not (matching). However, no matter how comprehensive the set of observed control variables, the possibility remains that there are additional unobserved factors that are different between MIS users and non-users. Because we cannot fully eliminate selection bias, our point estimates cannot be interpreted causally. However, we cautiously interpret them under the assumption that we observe and control for the most important drivers of selection.

Regression. Our regression specifications take the form:

$$Y_i = \alpha + \beta MIS_i + \mathbf{X}_i'\mathbf{\Pi} + \varepsilon_i$$

where Y_i is an outcome of interest for farmer i, MIS_i is a binary variable indicating whether farmer i used MIS on their primary farm, and $\mathbf{X}_i$ is a set of covariates. Standard errors are calculated using the Huber-White heteroskedasticity-consistent estimator. Outcomes include total energy use (to test whether selection explains the observed differences in this outcome), measures of cropping intensity (to directly test for evidence of rebound), and energy use per cropped area (to test whether rebound in cropped area can explain the lack of reduction in total energy consumption by MIS users).

Although our baseline survey provides us with a large set of possible covariates, selecting them is not completely straightforward. Many characteristics of farming, cropping, and irrigation patterns are likely determined after the decision of whether to adopt MIS. These may actually be outcome variables – channels through which the effects of MIS operate. Therefore, the best controls are *pre-treatment* variables – those that are unlikely to be affected by MIS adoption. We form several groups of pre-treatment control variables that we refer to throughout the analysis: village fixed effects, agricultural controls, economic controls, and demographic controls. In addition to these, we form one group of so-called behavioral controls that may violate the principle of choosing only pre-treatment variables. We include the behavioral controls in some specifications despite this because they might be especially crucial in explaining the differences in energy consumption. Results using this group of behavioral control variables should be interpreted with the understanding that these variables may block off some channels of the effects of MIS. The full set of variables in each group are shown in Appendix A.

To avoid cherry-picking control variables, we include full groups of pre-treatment control variables together. In some specifications, we implement the post-double-selection Lasso methodology of Belloni et al. (2017). This method guards against model overfitting in the presence of many control variables by selecting only the subset of controls that are most relevant in predicting either the outcome variable (energy consumption) or the independent variable of interest (MIS use). Our tables do not report the coefficients on control variables, because they are not the object of our analysis and are not interpretable as treatment effects. We evaluate results on the precision and stability of the estimated MIS effect rather than the overall fit of the model because our goal is to understand one specific factor, not all determinants of energy use. Given the high variance in individual energy use, we expect that any model will have modest explanatory power.

Matching. For our primary energy use outcomes, we also apply matching methods that estimate treatment effects by forming explicit matches between observations in our data. For each farmer with MIS, these methods attempt to locate the farmer or farmers without MIS who are otherwise most similar, according to our survey variables. Regression implicitly makes the same sorts of comparisons but also relies on linear extrapolation; matching makes the comparisons explicit and better enforces that they actually take similar values between MIS and non-MIS farmers (i.e., common support).

The variables we use for matching are the same sets of variables as listed above for regression covariates. We use two matching methods: nearest neighbor and kernel matching. Both are based on Mahalanobis distance matching, which calculates the pairwise similarity of observations across all matching variables in a way that takes into account the variance and covariance of each of the variables (Elizabeth A. Stuart, 2010). The difference between the two methods is that nearest neighbor matching compares each MIS farmer to the single non-MIS farmer with the closest Mahalanobis distance, while kernel matching compares each MIS farmer to all non-MIS farmers within a fixed Mahalanobis distance, called a kernel. The number of farmers within this kernel may be one, zero, or multiple.

4.2 Results

This section sheds light on the three potential explanations for the observation that MIS users consume somewhat more energy than non-users: selection, rebound effects, and non-efficiency. We first show that selection of high-energy-consumption farmers into MIS adoption does not appear to drive the observed differences in energy consumption. We then show evidence that rebound effects do play a role in these differences. However, even holding measures of cropping volume and intensity equal, we still find that MIS adoption does not bring energy efficiency gains. Thus, we conclude that non-efficiency also plays a key role.

4.2.1 Exploring Selection

Selection on observed factors. We first test whether selection into MIS adoption on observable characteristics drives the larger energy consumption among MIS users observed in the raw data. Table 3, Panel A reports coefficients from regressing the natural log of energy consumption on MIS use, along with different sets of control variables. Column 1 shows that the coefficient with no control variables is 0.366, indicating that the raw mean of energy consumption is approximately 37 percent higher for MIS users than for non-users of MIS (significant at a 95% confidence level).[11] How much of this can be explained by underlying differences between users and non-users of MIS?

Columns 2-5 show the coefficients from including each group of control variables listed above (village fixed effects, agricultural, economic, and demographic controls), while column 6 shows the coefficient from a regression that includes all four groups of controls. Column 7 uses the Lasso to select control variables from the full set of candidates. Finally, column 8 uses the "behavioral" set of controls which risk blocking some channels of the effects of MIS (such as rebound effects).

[11] This coefficient is numerically equal to the difference in log means shown in Table 2.

Across all specifications, the coefficient on MIS use is statistically significant and stable, ranging between 0.29 and 0.34. Because the outcome is in natural logs, these coefficients are semi-elasticities that can be interpreted as percentage changes. Users of MIS still use roughly 30–35 percent more energy than non-users, even after adjusting for a barrage of controls that describe the farm (including land area, water sources, and water availability as measured by water depth), a rich set of household characteristics (including many demographic and socioeconomic measures), and any unobserved factors that are common to a particular village (captured by the village fixed effects). Even adding behavioral characteristics such as planting density (as measured by inter-cropped share) and number of crop types does not substantially change the conclusion that MIS users consume more energy than non-users.

Turning to the matching approach, Table 4 reports average treatment effects estimated using matching methods. Columns 1-3 show the estimates from nearest-neighbor matching, while columns 4-6 show the estimates from kernel matching. Within each of these groups, the first column includes the agricultural, economic, and demographic controls, the second column adds village fixed effects, and the third column matches on the possibly endogenous behavioral controls. The effect of MIS on log energy consumption (Panel A) is approximately 30 to 50 percent across all of these specifications. These effects are larger than the estimates produced using regression, and all but one are significant.

Interestingly, the specifications yielding the smallest and least significant results include our so-called "behavioral" controls that might themselves be influenced by MIS adoption, including cultivated area, intercropping rates, and crop diversity. The fact that including these controls, which may each be a channel through which MIS effects energy use, reduces the point estimate on MIS adoption suggests that rebound effects may partly explain our results thus far. We will turn to this question in Section 4.2.2.

Selection on unobserved factors. The evidence from both regression and matching methods suggests that selection, at least on observed characteristics, is not responsible for the difference between users and non-users of MIS. If anything, the estimated difference is larger after adjusting for a large number of farm and household characteristics. However, it remains possible that users and non-users of MIS are different in ways that our survey variables do not capture.

What are these unobserved characteristics that might explain the large differences across farmers in irrigation amounts? The farmers in our sample nearly all grow the same primary crop (cotton), share social networks, and have access to similar input and output markets, so they are unlikely to be taking dramatically different approaches to agricultural production. Information and education about optimal irrigation practices could be a factor, but anecdotally, NGOs and extension services are widespread in our study region, and farmers often insist they know how much water they should be applying to their crops. Other factors might be important, however, such as planting density or the underlying care farmers give to crops.

One unobserved factor that might drive substantial differences in energy use is water availability: some farms simply have better groundwater availability than others. The hydrogeology of our study region is complex and it is often difficult to predict where drilling a well will yield abundant water vs. one that goes dry regularly. If farmers with limited water availability (and thus limited potential to use energy to pump groundwater) are more likely to adopt MIS, our estimates would be biased downwards. If instead farmers with more water availability tend to be more willing to invest in MIS, our estimates would be biased upwards.

We can try to adjust for water availability by making comparisons only among farmers whose well did not go dry during the period of meter reading. This is an imperfect proxy, but it at least allows us to exclude the most egregious cases, in which water availability was so poor that the well went completely dry at some point. We replicate our OLS and matching estimates among this subsample in Appendix B. Because of the smaller sample size, the point estimates are imprecise (and statistically indistinguishable from zero). However, we find that even among these farmers, MIS users have higher energy consumption – even controlling for a variety of observable characteristics. This suggests that higher unobserved water availability among MIS users is unlikely to be driving their higher energy consumption.

	OLS Regressions of Energy Consumption on MIS Use and Controls							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. Log Energy Consumption								
Used MIS	0.366**	0.346**	0.306**	0.362**	0.374**	0.291*	0.339**	0.318*
	[0.163]	[0.159]	[0.150]	[0.161]	[0.165]	[0.155]	[0.146]	[0.165]
R^2	0.014	0.233	0.169	0.034	0.051	0.355		0.042
Observations	401	397	401	401	400	396	400	392
B. Log Energy Consumption per Hectare Cultivated								
Used MIS	0.191	0.223	0.108	0.213	0.195	0.203	0.190	0.261
	[0.174]	[0.174]	[0.158]	[0.175]	[0.177]	[0.159]	[0.152]	[0.171]
R^2	0.003	0.207	0.203	0.035	0.030	0.403		0.086
Observations	392	388	392	392	391	387	391	392
Controls: Village FEs		X				X	X	
Agricultural			X			X	X	
Economic				X		X	X	
Demographic					X	X	X	
Behavioral								X
Lasso selection							X	

Table 3: Usage of micro-irrigation systems (MIS) positively predicts energy consumption.

Note: This table displays regressions of energy consumption and energy consumption per hectare cultivated on a dummy for whether the farmer uses MIS with different sets of controls. Village FEs, Agricultural, Economic, and Demographic controls are pre-treatment: that is, they are would not plausibly be impacted by MIS use. Behavioral controls are potentially endogenous to MIS use. Robust standard errors are in brackets. Significance levels: * 10%, ** 5%, *** 1%.

	Mahalanobis Distance Matching Regressions of Energy Consumption on MIS Use					
	(1)	(2)	(3)	(4)	(5)	(6)
A. Log Energy Consumption						
main						
Used MIS	0.492**	0.444*	0.279	0.450***	0.444**	0.355**
	[0.197]	[0.247]	[0.187]	[0.148]	[0.178]	[0.173]
Observations	399	399	391	399	399	391
B. Log Energy Consumption per Hectare Cultivated						
main						
Used MIS	0.327	0.323	0.268	0.227	0.250	0.241
	[0.202]	[0.253]	[0.194]	[0.198]	[0.180]	[0.186]
Observations	390	390	391	390	390	391
Match variables: Village FEs		X			X	
Agricultural	X	X		X	X	
Economic	X	X		X	X	
Demographic	X	X		X	X	
Behavioral			X			X
Matching algorithm	nearest-neighbor	nearest-neighbor	nearest-neighbor	kernel	kernel	kernel

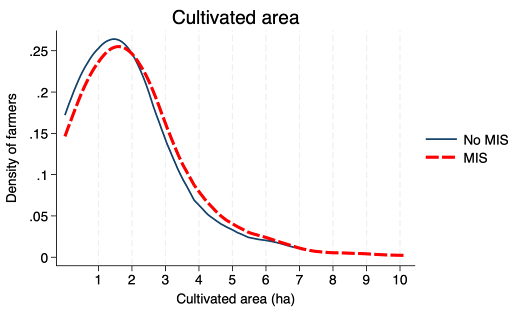
Table 4: Impact of micro-irrigation systems (MIS) on energy consumption: Matching estimates.

Note: This table displays matching-estimates of the impact of MIS use on energy consumption and energy consumption per hectare cultivated. Matching is performed using different sets of controls. Village FEs, Agricultural, Economic, and Demographic controls are pre-treatment: that is, they are would not plausibly be impacted by MIS use. Behavioral controls are potentially endogenous to MIS use. Robust standard errors are in brackets. Significance levels: * 10%, ** 5%, *** 1%.

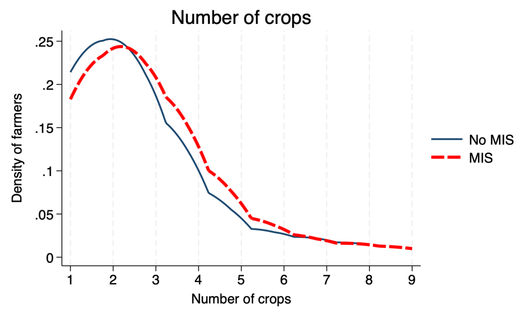
4.2.2 Exploring Rebound Effects

Rebound effects offer an alternative explanation for the lack of conservation. If MIS allows farmers to grow a given crop with less water, they may respond by intensifying production. The increased intensity could occur on the extensive margin (e.g., farming new plots or cropping more times per season) or on the intensive margin (e.g., planting thirstier crop varieties or inter-cropping more.)

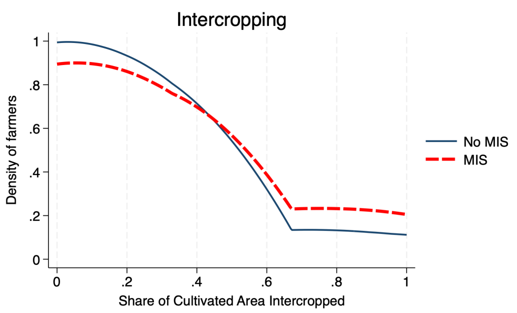
Do MIS users farm more intensively? In the presence of rebound effects, we expect MIS users to farm more land, or farm existing land more intensively, than non-users. The kernel density plots in Figure 3 show that both predictions are borne out in the raw data. MIS users tend to cultivate more area (Panel A),[12] plant a larger number of crops (Panel B), and intercrop a larger share of their land (Panel C). While these raw differences in farming intensity may partly be explained by more productive farmers selecting MIS, regression and matching methods using our suite of pre-treatment covariates do not substantially attenuate the results (Appendix C).[13] Overall, the results are consistent with rebound effects on both the extensive and intensive margins of cropping.



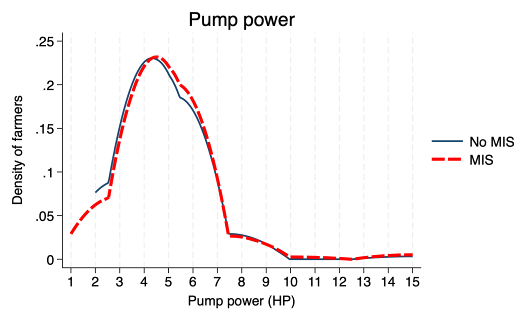
(a) Distribution of cultivated area



(b) Distribution of crop diversity



(c) Distribution of inter-cropping



(d) Distribution of pump power

Figure 3: Kernel densities of potential behavioral responses to MIS in the experimental sample.

Note: Panel (a) displays kernel density plots of total cultivated area for those with and without micro-irrigation systems (MIS) over the winter 2018-19 cropping season. Panel (b) shows the distribution of total number of crops grown, Panel (c) shows the distribution of fraction of area inter-cropped, and Panel (d) shows the distribution of pump power.

Is rebound the key driver of differential consumption? We next examine evidence on whether rebound effects can account for the lack of energy conservation among MIS users.

We first account for extensive margin rebound. Could the fact that MIS users do not appear to conserve energy in total be driven by their larger cropped area? Panel B of Table 3 reports estimated coefficients from the same regression specifications described above, except that the dependent variable is energy use per

[12] Recall that cultivated area is defined as the sum of the areas of all crops planted in the irrigation season, and thus a single plot can be counted multiple times.

[13] We do not include behavioral controls in these regressions because they are precisely the variables being used as outcomes.

hectare cultivated. These results show that, even on a per-hectare basis, MIS users still consume about 20 to 25 percent more energy than non-users. In all specifications, the estimated effect of MIS is a bit smaller, with slightly larger standard errors. While none of the estimates for log energy per hectare are statistically different from zero, neither are they statistically different from their counterparts for log energy. Matching estimates of the effect on MIS on log energy consumption per cultivated area (Panel B of Table 4) also appear slightly smaller and noisier, just as in the regression results, but again they are not statistically different from the Panel A results.

In order to account for intensive margin rebound effects, we include the cropping intensity variables we observe (number of crops and share of area inter-cropped) as covariates. While including these covariates does not substantially attenuate the estimated impact of MIS on energy use (total or per hectare) using the regression approach (column 8 of Table 3), we do see smaller coefficients if we match farmers on these covariates (columns 3 and 6 of Table 4).

However, in all cases, we can rule out that MIS users are achieving anything near the expected energy efficiency improvement per hectare of 25–50% (Jamali et al., 2021; Qin et al., 2024). Rebound effects in both increased cropping area and increased intensity per area – while likely present – cannot explain the lack of conservation among MIS users.

4.2.3 Exploring Non-efficiency

One candidate explanation for why MIS users consume more energy, despite the technology's reputation for resource efficiency, lies in how efficiency gains from MIS are generated in practice. MIS reduces water needs per crop, and since pumping less water requires less energy, adoption can translate to energy savings. There are three key reasons why the potential energy efficiency gains may not be realized: poor water efficiency gains, high pressurization of lines, and oversized pumps.

A first explanation is that some farmers may use MIS systems to deliver more water to crops than necessary, reducing the water efficiency gains. This may be more common in settings with limited crop-specific information available about optimal water use with drip systems. Anecdotally, some farmers go so far as to flood fields with drip systems.

Even if MIS does lead to water efficiency gains, how much these translate to energy savings depends critically on how total dynamic head, or the total resistance in the irrigation delivery system, responds to the change in irrigation technology.[14] MIS delivers water through pressurized lateral lines, which substantially increases dynamic head relative to flood or furrow systems. As a result, while MIS reduces water needs, it simultaneously raises the energy required per unit of water delivered (Qin et al., 2024). If drip lines are highly pressurized, energy efficiency gains per crop can be minimal and can even reverse. High pressure can result from poor system tuning or poor maintenance resulting in clogs.

A related complication is that of oversized pumps. A pump draws energy in proportion to its rated horsepower regardless of how much water is flowing through it. Realizing the theoretical energy savings from MIS would therefore require downsizing the pump to match the lower flow rates demanded by the new system —a step that involves additional equipment costs not covered by MIS subsidies. Previous work has documented that farmers rarely replace their pumps as part of MIS installation (Shroff and Miglani, 2024). An over-sized pump may deliver less volume but with higher pressure, and thus a lack of pump replacement is often linked with an over-pressurized system by design. Otherwise, an over-sized pump can deliver the same amount of water, but re-direct some of the water away from the drip system. While water can theoretically be stored in a surface storage tank, this would require another costly complementary investment. Anecdotal evidence suggests that a common solution in our setting is to simply install an overflow valve that allows excess water to escape the drip system off the field.

Over-sized pumps appear to be a concern among the farmers in our sample. Panel D of Table C.1 reports regressions of pump power rating (horsepower) on MIS adoption and controls. The coefficients on MIS use are positive and insignificant across all seven specifications, ranging from 0.123 HP (column 7) to

[14] Total dynamic head combines static head (vertical lift from the water table to the surface) with dynamic head (pressure and friction losses within the delivery system).

0.269 HP (column 6).[15] Thus we find no evidence that MIS adopters have downsized their pumps relative to non-adopters.

A unifying economic explanation underlies all three of these channels. In our setting, farmers face no marginal cost for either water or energy used for irrigation: electricity for agricultural pumping in Gujarat is heavily subsidized and typically delivered on a flat-tariff or free basis, and groundwater is unpriced. As a result, farmers have no economic incentive to minimize energy or water consumption.[16] In this incentive environment, there is no market signal encouraging farmers to downsize their pumps, monitor irrigation duration, or operate their MIS systems according to energy-minimizing guidelines. Absent any cost-minimization incentive, the potential efficiency gains to MIS are unlikely to be realized. This dynamic is likely common across the many regions of India and other developing countries where energy and water for irrigation are unpriced or heavily subsidized.

5 Policy implications and conclusion

By combining direct meter-based measurements of groundwater pumping with comprehensive survey data, we provide a unique description of energy use patterns among smallholder farmers in a water-scarce region of Gujarat. We find two basic facts that are striking. First, energy use varies widely across farmers, a pattern that does not appear to be explained by other observed factors such as crop area. Second, micro-irrigation (MIS) users in our sample consume 30 to 40 percent more energy than non-users of MIS. This contrasts with the conventional wisdom on MIS, which holds that water savings should translate to energy savings. We propose three hypotheses that might explain this basic fact: non-efficiency (MIS does not actually reduce energy for the same crop), rebound effects, and selection.

We find little evidence for selection bias. The large difference in energy consumption by irrigation technology persists even after adjusting for farm size, well depth, pump power, other farm and water access descriptors, and a wide range of socioeconomic and demographic characteristics. Not only does a difference remain after adjusting for all these factors, its size changes little across specifications. This stability is an indirect test of the influence of other unobserved factors: if the estimated magnitude is not sensitive to observed factors that are likely to be important, it suggests that it also might be robust to unobserved factors. It remains possible that unobserved factors might be confounding the relationship between MIS use and energy consumption, but it is difficult to think of such factors that could make up for such a large difference.

We find some evidence of rebound effects, though they do not appear to fully account for the energy consumption gap. MIS users tend to cultivate more area, plant more crops, and intercrop a significantly larger share of their land than non-users — patterns consistent with farmers expanding and intensifying production in response to lower per-crop water requirements. However, even on a per-hectare basis and after conditioning on measures of cropping intensity, MIS users still consume substantially more energy than non-users. Rebound effects thus appear to be present but are unlikely to be the full explanation for the higher energy consumption among MIS users.

The limited evidence for selection bias, combined with rebound effects that are present but cannot fully account for the energy gap, suggests that there is a real possibility that MIS actually does not save energy in a real-world setting. This could be true if farmers are not operating their systems according to best practices, resulting in over-pressurization, or if they are using pumps that are too powerful for their MIS system. This conclusion would be consistent with evidence in the prior literature (Fishman et al., 2015).

Further research is needed to more definitively understand the causal effects of MIS on energy consumption and the extent of the rebound effect vs non-efficiency. An improved study design would track farmers over several years so that energy consumption could be compared for the same farmer before and after adoption of MIS. This has been difficult to implement since very few farmers adopt MIS in any given year. The best-identified approach would randomly offer free MIS technology to farmers, but not only

[15] We also compare the raw distributions of pump power among MIS users and non-users in Figure 3 Panel D.

[16] When farmers adopt MIS, the intrinsic motivation may be to improve crop yields and quality rather than reduce input costs they are not paying.

would this be expensive, but adopting farmers might implement their MIS systems differently were they made available for free. Absent these kinds of studies, our analysis provides some suggestive evidence that the energy impacts of MIS under real-world conditions may be disappointing.

If it is true that MIS adoption actually increases energy consumption, this result would carry several implications for policy. First, government subsidies for MIS adoption may be a less attractive investment than previously thought. MIS likely provides multiple benefits to farmers, from higher yields to conserved groundwater, but the extent to which energy efficiency can justify subsidies may need to be reassessed. Second, if improving energy efficiency is an explicit policy goal, it may need to be pursued through more direct policy tools such as metering, volumetric pricing, and/or requirements for complementary efficiency investments such as a right-sized pump or surface storage facility.

Third, it may be worthwhile to increase funding for training and extension services. If energy consumption goes up after adopting MIS, it may indicate that the systems are being installed without appropriate complementary technologies, such as updated pumps and pressure regulators, or are maintained incorrectly. Providing greater access to complementary technologies as well as ongoing education and maintenance services might improve the chances that farmers enjoy the full benefits of the new technology.

Finally, there is a need for more detailed, quantitative monitoring of energy efficiency and resource consumption in real-world settings. Our relatively small endeavor has yielded one result with potentially unexpected consequences. Widespread, longer-term measurements of energy and water consumption are critical for policymakers and stakeholders to understand the reality of the situation on the ground and to guide appropriate policy responses.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process
During the preparation of this work the authors used Claude.ai to check data cleaning and analysis for errors, to survey and summarize academic literature on MIS efficiency, and to trim the length of the manuscript. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

References

Belloni, A., Chernozhukov, V., Fernandez-Val, I., and Hansen, C. (2017). Program evaluation and causal inference with high-dimensional data. *Econometrica*, 85(1):233–298.

Blog at Jains (2015). Improving the water and energy efficiency for food production through drip irrigation in india. `https://www.jains.com/Company/news/blog/Improving_the_water_\and_energy_efficiency_for_food_production_through_drip_irrigation_in_India.htm`. [Online; accessed 08-August-2025].

California Department of Food and Agriculture (2025). State Water Efficiency & Enhancement Program. `https://www.cdfa.ca.gov/oars/sweep/`. [Online; accessed 28-August-2025].

Dagnino, M. and Ward, F. A. (2012). Economics of agricultural water conservation: Empirical analysis and policy implications. *International Journal of Water Resources Development*, 28(4):577–600.

Elizabeth A. Stuart (2010). Matching methods for causal inference: A review and a look forward. *Statistical Science*, 25(1):1–21.

Fishman, R., Devineni, N., and Raman, S. (2015). Can improved agricultural water use efficiency save India's groundwater? *Environmental Research Letters*, 10(8):84022.

Fishman, R., Giné, X., and Jacoby, H. G. (2023). Efficient irrigation and water conservation: Evidence from south india. *Journal of Development Economics*, 162.

Fowlie, M., Greenstone, M., and Wolfram, C. D. (2018). Do energy efficiency investments deliver? Evidence from the weatherization assistance program. *Becker Friedman Institute for Research in Economics Working Paper No. 2621817*.

Gillingham, K., Rapson, D., and Wagner, G. (2015). The rebound effect and energy efficiency policy. *Review of Environmental Economics and Policy*, 10(1).

Jamali, M., Soufizadeh, S., Yeganeh, B., and Emam, Y. (2021). A comparative study of irrigation techniques for energy flow and greenhouse gas (ghg) emissions in wheat agroecosystems under contrasting environments in south of iran. *Renewable and Sustainable Energy Reviews*, 139:110704.

Kumar, D. S. and Palanisami, K. (2010). Impact of drip irrigation on farming system: Evidence from southern India. *Agricultural Economics Research Review*, 23:265–272.

McCarthy, B., Anex, R., Wang, Y., Kendall, A. D., Anctil, A., Haacker, E. M., and Hyndman, D. W. (2020). Trends in water use, energy consumption, and carbon emissions from irrigation: Role of shifting technologies and energy sources. *Environmental Science and Technology*, 54:15329–15337.

Narayanamoorthy, A., Bhattarai, M., and Jothi, P. (2018). An assessment of the economic impact of drip irrigation in vegetable production in India. *Agricultural Economics Research Review*, 31(1):105–112.

National Center for Appropriate Technology (2023). The California microirrigation pocket guide. `https://attra.ncat.org/wp-content/uploads/2023/05/CA-Pumps-Motors-Engines.pdf`. [Online; accessed 27-August-2025].

National Portal of India (2018). Pradhan Mantri Krishi Sinchayee Yojana. `https://www.india.gov.in/spotlight/pradhan-mantri-krishi-sinchayee-yojana`. [Online; accessed 28-August-2025].

Natural Resources Conservation Service (2022). Environmental Quality Incentives Program. https://www.nrcs.usda.gov/sites/default/files/2022-10/Conservation%20Incentive%20Contracts.pdf. [Online; accessed 28-August-2025].

Patel, P. M., Saha, D., and Shah, T. (2020). Sustainability of groundwater through community-driven distributed recharge: An analysis of arguments for water scarce regions of semi-arid India. *Journal of Hydrology: Regional Studies*, 29:100680.

Pfeiffer, L. and Lin, C. (2014). Does efficient irrigation technology lead to reduced groundwater extraction? empirical evidence. *Journal of Environmental Economics and Management*, 67(2):189–208.

Qin, J., Duan, W., Zou, S., Chen, Y., Huang, W., and Rosa, L. (2024). Global energy use and carbon emissions from irrigated agriculture. *Nature Communications*, 15(1):3084.

Raman, S. (2009). Micro irrigation for electricity saving in Gujarat - A potentiality assessment. *GGRCL*.

Rao, K. R., Gangwar, S., Bajpai, A., Chourasia, L., and Soni, K. (2017). Energy assessment of rice under conventional and drip irrigation systems. In *Water Resources Management: Select Proceedings of ICWEES-2016*, pages 19–29. Springer.

Shah, T. (2020). Climate change and groundwater: India's opportunities for mitigation and adaptation. In *Water resources policies in South Asia*, pages 213–243. Routledge India.

Shroff, S. and Miglani, V. (2024). Water-saving and economic gains of micro irrigation adoption scheme "per drop more crop": A case of sugarcane, banana and cotton cultivation in maharashtra. *Economic Affairs*, 69(1):487–502.

Sinha, I., Buttar, G., and Brar, A. (2017). Drip irrigation and fertigation improve economics, water and energy productivity of spring sunflower (Helianthus annuus L.) in Indian Punjab. *Agricultural Water Management*, 185:58–64.

Surendran, U., Jayakumar, M., and Marimuthu, S. (2016). Low cost drip irrigation: Impact on sugarcane yield, water and energy saving in semiarid tropical agro ecosystem in India. *Science of The Total Environment*, 573:1430–1440.

Viswanathan, P., Bahinipati, C. S., and Mohanty, B. K. (2022). Impacts of water and energy sector reforms in gujarat: The case of expansion of micro irrigation schemes and rationalisation of agricultural power tariff. *Journal of Land and Rural Studies*, 10(2):157–178.

Appendices

A Description of control variables

We group our strictly pre-treatment controls as follows:

- **Village fixed effects:** Binary indicators for each of the 44 villages in our sample.
- **Agricultural controls:** Total area of primary farm; whether the farm is larger than two hectares; whether the metered well is a borewell; number of active wells on the primary farm; whether wells on primary farm also irrigate any other farms; whether farm uses water from wells on other farms; rated brake horsepower of the electric pump on the primary well.
- **Economic controls:** Whether household has a *pucca* floor; whether household has a *pucca* roof, whether household is electrified; whether household has a private water tap; number of cattle or buffalo; number of bullocks; number of pieces of mechanized farm equipment; whether household earned agricultural income from own land; whether household earned agricultural income from rented land; whether household earned sharecropping income; whether household earned labor income; whether household earned business income outside of the farm.
- **Demographic controls:** Number of people in the household; whether household identifies as Hindu; whether household identifies as SC/ST/OBC, whether head of household is literate, whether head of household has any formal education; whether head of household has primary or secondary education; whether head of household has post-secondary education.

We also include the following controls in some specifications, despite them likely being influenced by treatment (i.e., these might be causally impacted by MIS use). We only include controls that theoretically would increase water use. Specifications including these covariates likely "over-control" for the effect of MIS adoption by partially controlling for rebound effects, thereby introducing a negative bias.

- **Behavioral controls:** Whether grew cotton; Number of crops grown; Cultivated area (ha); Fraction of cultivated area inter-cropped.

B Selection on unobservables: Additional evidence

This appendix presents suggestive evidence that unobserved water availability is unlikely to be driving the differential energy consumption between MIS users and non-users.

Water availability as an unobserved factor Tables B.1-B.2 present the same results from regression and matching as Tables 3-4, but for the sub-sample of farmers whose wells did not go dry during the study period. Regression coefficients reported in Table B.1 tend to be smaller than for the full sample, for both log energy consumption and log energy consumption per hectare. Matching estimates reported in Table B.2 are also smaller. Because this sample is smaller than the full sample, the standard errors are larger for all of these estimates.

A caveat is that a well going dry may itself be endogenous: if MIS conserves water, MIS users will be less likely to find their well dry at a given level of energy consumption. Since farmers remaining in the sample are either MIS users or MIS non-users who pumped less, this introduces an artificial positive correlation between using MIS and energy consumption. Still, we think this comparison is worth considering, since it might help to reduce selection bias into MIS according to water availability.

The point estimates in Panel A of each table show that, even among farmers whose wells do not go dry, MIS-users consumed more energy than MIS non-users. However, while we cannot distinguish the point estimates from the results for the full sample, we also cannot statistically distinguish most estimates from a zero effect. Therefore we interpret these results as suggestive, but not conclusive, that unobserved differences in water availability among MIS users and non-users are unlikely to be driving the higher energy use among MIS users. On the other hand, for these farmers the point estimates in Panel B are quite small and in some specifications even negative. This suggests that, for farmers with sufficient water availability, rebound effects in cultivated area may be an important reason that MIS users consume more water.

	OLS Regressions of Energy Consumption on MIS Use and Controls: Farmers whose wells do not dry							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. Log Energy Consumption								
Used MIS	0.219	0.290	0.120	0.245	0.210	0.191	0.229	0.146
	[0.225]	[0.228]	[0.198]	[0.228]	[0.232]	[0.225]	[0.213]	[0.222]
R^2	0.004	0.241	0.212	0.032	0.064	0.393		0.059
Observations	249	246	249	249	249	246	249	249
B. Log Energy Consumption per Hectare Cultivated								
Used MIS	-0.0222	0.0495	-0.0964	0.0289	-0.0471	0.0423	0.160	0.0711
	[0.239]	[0.251]	[0.204]	[0.238]	[0.245]	[0.228]	[0.221]	[0.230]
R^2	0.000	0.224	0.234	0.035	0.032	0.415		0.083
Observations	249	246	249	249	249	246	249	249
Controls: Village FEs		X				X	X	
Agricultural			X			X	X	
Economic				X		X	X	
Demographic					X	X	X	
Behavioral								X
Lasso selection							X	

Appendix Table B.1: Usage of micro-irrigation systems (MIS) and energy consumption for farmers with plentiful water.

Note: This table displays regressions of energy consumption and energy consumption per hectare cultivated on a dummy for whether the farmer uses MIS. The sample is limited to farmers whose wells do not go dry for the full season, and therefore have access to plentiful water. Robust standard errors are in brackets. Significance levels: * 10%, ** 5%, *** 1%.

	Mahalanobis Distance Matching Regressions of Energy Consumption on MIS Use: Farmers whose wells do not dry					
	(1)	(2)	(3)	(4)	(5)	(6)
A. Log Energy Consumption						
main						
Used MIS	0.285	0.813	0.0152	0.335	0.265	0.112
	[0.269]	[0.555]	[0.230]	[0.209]	[0.220]	[0.222]
Observations	249	249	249	249	249	249
B. Log Energy Consumption per Hectare Cultivated						
main						
Used MIS	-0.0632	0.591	-0.0384	0.0583	0.0343	-0.0694
	[0.265]	[0.562]	[0.253]	[0.255]	[0.298]	[0.203]
Observations	249	249	249	249	249	249
Match variables: Village FEs		X			X	
Agricultural	X	X		X	X	
Economic	X	X		X	X	
Demographic	X	X		X	X	
Behavioral			X			X
Matching algorithm	nearest-neighbor	nearest-neighbor	nearest-neighbor	kernel	kernel	kernel

Appendix Table B.2: Impact of micro-irrigation systems (MIS) on energy consumption: Matching estimates for farmers with plentiful water.

Note: This table displays matching-estimates of the impact of MIS use on energy consumption and energy consumption per hectare cultivated. The sample is limited to farmers whose wells do not go dry for the full season, and therefore have access to plentiful water. Robust standard errors are in brackets. Significance levels: * 10%, ** 5%, *** 1%.

C Behavioral responses to MIS adoption: Regression estimates

This appendix presents OLS regression estimates of potential behavioral responses to MIS adoption. We present all four outcomes in Table C.1: cultivated area (Panel A), crop diversity (Panel B), inter-cropping rates (Panel C), and pump power (Panel D) which is a measure of complementary energy efficiency investments: realizing the full energy efficiency gains from MIS typically requires a reduction in pump power.

We do not include behavioral covariates as they are used as outcomes in these specifications. Matching estimates yield similar results (results not shown).

	OLS Regressions of Behavioral Outcomes on MIS Use and Controls						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A. Cultivated Area (ha)							
Used MIS	0.263*	0.167	0.302***	0.234	0.268*	0.125	0.190**
	[0.154]	[0.158]	[0.0908]	[0.166]	[0.156]	[0.109]	[0.0893]
R^2	0.006	0.203	0.583	0.057	0.031	0.692	
Observations	409	405	409	409	408	404	408
B. Number of Crops							
Used MIS	0.377**	0.429**	0.308*	0.419**	0.393**	0.352	0.475**
	[0.184]	[0.213]	[0.181]	[0.185]	[0.190]	[0.219]	[0.185]
R^2	0.009	0.216	0.071	0.083	0.060	0.312	
Observations	409	405	409	409	408	404	408
C. Fraction of Area Intercropped							
Used MIS	0.0836**	0.0865**	0.0809**	0.0914***	0.0918***	0.0820**	0.102***
	[0.0326]	[0.0386]	[0.0335]	[0.0333]	[0.0325]	[0.0407]	[0.0325]
R^2	0.014	0.203	0.037	0.057	0.040	0.263	
Observations	400	396	400	400	399	395	399
D. Pump Power (HP)							
Used MIS	0.124	0.260	0.120	0.137	0.125	0.269	0.123
	[0.173]	[0.187]	[0.168]	[0.176]	[0.174]	[0.194]	[0.178]
R^2	0.001	0.228	0.155	0.032	0.018	0.365	
Observations	409	405	409	409	408	404	408
Controls: Village FEs		X				X	X
Agricultural (excl. pump power)			X			X	X
Economic				X		X	X
Demographic					X	X	X
Lasso selection							X

Appendix Table C.1: Usage of MIS and potential behavioral responses.

Note: The dependent variables are as follows: Panel A is the total cultivated area (in hectares), Panel B is number of crops planted, Panel C is the fraction of total cultivated area (in hectares) that is under inter-cropped patterns, and Panel D is the power rating (HP) of the metered pump. Agricultural controls in Panel D exclude pump power since it is the outcome. Village FEs, Agricultural, Economic, and Demographic controls are pre-treatment. Significance levels: * 10%, ** 5%, *** 1%.