Adopting Solar Power for Irrigation:
Implications for Groundwater Depletion in Gujarat *

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Abstract

Groundwater is a vital resource for irrigation in India supporting food security and rural livelihoods. Energy subsidies for groundwater pumping improve short-term water access but worsen over-extraction incentives, accelerating depletion of this already overused common-pool resource. Economic theory supports pricing or taxing groundwater, but even removing subsidies is politically difficult. Grid-connected solar irrigation offers a potential solution by creating an incentive to conserve groundwater from selling unused energy back to the grid. This study evaluates the impact of grid-connected solar irrigation under the *Suryashakti Kisan Yojna* (SKY) policy through a survey of 2,798 farmers. Our findings indicate that major implementation challenges limit the ability of solar irrigation to incentivize groundwater conservation. These findings highlight the importance of policy implementation to meet policy objectives.

Key Words: Groundwater, Solar Irrigation, Opportunity Cost, Energy Pricing, Water-Energy-Food-Carbon Nexus
JEL Code: Q18, Q21, Q25, Q28

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1 Introduction

Agricultural sustainability is essential for ensuring food security and supporting rural livelihoods in India, where nearly half of the country's 600 million workforce depends on agriculture for their livelihood (*Economic Survey 2024-25*, 2025; Ministry of Statistics and Programme Implementation, Government of India, 2023). Access to irrigation boosts productivity and mitigates impacts from extreme climate, including droughts and heat waves (Bhattarai et al., 2023). Over the last few decades groundwater has been championed as a critical resource for irrigation and domestic water needs given constrained surface water supplies in India (Shah, 2009). Groundwater access depends on the access to energy for pumping which is facilitated through subsidized power for irrigation by the governments.

In India, farmers receive up to 85% subsidy on the average cost of energy (Badiani et al., 2012; Shah & Rai, 2021) for groundwater-based irrigation. While energy subsidies supported the expansion of a groundwater-based irrigation economy, agriculture —which accounts for over 80% of total groundwater withdrawals— has become a major driver of groundwater depletion in India. These subsidies also place a significant financial burden on state governments.India's notifications to the World Trade Organization (WTO) show that input subsidies for agricultural energy totaled USD 14.4 billion in 2022–2023, which was approximately 2.4% of the total agriculture output. For comparison, the Government of India's total expenditure on education during the same year was approximately USD 12.5 billion (PRS Legislative Research, 2022; Sengupta, 2024). Despite this substantial expenditure, nearly 60% of cultivated land still lacks reliable irrigation access due to the uneven geographic and demographic distribution of groundwater availability, quality, and subsidies (World Bank, 2024).

While there is a need to increase the irrigation access, it is crucial that the resulting increase in energy demand does not increase carbon emissions. India needs a transition to cleaner energy sources that avoids straining on government budgets through subsidies. In summary, India's irrigation sector must confront four pressing challenges: (1) meeting the growing demand for reliable irrigation, (2) addressing groundwater depletion, (3) limiting carbon emissions, and (4) alleviating the fiscal burden on state governments from energy subsidies (Patel et al., 2024). Solar Irrigation Pumps (SIPs), the irrigation systems powered by solar photovoltaic energy, offer a promising solution to three of these four challenges. First, SIPs enhance energy access for irrigation, including in areas with limited grid connectivity. Second, solar power is renewable and thus supports carbon mitigation goals. Third, once installed, they eliminate the need for fuel, thereby easing the financial pressure of irrigation energy subsidies on state governments. However, whether they can help mitigate groundwater depletion is an open question (Sahasranaman et al., 2018; Shah et al., 2018).

This paper's primary research question asks whether grid-connected SIPs can incentivize reduction in groundwater use. We address this question in the context of the Gujarat's *Suryashakti Kisan Yojna* (SKY) policy. Gujarat, a western Indian state, piloted grid-connected solar irrigation promotion through quasi-autonomous electricity distribution companies (DISCOMs).[1] Between November 2018 and March 2020, the SKY policy installed around 4,500 grid-connected, subsidized SIPs. Under the policy, farmers were allowed to sell surplus electricity generated by their solar systems back to the grid, with DISCOMs providing a guaranteed buy-back mechanism. Smart meters tracked both electricity generation and on-farm consumption, and farmers were compensated based on the net electricity exported to the grid and generated real time data of electricity generation, consumption, and net export. We address the research questions on groundwater conservation, along with key implementation factors influencing the SKY policy's design, execution, and effectiveness, using primary survey data collected from 2,798 farmers across Gujarat. The survey sampling was designed to analyze three groups of farmers: (1) *SKY adopters*—eligible farmers who adopted SIPs; (2) *SKY non-adopters*—eligible but non-participating farmers; and (3) *ineligible* farmers—those in nearby areas ineligible for the policy. The sampling strategy allowed for developing different counterfactual groups to SKY adopters to test for differences in groundwater usage, crop choices, and irrigation practices. Additional questions about demographics and experiences with SKY allow use to answer our secondary research questions.

We find that the SIP adoption did not lead to measurable reductions in groundwater use as measured through groundwater irrigation metrics and cropping intensity. Notably, SKY adopters were more likely to report increased energy consumption and water sales, suggesting farmers used the increased groundwater supply to pump and sell excess water. Since increased wa-

[1] DISCOMs are public utility firms with majority ownership by state governments. Thus, governments retain significant managerial control.

ter sales did not lead to aggregate increases in groundwater use it is possible farmers reduced irrigation on their own fields and increased pumping to sell water to other farmers, although we cannot directly test this mechanisms. Survey results show that socioeconomically better-off farmers were more likely to adopt SIPs. The primary driver for adoption was day-time electricity and not the potential earnings from selling electricity back to the grid, which would motivate groundwater conservation.

This study advances understanding of solar irrigation adoption, pricing incentives, and governance challenges, particularly the role of electricity distribution companies (DISCOMs) through the world's largest government-sponsored pilot policy on grid-connected SIPs, SKY. While we do not find that SIPs reduce groundwater use, we also do not find any increase in groundwater consumption. The incentive for conservation may therefore cancel out any upward pressure on groundwater use from increasing supply. Understanding the implications for groundwater is important as SIPs expand irrigation access in water-stressed locations. It is also important to understand the context; groundwater use may differ in areas without an incentive to conserve such as isolated SIPs that are not connected to the grid.

The rest of the paper is organized as follows: Section 2 reviews relevant background on groundwater and solar irrigation. Section 3 outlines data and methodology. Section 4 presents results, followed by limitations in Section 6. Section 7 concludes with key findings and policy implications.

2 Background

2.1 Groundwater in India

Pumping approximately $240km^3/year$, India is the largest consumer of groundwater in the world, surpassing the combined groundwater extraction of the US and China (approximately $120km^3/year$ each) (Gino Sophia et al., 2020). The Central Groundwater Board (CGWB), a body that governs groundwater in India, estimates that nearly 87 percent of groundwater is used for irrigation (Central Ground Water Board, 2022). More than two-thirds of Indian agricultural irrigation relies on groundwater (Siebert et al., 2010). This extraction, driven by increasing irrigation demands, has led to irreversible groundwater depletion, threatening future food security and rural livelihoods

(Chatterjee et al., 2024; Shah, 2009).

Groundwater depletion is widespread due to the coupling of groundwater rights with land ownership, the ease of access, and the reliability of groundwater as an irrigation source—even in regions with extensive canal networks and perennial Himalayan rivers. The importance of groundwater stems from its capacity to meet critical irrigation needs, especially as surface water availability declines due to erratic rainfall, land encroachment, and severe contamination. Bureaucratic hurdles further restrict timely access to surface water during periods of urgent need, deepening farmers' dependence on groundwater.

Because groundwater rights are attached to land rights in India, the government has limited authority to regulate its use (Shah, 2009). Technological advancements, such as diesel and electric pumps, have made groundwater extraction more affordable, enabling widespread expansion of irrigation infrastructure and increasing agricultural output. However, this largely unregulated access has led to serious depletion—and in some regions, salinization. As a result, sustainable groundwater management has become a pressing policy priority.

Governments have developed policies that directly or indirectly influence groundwater use, which can be grouped into three broad intervention. First, *command-and-control* policies restrict groundwater withdrawals—for example, the *Subsoil Water Acts* in Punjab and Haryana, which ban pre-monsoon paddy sowing, and Gujarat's dark zone policy, which restricts electricity access in over-exploited areas (e.g., *Gujarat's Jyotigram policy* limiting irrigation electricity to 8 hours (Chindarkar & Grafton, 2019; Shah, 2009; Sharma et al., 2010)). Second are incentive-based approaches. Punjab experimented with the *Pani Bachao Paisa Kamao* policy, which continued farmer subsidies but attempted to reduce irrigation energy consumption (Amarasinghe et al., 2020). Incentives are also provided through subsidies for technologies like drip irrigation or for crop switching—such as Haryana's monetary incentives for farmers shifting from paddy to cotton (Saha et al., 2022; Shah & Verma, 2014). Third, community-based management, such as participatory groundwater management and managed aquifer recharge, promote sustainable water use through local stakeholder engagement and participatory groundwater governance and management (Patel et al., 2020). The *Atal Bhujal Yojna* is a policy promoted by the World Bank and *Jal Shakti Ministry* (Ministry of Water Resources, Govt of India) that formalizes decentralized groundwater management through participatory management (Khanduja & Chaturvedi, 2023).

The range and cost of these interventions highlight the severity of the groundwater crisis and governments' urgency in addressing it.

2.2 Solar irrigation

Solar irrigation refers to the use of electricity generated by solar photovoltaic (solar PV) panels to power groundwater irrigation pumps. Over the past decade, it has gained significant attention in policy discourse, driven by advancements in solar technology and declining costs of solar energy—making it a viable and potentially more sustainable option for agricultural water management (Patel et al., 2024). Policy innovations have focused on creating incentives and mechanisms such as subsidies, flexible ownership models (individual, corporate, or community-based), and energy buy-back tariffs to make solar irrigation financially viable, economically efficient, socially acceptable, and environmentally beneficial—particularly through carbon mitigation.

Promotion of *Solar Irrigation Pumps* (SIPs) can follow multiple strategies, as proposed by researchers and stakeholders. These policy models often rely on distinct market actors and economic incentives such as subsidies, feed-in tariffs, and guaranteed energy buy-backs (Shah et al., 2018). Broadly, SIP deployment policies can be categorized into three types:

1. **Feeder-level solarization**, where large solar power plants replace conventional power sources at the feeder level;[2]

2. **Off-grid solar pumps**, where solar panels are installed directly on farms and supply electricity to irrigation pumps without connecting to the grid; and

3. **Grid-connected individual solar pumps**, which are installed on farms but connected to the grid, allowing surplus energy to be exported and sold.

The Ministry of New and Renewable Energy (MNRE) has set ambitious targets for solar irrigation in India (Rahman et al., 2021). Its flagship policy, the *Pradhan Mantri Kisan Urja Suraksha evam Utthaan Maha-abhiyan* (PM-KUSUM), launched in 2019, aims to enhance energy security

[2] In the context of electricity distribution, a feeder is a power line or circuit that carries electricity from a substation to distribution transformers or directly to end-users (like homes, businesses, or farms). In rural areas, agriculture feeders are often separate lines that supply electricity only to irrigation pumps, sometimes with scheduled or rationed supply hours (e.g., 8 hours per day).

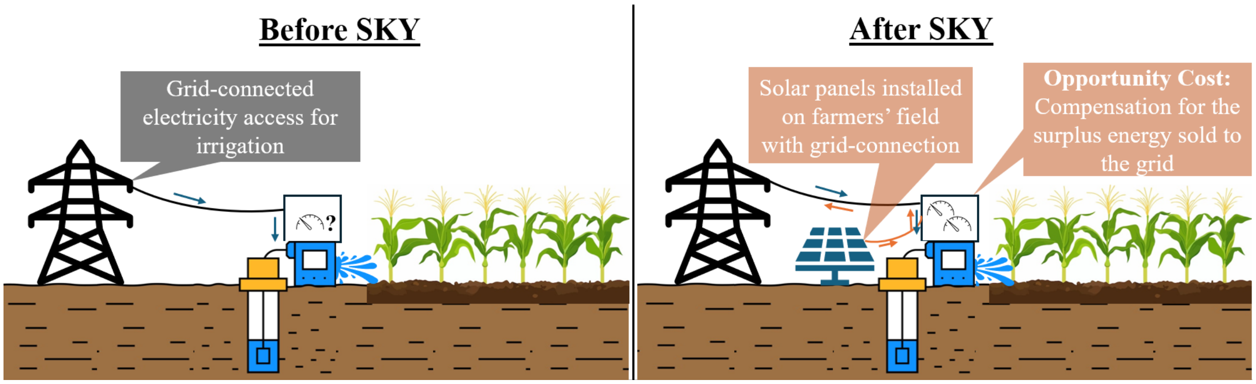
for Indian farmers while contributing to national goals of expanding non-fossil fuel-based electricity generation (Ministry of New & Renewable Energy, 2023) (Appendix A illustrates type of SIPs promoted and installation targets to achieve through the program). Several Indian states have initiated pilot projects and large-scale programs aligned with PM-KUSUM's guidelines and financial mechanisms to promote solar irrigation.

2.3 The *Suryashakti Kisan Yojna* (SKY) policy of Gujarat

Gujarat, a western Indian state, is known for its aggressive reforms in the agricultural and electricity sectors (Gulati et al., 2009). In 2009, it became one of the first states to announce a comprehensive state-level *Solar Power Policy*, providing a road map for solar energy adoption (Bhatt et al., 2019). Gujarat has implemented and piloted initiatives across all three SIP deployment strategies: *feeder-level solarization*, *off-grid solar pumps*, and *grid-connected individual solar pumps*, as discussed in the previous section. Among these, the *Suryashakti Kisan Yojna (SKY)* policy specifically promotes grid-connected SIPs. It was implemented across 83 feeders covering over 4,500 connections, with a cumulative capacity of 80 MW (see Figure 3 for locations).

SKY is India's only large-scale implementation of farmer-owned, grid-connected SIPs. The policy is technically and financially complex, involving three key stakeholders with shared responsibilities for maintenance and operations. *State-run power distribution companies* (DISCOMs) signed power purchase agreements and arranged loan and subsidy to reduce upfront cost for the farmers. They are also responsible for maintaining grid infrastructure. *Solar system installation companies* handled installation and ongoing maintenance to ensure effective energy evacuation to the grid. *Farmers* used the solar panels for electricity generation, were expected to clean the panels regularly to maintain efficiency and manage electricity usage judiciously to realize the financial returns. The field-level change in installation of systems is explained in Figure 1.

Figure 1: Conceptual diagram of SKY policy field implementation



Note: This figure illustrates schema to understand the grid-connected solar irrigation introduced through SKY policy. Before SKY the farmers had grid-connected electricity access but they may or may not have been metered (hence "?"). The SKY adopters were metered with two meters, one for the electricity consumed for pump and another indicating the electricity generated through solar panels and sent to the grid. The blue arrow indicates the direction of the grid electricity flow for the pumping and orange arrow indicates the energy produced by the solar panels. Figure 5 has the electrical circuit diagram.

SKY leveraged existing or new grid-connected alternating current (AC) pumps without any restriction on pump size. To ensure technical feasibility, at least 70% of farmers on a given feeder had to consent to participate in the policy. The panels are installed on individual farmers' field and are separately connected to the feeders. The financial model provided a 30% subsidy from the central government and 30% from the state government, with farmers covering the remaining 40%. To ease the burden, 35% of the farmers' share was financed through a loan guaranteed by the DISCOMs. Loan repayments were collected via fixed Equated Monthly Installments (EMIs) through net metering-based electricity billing.

The state government implemented an additional feed-in tariff directly funded farmers' EMI payments. Farmers received INR 7/kWh for the first 1,000 kWh of electricity evacuated per kW of installed capacity each year. Beyond that, the tariff dropped to the base rate of INR 3.5/kWh. This additional component —known as the Evacuation-Based Incentive (EBI)— was applicable during the seven-year loan repayment period. The farmer's net payment was calculated by subtracting the loan installment from total earnings through the feed-in tariffs based on equation 1.

$$
\begin{aligned}
\textit{Net Payment} = {} & (\text{Feed-in-Tariff} + \text{Evacuation-Based Incentive}) \times (\text{Net Evacuation}) \\
& - \text{Loan Installment}
\end{aligned}
\tag{1}
$$

This calculation was described to farmers through a worked example explained in an information brochure (see Appendix B). For example, a farmer operating a 10 hp pump, under certain assumptions, was expected to earn a net income of INR 25,624 annually during the 7-year loan period, and INR 49,000 annually once the EBI expired. This post-loan payment was equivalent to roughly four months of income, based on the July 2018–June 2019 Situation Assessment Survey (SAS), which estimated average monthly farm income in Gujarat at INR 12,631 (Ministry of Agriculture & Farmers Welfare, 2022).

These financial projections were based on four critical assumptions. First, farmers consume 800 kWh per hp per year for irrigation. Second, solar panels produce an average of 6 kWh per kW capacity daily. Third, there are 300 days of effective sunshine annually, enabling $\approx$ 20,000 kWh/year generation and transmission related losses for the electricity generated on the feeder would be less than 10%. Fourth, farmers reduce electricity use to 600 kWh per hp per year after adopting SKY.

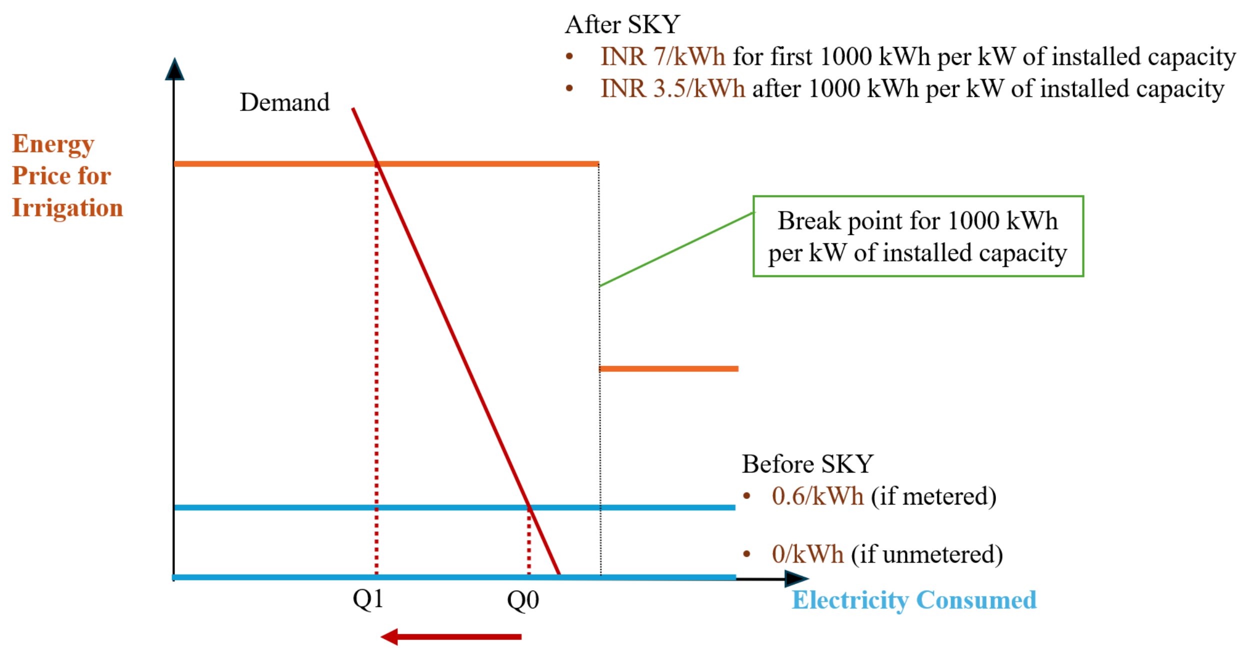
The fourth assumption hinges on farmers understanding the SKY electricity pricing structure. This can be illustrated using a simplistic demand curve in Figure 2. Before SKY, farmers paid either a flat fee or INR 0.6/kWh if metered, effectively a negligible marginal cost.[3] In contrast, SKY introduced an implicit marginal price of INR 7/kWh: the foregone income by using rather than selling an extra unit of electricity. This foregone revenue constitutes the *opportunity cost* of consumption.

If electricity use is elastic and pumping efficiency remains constant, this opportunity cost should incentivize reduced electricity—and hence groundwater—use, *ceteris paribus*. However, this outcome depends on farmers fully understanding the pricing mechanism and reacting to the price signals. It is also important to recognize the broader appeal of the SKY policy: it promised reliable daytime electricity for irrigation, potential income generation, and extended

[3]For reference, the average rate for electricity supplied is around INR 6/kWh in Gujarat (NITI Aayog, India, 2025).

supply hours—from 8 to 12 hours. These features effectively increased the supply of groundwater irrigation and therefore could be expected to increase pumping.

Figure 2: Theoretical demand response to opportunity cost mechanism



Note: The marginal price for irrigation electricity is 0 (in case of unmetered connections) or INR 0.6/kWh (metered) without SKY. The opportunity cost under SKY increases the marginal price to INR 7/kWh for the first 1,000 units, and INR 3.5/kWh thereafter.

3 Data & Methodology

To understand the impact of grid-connected solar irrigation promotion on groundwater consumption, we collected primary data through field visits and a farmer survey in Gujarat. The fieldwork asked questions about farmers' experiences with the SKY policy and whether they had changed or anticipated changing their agricultural and/or irrigation practices.

3.1 Solar irrigation fieldwork and survey in Gujarat

We designed and conducted fieldwork in Gujarat that included in-person field visits, unstructured interviews with stakeholders, and a digital household survey. The objectives and key features of each phase are described below.

3.1.1 Exploratory field visits and stakeholder interviews

In December 2021, before collecting the survey data, the author conducted in-person field visits and held interviews with farmers, policymakers, representatives of implementing agencies/companies, and solar system maintenance staff. The objective was to familiarize the research team with on-the-ground implementation of solar policies, identify groups of farmers for inclusion in the survey, and compile qualitative insights.[4]

The comparison groups in the study include three categories: **SKY adopters**, **SKY non-adopters**, and **ineligible farmers**. ***SKY adopters*** are farmers who participated in the SKY program and installed solar PV panels on their fields, typically near their irrigation pumps.

SKY non-adopters are farmers who were eligible for the SKY program and are connected to the same feeder lines as the adopters but chose not to install solar panels. These farmers remain connected to the conventional electricity grid. Since the SKY feeder lines must remain active during the day to supply and/or evacuate power to/from SKY adopters, Non-adopters also receive daytime electricity. However, to limit their access, the electricity distribution companies (DISCOMs) installed devices called "watchdog" timers on the circuits that are designed to cut off supply to Non-adopters after 8 hours of usage. In practice, the effectiveness of these watchdog devices is questionable. Field observations suggest that farmers have learned to bypass or manipulate these devices, enabling them to access electricity for up to 12 hours instead of the restricted 8 hours.

Ineligible respondents are farmers from nearby villages that are not covered by the SKY program. They continue to receive the standard rationed electricity supply of 8 hours, which may be scheduled during the daytime or nighttime, often on a bi-weekly rotation.

Twenty-two sites were visited from December 2021 to January 2022. These visits helped identify suitable locations for household surveys and engage local leaders and facilitators to reach the target sample size of approximately 3000 farmers. 16 enumerators were trained, and the survey instrument was field-tested during December 2021.

Field observations revealed that the allocation of SKY was not random. Because implemen-

[4]These insights were used to identify opportunities and challenges in solar irrigation adoption and to understand the roles of stakeholders in improving planning, implementation, and monitoring of solar irrigation policies. The findings were published in Patel et al.(2024).

tation required at least 70% participation on a feeder, adoption was driven by two main factors: (1) techno-economic feasibility—how easily and economically electrical components could be installed—and (2) socio-economic acceptability—whether a community within a feeder could be collectively persuaded and where they can achieve 70% enrollment within the village. This created inherent selection bias of the policy by favoring relatively well-off farmers and socially homogeneous communities for SKY adoption.

3.1.2 Household survey in Gujarat

Following the site identification, survey enumerators conducted in-person survey at 37 locations. Each locations had varying number of villages and respondents.[5] We surveyed nearly half the functional SKY feeders to obtain a representative sample of adopters. Respondents were drawn from three groups: SKY adopters, SKY-eligible but Non-adopters, and ineligible farmers from nearby areas using snowball sampling.[6] We aimed to cover 37 sites (defined as clusters of villages and farmers), targeting approximately half of SKY adopters across four DISCOMs. We selected half the SKY feeders under each DISCOM and maintained a 50-50 split between adopters and comparison groups (Non-adopters and ineligible) at each site. Locations were selected to ensure geographic diversity. (See Figure 3 for the distribution of SKY feeders and surveyed sites.)

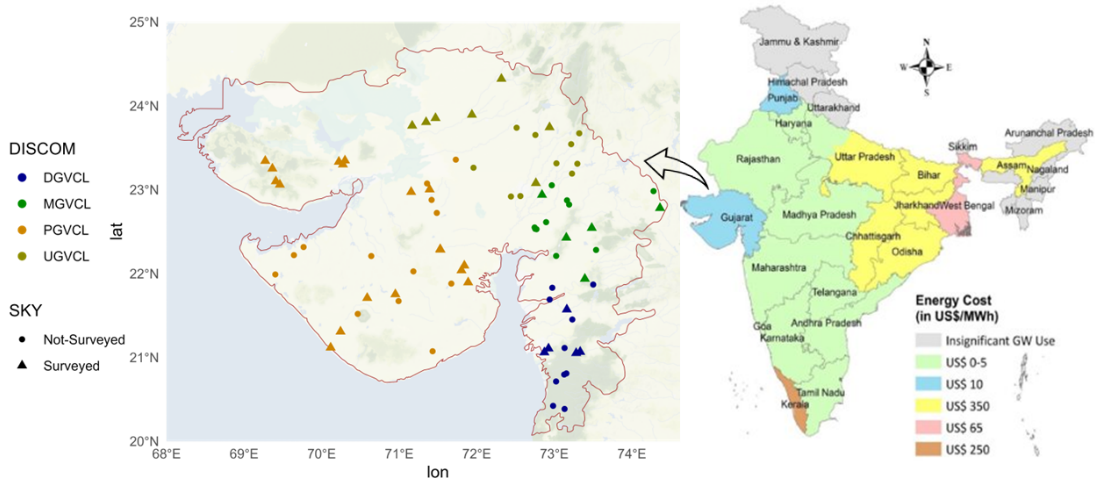
The survey focused on irrigation and agricultural practices as well as demographic characteristics. The survey instrument was divided into three sections and took 15–20 minutes to complete. Section 1 of the survey gathered demographic and groundwater access information. Section 2 focused on crop and irrigation choices, including seasonal cropping patterns, cultivated area, and irrigation frequency. Section 3 addressed solar irrigation adoption and perceptions of change.

The survey was conducted from December 2021 to June 2022, during which 13 enumerators and 3 survey managers collected responses from approximately 3,000 farmers.

[5] The survey was conducted using tablet computers and the *Qualtrics* survey tool. The instrument is available upon request. Email: praharsh@psu.edu.

[6] Snowball sampling is a non-probability survey sampling method in which new respondents are acquaintances of the participants who already completed the survey. The sample thus "snowballs," growing larger as more participants are identified through referrals. This approach helps reach hard-to-access populations but may introduce selection bias due to its reliance on social networks.

Figure 3: Survey locations



Note: The figure shows the approximate locations of SKY policy feeders. Gujarat's four DISCOM zones are marked with different colors. ineligible farmers were recruited from nearby villages outside the SKY feeders. The map provides a rough geographic distribution and is not intended for precise geotagging. The map on right indicates average energy cost for irrigation for different Indian states (Rajan et al., 2020).

3.2 Survey data description

After data collection ended in June 2022, the dataset was cleaned to remove typographical errors and inconsistencies. Following the removal of incomplete responses, 2,798 records were retained for analysis. The outcome of interest in this analysis is groundwater use. However, direct observations of groundwater extraction are unavailable, a close proxy would have been electricity consumption. But, we do not have access to individual-level electricity usage data (or it does not exist if the farmers were not metered and charged flat-fee). To address this, we construct a novel indicator—the ***Groundwater Irrigation Metric (GWIM)***—which is derived from farmers' revealed irrigation practices and serves as a proxy for groundwater use per unit area. GWIM captures differences along the intensive margin of groundwater irrigation. Given that increased irrigation access may also lead to greater land being brought under cultivation or an additional cropping season, we complement GWIM with a second metric: ***Cropping Intensity (CI)***. CI is defined as the ratio of net cultivated area to total land managed. The short-hand mathematical formulae of GWIM and CI are as below. Detailed, step-by-step calculations for both GWIM and

CI are provided in Appendix C.1 and Appendix C.2, respectively.

$$GWIM_f = \sum_s [Irrigation_{fs} * MIF_{fs} * Weighted\ Area_{fs}] * (\%GW) \tag{2}$$

The Micro-Irrigation Factor (MIF) is determined based on the level of micro-irrigation adoption. Specifically, MIF is assigned a value of 0.50 when micro-irrigation is fully implemented, 0.75 when micro-irrigation is partially implemented, and 1 in all other cases where micro-irrigation is either absent or not specified.

$$CI_f = \sum_s [Cultivated\ Area_{fs}] / [Land\ Managed_f] \tag{3}$$

We also asked Likert-scale questions to assess farmers' perceived changes in agricultural practices. These included perceptions of shifts to water-intensive or high-value crops, changes in electricity and water use, and water sales. The framing enabled comparative analysis across the three farmer groups. For instance, the question "Increased water sold" was phrased as: "*Do you think you have increased water sales since (solar irrigation adoption)/(pre-2018 levels)?*". Responses were captured on a five-point Likert scale: "*Strongly Disagree*", "*Disagree*", "*Neutral*", "*Agree*", and "*Strongly Agree*". Further details of the variables of interests are available in Appendix C. These questions were asked retrospectively to capture any changes from the period before SKY was implemented.

Descriptive statistics of the key outcome variables are summarized in Table 1. The sample includes 1,447 SKY adopters, 581 Non-adopters, and 770 ineligible farmers. Mean GWIM is comparable for SKY adopters and ineligible farmers, while SKY non-adopters report lower usage. Cropping intensity is similar across groups, though SKY adopters are more likely to report switching to high-value, water-intensive crops. They also report greater increases in water and energy consumption, and more frequent water sales.

These findings suggest that while SKY adopters may exhibit similar irrigation demand based on revealed agricultural practices, their stated behaviors suggests higher groundwater use. To better assess the effect of solar adoption, it is necessary to control for demographic and locational heterogeneity among farmers.

Table 1: Descriptive statistics

Variable	SKY adopters	SKY non-adopters			Ineligible		
	N = 1,447	*N = 581*			*N = 770*		
	Mean (1)	**Mean** (2)	**Difference** (3)	**p-value** (4)	**Mean** (5)	**Difference** (6)	**p-value** (7)
				Outcome Variables			
Groundwater Irrigation Metric	4.78	5.44	0.66	0.04**	5.58	-0.15	0.75
Cropping Intensity	1.30	1.38	0.08	0.08*	1.42	-0.04	0.49
Switched to High Value Crops^{+}	0.12	0.14	0.02	0.20	0.13	0.01	0.84
Switched to High Water Crops^{+}	0.08	0.14	0.06*	0.001**	0.11	0.03	0.62
Increased Water Consumption^{+}	0.11	0.16	0.06	0.003***	0.12	0.04	0.46
Increased Energy Consumption^{+}	0.10	0.17	0.07	0.003***	0.09	0.08	0.02**
Increased Water Selling^{+}	0.08	0.10	0.02	0.26	0.05	0.05	0.01**
				Household Characteristics			
Family members	5.81	5.43	0.38	0.01**	5.46	0.36	0.00***
No earning members	1.33	1.35	-0.02	0.70	1.46	-0.13	0.38
Land managed (acre)	8.93	7.07	1.86	0.00***	9.67	-0.74	0.57
Parcels	2.25	2.02	0.23	0.09*	2.05	0.20	0.28
Groundwater (%)	96.49	96.51	-0.02	0.99	94.04	2.45	0.41
Head of family education	2.09	1.86	0.23	0.01***	2.15	-0.05	0.64
Unmetered electricity access^{+}	0.16	0.00	0.16	0.00***	0.17	-0.01	0.85
Housing quality	3.08	3.17	-0.08	0.22	3.11	-0.03	0.90
General Category^{+}	0.72	0.61	0.11	0.00***	0.66	0.07	0.34

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$ | $^{+}$ Binary variable

Note: The table provides Mean (Standard Deviation) for Groundwater Irrigation Metric (GWIM) and Cropping Intensity (CI). The GWIM can be interpreted as number of irrigation applied on unit area annually. It is a proxy for change in intensive margin for water consumption. The CI indicate how extensive the land in cropped. A proxy for the extensive margin. GWIM and CI are unit-less counts where as rest of the five indicate the binary responses to the direct questions about behavior change. The table also lists the household characteristics that can affect the outcome of the policy but themselves would not be affected by being assigned to SKY policy in a short-term after the implementation. Difference indicates value of the variable for SKY adopters minus SKY non-adopters/ineligible. The p-values are derived by using standard errors clustered at the site-level.

3.3 Empirical strategy

The survey captured the farmers' demographic information, cropping patterns, and SKY adoption-related decision variables. Our empirical analyses use a set of demographic and agriculture/irrigation related indicators and compare the three types of respondents. First, we control for the number of family members, earning members, and education level of head of the family. They can be deciding factors for the family's ability to adopt and maintain the system. We use the total land managed (Land Managed (Acre)) by the household and fragmentation of land (number of parcels). Larger land size is a good proxy of wealth whereas more fragmented is harder to build irrigation system. Although we have data on the revealed annual income and farm mechanization as potential proxies for wealth, we do not include them as controls as they can be affected by SKY adoption (Table D lists these variables). We use the binary variable for caste, assigned 1 for "General" caste and 0 otherwise. The General class typically indicates better socio-economic background. We control for whether the farmer is metered since it affects the differential opportunity cost of pumping due to SKY.

We estimate regressions using the following equation:

$$Y_f = \alpha D_f + \beta A_f + g(X_f) + \epsilon_f \tag{4}$$

In this equation f indexes individual farmersY_f denotes the outcome variable for farmer f, D_f represents survey site fixed effects, A_f is an indicator for SKY adoption, X_f is a vector of control variables.

We use Post Double Selection-Least Absolute Shrinkage and Selection Operator regression (PDS-LASSO), which is a variable selection tool that reduces multicollinearity and improves robustness, especially in high-dimensional settings (Belloni et al., 2013; Chernozhukov et al., 2015; Danquah et al., 2021). The PDS-LASSO method is well-suited for estimating treatment effects using cross-sectional survey data by controlling for factors related to the treatment and outcome variables. We use PDS-LASSO to identify the vector of control variables in estimating the coefficient of interest β in equation 4. Additionally, we use the site-fixed effects to control for any unobserved site-specific characteristics and standard errors are clustered by site.

4 Survey Data Analysis

4.1 Descriptive analysis

SKY policy is unique in multiple aspects and grid-connected solar pumps was being piloted at this scale fo the first time. Thus, we first analyze drivers of SKY adoption. SKY increased daytime irrigation supply, created a marginal cost of pumping, and provided a new income source. As shown in Table 2, farmers predominantly adopted grid-connected solar for day-time irrigation access. The field insights suggests that the farmers were highly motivated to reduce night-time labor. The motivation to adopt solar irrigation for day-time irrigation is not directly related to changes in the total quantity of groundwater pumping. The second most common reason to adopt is additional income (60 percent). Since income is tied to groundwater conservation, this would motivate farmers to decrease pumping.

The survey also provides farmers' rationale for not adopting (avoiding) grid-connected solar irrigation as we surveyed non-adopters. The primary reason for not adopting SKY was a lack of trust in the policy among the farmers. As the SKY policy heavily subsidized the initial capital cost and was piloted with high socioeconomic farmers, less than one fifth of non-adopters expressed money as a challenge for adoption. Potential challenges with the documentation and leased land are negligible, as are the perception of wild animals (mostly monkeys) damaging the solar panels and the potential to get electrocuted by the solar hardware on the ground.

The SKY policy was not a random selection of feeders and eligible farmers are not necessarily representative of farmers in the state. If SKY were expanded to new areas the typical farmer might face more financial challenges than eligible farmers. Table 1 provides descriptive statistics for key demographic, agriculture, and irrigation-related variables. We can see that the SKY adopters and control group (SKY non-adopters and ineligible) do have significant differences in income, education level, land size, percentage groundwater usage, motor depth as well as several irrigation structures and sources.

4.2 Factors affecting the SKY eligibility and adoption

We use the LASSO-based regression to compare SKY policy adoption and eligibility and identify the observable characteristics within the sampled groups that may determine eligibility and

Table 2: Motivation for SKY adoption and avoidance

SKY adopters		SKY non-adopters	
Reason to Adopt SKY		Reason to Avoid SKY	
N = 1447		*N = 581*	
Day-time electricity	97.4%	Did not trust benefits	83.8%
Additional income	60.3%	Wait and watch	56.6%
Increased energy access	47.6%	No money	18.2%
Cheaper energy	8.0%	Wild animals	3.3%
Easy technology to adopt	3.2%	Documentation issue	2.9%
Grid price may increase	1.7%	Can be hazardous	2.8%
		Leased land	0.2%

Note: The table presents the reasons cited by farmers for adopting or choosing not to adopt grid-connected solar pumps. If the response for "Would Adopt in Future" was "Maybe", they were asked the reason for both the cases, adopt and avoid. There are 20 such responses.

adoption. We include site-specific fixed effects and cluster our standard errors at site level assuming the comparison groups within the site would be more comparable than across the sites. If SKY were randomly assigned we would expect no significant predictors of adoption. Therefore, these regressions can be interpreted as potential confounders for our regressions on water use that are correlated with Adoption. We have two potential control groups: non-adopters and ineligible farmers. The regressions on adoption and eligibility test which sample is more appropriate; fewer significant predictors indicate less potential confounders in the outcome regressions.

The results are presented in Table 3. Education, caste, family size, and land managed by the household are significant predictors of the adoption in the combined sample in column (1). Adopters are relatively better off than Non-adopters on these factors. Farmers with unmetered access to electricity are more likely to adopt. Within the eligible sample adopters have more land and, higher income than non-adopters. The only significant predictor for eligibility is the number of family members. Eligible households have larger families which could lead to additional labor available to invest on initial enrollment for SKY.

Columns (3) and (4) predict adoption using the non-adopters and ineligible samples as control groups, respectively. There are more variables selected and more significant variables when comparing adopters to non-adopters (column (3)) relative to ineligible farmers (column (4)). This indicates that there are more observable differences between the adopters and non-adopters. Therefore, selection bias in adoption appears to be more severe than selection bias in eligibility. This is consistent with the balance tests on the two samples presented in Table 1. Based on these tests we prefer using the inelgible sample as the control group in our regressions on the impact of SIPs on groundwater use. We check robustness of our results by considering a combined control group (Non-adopters + ineligible) in Section 4.4.

4.3 Effects of SKY on groundwater use, farming practices, and perceived changes

We estimate the treatment effect on the outcome variables of interest using the ineligible farmers as a control group. Identification uses the PDS-LASSO estimator with site-fixed effects and standard errors clustered at site-level. Table 4 reports the results of regression model described in Equation 4. We consider outcomes related to groundwater use (Column 1), farming practices (Columns 2-4), and perceptions of changes in electricity and water use (Columns 5-7). We find no significant difference in groundwater-based irrigation demand between SKY adopters and ineligible farmers using GWIM as a proxy. The metric is complex and noisy - as indicated by the large standard error - so we also use the direct Likert-scale question about farming practices. The practice variables are 1) switching to high-value crops, 2) switching to high-water requiring crops, 3) increased own water consumption of irrigation, 4) increased energy consumption for irrigation, and 5) increased water selling.

SKY adopters were more likely to switch to increase their electricity consumption for pumping. They also anticipate increased water sold (for irrigation or water tanker supplies) from their irrigation structures. The discussion with stakeholder revealed that farmers sometime sell water to tanker suppliers for domestic water use in nearby rural and peri-urban households. This result goes against the primary hypothesis that the farmers would reduce their electricity (hence water) consumption on adopting SKY. What we find suggests exactly the opposite, they increase pumping in order to sell water.

Table 3: Predictors of adoption and eligibility

	Adoption	Eligibility	Adoption	Adoption
	(1)	(2)	(3)	(4)
Family members	0.021***	0.015**	0.013**	0.019***
	(0.007)	(0.006)	(0.005)	(0.007)
No earning members	−0.058	−0.043		−0.055
	(0.037)	(0.039)		(0.046)
Land managed		−0.002	0.004**	
		(0.005)	(0.002)	
Parcels	0.007			
	(0.009)			
Groundwater (%)	0.001	0.004		0.003
	(0.003)	(0.003)		(0.004)
Head of the family education	0.011		0.032**	
	(0.017)		(0.013)	
Unmetered electricity access +	0.149	−0.057	0.302***	
	(0.107)	(0.120)	(0.047)	
Housing quality	−0.021			
	(0.031)			
General category +	0.073		0.069*	0.056
	(0.057)		(0.038)	(0.098)
SKY Adopters	Yes	Yes	Yes	Yes
SKY Non-adopterss	Yes	Yes	Yes	No
SKY Non-Eligible	Yes	Yes	No	Yes
Fixed-Effects	Site	Site	Site	Site
Observations	2,798	2,798	2,028	2,217
R^2	0.097	0.127	0.137	0.135
Adjusted R^2	0.083	0.114	0.119	0.119

* :p<0.1; ** :p<0.05; *** :p<0.01 | +: Binary variable

Note: The estimates are derived using the LASSO regression. The missing values indicate that the variable was not picked by LASSO as an important variable. Same set of control variables are used for PDS-LASSO estimates in Table 4,5a, 5b & 7.

Table 4: Treatment effect estimates

	log(Groundwater Irrigation Metric)	log(Cropping Intensity)	High Value Crop	High Water Crop	Increased Water Consumption	Increased Electricity Consumption	Increased Water Selling
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
SKY adopters	0.094	−0.054	0.005	0.024	0.039	**0.092*****	**0.041****
	(0.154)	(0.033)	(0.041)	(0.033)	(0.035)	**(0.026)**	**(0.016)**
Observations	2,217	2,217	2,217	2,217	2,217	2,217	2,217
R^2	0.489	0.425	0.208	0.219	0.213	0.204	0.188
Adjusted R^2	0.478	0.413	0.191	0.202	0.197	0.187	0.173

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Note: All the estimates are based on PDS-LASSO with site-specific fixed-effects and cluster the standard errors at the site-level. Outcome Variables in column (1) and (2) are numerical variables. We expect them to be left skewed thus they are log transformed which also helps to understand the point estimates as percentage change.

The increase in water sold may reflect both irrigation-related use and sales for other purposes, such as supplying domestic water to peri-urban areas through tanker services. These results suggest that SKY-adopting farmers did not significantly reduce their own groundwater consumption. Instead, the observed rise in energy use and water sales indicates that some farmers may have begun selling water to neighboring farmers for irrigation or, as observed in certain cases, to meet domestic water demands in peri-urban and suburban areas where reliable water supply is limited.

Overall these findings suggest that in the short-run, the SKY policy has not incentivized reductions in overall groundwater use. Since the hypothetical reduction in groundwater use hinges on the assumption that farmers understand and respond to the marginal cost incentives for water consumption, it is critical to better understand the experiences of the SKY adopters. The theory of change is based on salient marginal prices that will cause consumers to respond to the incentives imposed by the grid-connected solar. To expect any behavioral change, the physical infrastructure needs to be properly installed, maintained, as well as the critical assumptions for the financial models shall hold true, and the policy rollout, including transparency on pricing and electricity feed-in-tariff, and their enforcement over time, must be strictly adhered to.

4.4 Robustness check for main results

While ineligible farmers constitute a better control group to estimate the difference in key outcome variable, we check the robustness of results by using the combined control group that includes the Non-adopters as well as ineligible farmers. First we use the combined control group with additional dummy indicating eligibility but not the adoption, essentially non-adopters. Increasing the sample size will also improve the statistical power. The point estimates listed in Table 5a are close to the main results discussed in the previous section. Point estimates for GWIM changed from 0.094 to -0.01, both statistically insignificant. This reflects that the GWIM indicator has high variability hence large standard errors (SE) that limits the statistical inference. Another difference is the increased SE for Increase Water Selling rendering the estimate statistically insignificant. The additional control group of non-adopters increases the variation in baseline and leading to higher SE for the treatment effect.

Table 5: Treatment effect estimation using different control group specifications

(a) Combined control group and dummy for Non-adopters

	log(Groundwater Irrigation Metric)	log(Cropping Intensity)	High Value Crop	High Water Crop	Increased Water Consumption	Increased Electricity Consumption	Increased Water Sold
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
SKY adopters	−0.010	**−0.059***	0.005	0.020	0.038	**0.089*****	0.044
	(0.079)	**(0.034)**	(0.044)	(0.038)	(0.037)	**(0.031)**	(0.027)
SKY non-adopters	−0.088	−0.054	0.023	−0.004	0.016	**0.056***	**0.041***
	(0.080)	(0.033)	(0.043)	(0.034)	(0.035)	**(0.028)**	**(0.022)**
Observations	2,798	2,798	2,798	2,798	2,798	2,798	2,798
R^2	0.648	0.438	0.211	0.217	0.234	0.214	0.209
Adjusted R^2	0.642	0.429	0.197	0.204	0.220	0.201	0.195

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

(b) Combined control group

	log(Groundwater Irrigation Metric)	log(Cropping Intensity)	High Value Crop	High Water Crop	Increased Water Consumption	Increased Electricity Consumption	Increased Water Sold
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
SKY adopters	0.028	−0.036	−0.005	0.021	0.032	**0.065****	0.026
	(0.052)	(0.022)	(0.027)	(0.023)	(0.026)	**(0.026)**	(0.020)
Observations	2,798	2,798	2,798	2,798	2,798	2,798	2,798
R^2	0.647	0.436	0.210	0.226	0.223	0.186	0.206
Adjusted R^2	0.641	0.427	0.197	0.213	0.210	0.172	0.193

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Note: The estimates are derived using the same estimation using site fixed-effects, clustered standard errors and PDS-LASSO regression.

We further assess the robustness of our results by using a combined control group without including a separate dummy for Non-adopters (Table 5b). Overall, our results remain largely consistent when using the combined control group, with one notable exception: the coefficient for increased water sold becomes statistically insignificant in this specification. This suggests that Non-adopters may also engage in higher water sales, which is plausible given their access to daytime electricity similar to SKY adopters, since they are connected to the same feeder lines. Unlike the status quo control group, which is limited to eight hours of electricity supply, SKY feeders remain energized for 12 hours per day. Although Non-adopters were initially subject to "watchdog" devices designed to restrict their access to eight hours, field observations indicate that farmers often learned how to bypass these devices and continued using electricity beyond the intended limit. This additional electricity access likely facilitated the increase in water sales as non-adopters continue enjoying highly subsidized electricity access.

We further test robustness of the identification strategy by applying matching-based estimation in Appendix F. The overall results are consistent. We find increased electricity consumption and water sold but no significant change on own groundwater use, cropping intensity, or cultivation of high value or high water consuming crops.

5 SKY adoption experiences

To further investigate the observed relationship between SKY adoption and groundwater use, we turn to qualitative insights from the field. The fieldwork revealed varying experiences and challenges with policy implementation. The survey collected several indicators to assess experiences related to installation, operation, and management. These are summarized in Table 6 across the four DISCOMs in Gujarat. Notably, the boundaries of these DISCOMs align with four distinct geographical regions, which may also influence operational differences. Therefore, DISCOM-level experiences can vary due to two potential mechanisms: differences in governance and operations across DISCOMs, and structural variations arising from the unique geographical characteristics of each region.[7]

[7] The four DISCOMs in Gujarat operate across regions with distinct agroecological characteristics. DGVCL (South Gujarat) covers areas with high rainfall, abundant surface water, alluvial aquifers, and generally higher water availability. MGVCL (Central Gujarat) receives moderate rainfall—less than South Gujarat but more than the western and

Table 6 indicates significant differences in income from SKY experiences. Also, the program was predominantly adopted by farmers belonging to the "General" caste across the four DISCOMs.[8] Except MGVCL, SKY adopters are not involved in selling or providing water for irrigation. Thus the results showing increased water sold are most pertinent to the MGVCL farmers.

SKY adopters in South Gujarat (under DGVCL DISCOM) reported the worst experiences, often citing damaged systems and substantial financial losses, largely attributed to non-functional systems or metering challenges. The survey indicators and field insights suggest two major issues: (1) theft of copper cables, and (2) infrastructure damage that complicated maintenance. Discussions with operations and maintenance contractors revealed two additional structural challenges. First, rural electricity distribution systems were poorly maintained, causing voltage fluctuations that damaged key components like DC-to-AC inverters. Inverters typically constitute 10–15% of the installed system cost, so frequent replacements imposed significant financial burdens on maintenance providers and insurers. Second, sugarcane—a common crop in the region—creates access and shading problems once it grows above 4–5 feet. Since panels are often installed within the field, they become inaccessible for routine cleaning and are frequently shaded, thereby reducing electricity generation.

By contrast, SKY adopters in North Gujarat generally had more positive experiences. There were no reports of damaged systems, and most adopters reported positive financial returns. This was partly due to better DISCOM governance and the absence of the kinds of infrastructure-related threats found in South Gujarat. Additionally, an important factor that contributed to positive returns was the practice of system "oversizing." The SKY payback calculations assumed that a 1.25x solar panel-to-pump capacity ratio would allow farmers to become net electricity exporters. However, DISCOM officials, recognizing that this assumption might not hold in real-world conditions, informally advised farmers to petition for increased load allocation. For

northern regions, features alluvial aquifers, and is characterized by the smallest average farm sizes. PGVCL (West Gujarat) serves two geophysically distinct regions: Kachchh, known for its desert and arid climate, extremely low rainfall, and sandy soils; and Saurashtra, which experiences highly variable rainfall with hard rock aquifers. Both regions within PGVCL generally have lower population densities and larger landholdings. UGVCL (North Gujarat) covers areas with mixed soil types, low rainfall, and a combination of hard rock and alluvial aquifers. This region is also marked by relatively larger average landholdings.

[8] In India, the government recognizes certain communities as Scheduled Castes and Scheduled Tribes due to their historically lower socio-economic status. The "General" caste refers to those not included in these categories and who are typically better off socio-economically.

instance, a farmer with a 10 hp pump could request reclassification as a 15–20 hp user, enabling them to install a larger (e.g., 25 kW) solar panel system instead of the originally prescribed 12.5 kW. Our survey data confirm this practice: nearly two-thirds of connections were oversized beyond the official 1.25x condition.[9] Even under a stricter threshold—where installed panel capacity exceeds 1.5x but is below 20x of pump capacity—oversizing remains evident across all DISCOMs, with the highest rates observed in North Gujarat. This additional panel capacity almost guaranteed higher returns, independent of any actual change in irrigation behavior. In PGVCL, and parts of UGVCL, many farmers were also satisfied with the policy due to access to sufficiently large systems. However, outcomes within PGVCL were mixed. Some farmers were dissatisfied due to poor-quality installations and lack of proper system maintenance, particularly in Kachchh district. These groups expressed their grievances to DISCOM officials and demanded waiver of dues while keeping system use suspended.

Most interestingly, farmers in Central Gujarat (MGVCL) report a distinctly different experience. In this region, it is common for farmers to sell irrigation water to neighboring farms. This is far less prevalent in other areas. As a result, the increased energy access provided by SKY, combined with a limited understanding of the financial model and prior negative experiences with system maintenance and billing, further incentivized groundwater extraction and extended pumping hours. This additional water demand was not accounted for in the baseline financial projections, contributing to deeper financial shortfalls.

Furthermore, the policy's payment structure was not always clear to farmers. Many did not fully understand how their electricity usage would impact their income. Bills were typically issued only once per year with significant delays, making it difficult for farmers to link their pumping behavior to income generation. In both MGVCL and DGVCL, most farmers reported net losses contrary to increasing income. In PGVCL, although fewer farmers reported losses, those who did often faced substantial bills. Importantly, these losses were not always the result of system failures. In several cases, the systems operated correctly, but electricity generation was lower than expected, or the baseline assumptions about consumption were inaccurate. Some farmers also reported frequent meter malfunctions, though we were unable to independently

[9] We use 1.3x definition in Table 6 since the solar panels size are typically 330-350W. Thus, for 5 hp pump, the farmers would be allowed 6.25 kW, but if the supplier uses 350W panels, 18 panels would amount to 6.3 kW, 1.26x. Thus 5% rounding up error i expected.

Table 6: Solar adoption experiences [across DISCOMs]

DISSCOM	DGVCL (South Gujarat) (1)	MGVCL (Central Gujarat) (2)	PGVCL (West Gujarat) (3)	UGVCL (North Gujarat) (4)
Sample (SKY adopters) $*$	200	341	655	251
Not Functional $*$	37	2	1	0
Land Managed (Acre)	7.08 (6.78)	6.67 (7.97)	8.67 (7.57)	14.14 (10.64)
No of Parcels	1.79 (1.47)	2.07 (1.78)	2.25 (2.20)	2.87 (2.17)
No of SKY Connections	1.22 (0.48)	1.07 (0.31)	1.08 (0.32)	1.09 (0.32)
Average Installed Solar Capacity (kW)	8.94 (5.28)	14.96 (13.72)	27.44 (32.81)	19.66 (23.43)
General Category Adopters $^{\%}$	65.0%	69.2%	76.2%	71.3%
Income from SKY				
Profit $*$	8	64	508	170
Net Income	INR 24,162.50 (28,428.55)	INR 31,012.50 (39,899.82)	INR 56,123.74 (1,20,049.59)	INR 94,475.39 (1,73,130.43)
Loss $*$	129	219	118	73
Net Losses	INR 42,638.08 (41,509.20)	INR 48,046.74 (56,741.02)	INR 1,12,888.64 (1,52,037.52)	INR 24,427.38 (27,079.39)
SKY Experiences				
Adopted for Money	53.5%	48.4%	69.1%	59.0%
Adopted for Electricity	45.0%	26.7%	48.1%	76.9%
Installer Performance Ratings $**$	2.71 (1.54)	3.28 (1.28)	3.37 (1.53)	4.28 (0.59)
Overall SKY Performance Ratings $**$	2.59 (1.35)	3.29 (1.17)	3.63 (1.18)	4.39 (0.54)
Oversizing				
Installed SKY Capacity (> 1.3x) $^{+\ \%}$	38.0%	33.3%	39.1%	42.6%
Installed SKY Capacity (> 1.5x & < 20x) $^{++\ \%}$	26.0%	24.8%	32.1%	35.5%
Water Access				
SKY Increased Water Access $^{\%}$	23.5%	21.4%	19.8%	38.6%
Selling Water for Irrigation $^{\%}$	0.0%	14.7%	0.2%	2.8%
Changed Pump or Motor $^{\%}$	29.0%	33.7%	29.5%	20.3%

Note: Values within parenthesis represent standard deviation. $*$: Number of responses.$**$: Mean score on a scale 1-5 across installation, maintenance, and grievance redressal.$^{+}$: Estimated using the installed pump capacity and installed SKY capacity.$^{++}$: Applying stricter condition and limiting the oversizing upto 20x to consider potential rounding off errors, data entry glitch, or misreporting.$^{\%}$:Percentage values indicate percentage of total sample fulfilling the given criteria.i.e., 65% General Category adopters for DGVCL means, out of 200 households surveyed 65% = 130 were from General Category.

verify these claims.

5.1 Heterogeneity analysis

There is a distinct theme emerging from the divergent experiences with the SKY policy and its implementation. The substantial heterogeneity in farmers' experiences of the SKY policy as discussed earlier. The implementation challenges can potentially void the foundation of the hypothesis that the SKY policy would incentivize reduced groundwater consumption. If the farmers are not realizing the expected marginal price or full payments out of the grid-connected solar pumps, and they have more electricity available since SKY increased access to electricity from 8 hours to 12 hours, they might increase electricity consumption.

To explore the overall experience with the policy as a source of heterogeneity, we divide the sample into "Good" and "Bad" experience clusters of the sites.[10] Our sampling design allows us to identify 37 distinct sites (or clusters). Each farmer rated their overall experience with the SKY policy out of five points across three parameters: Installation, Grievance Redressal, and Maintenance. We compute the average of these three ratings to derive an overall experience index which is rating on a scale 1 to 5. Sites with scores above the median are classified as "Good Experience" sites (18 sites), and those below the median as "Bad Experience" sites (19 sites).

As shown in Figure 7, the overall ratings reported by farmers in these two groups differ significantly. We estimate the treatment effects separately for "Good Experience" and "Bad Experience" sites using ineligible farmers as the control group. These estimates follow the same identification strategy as the main results in Section 4.3. The estimates suggest that farmers in "Good Experience" sites exhibit no statistically significant behavioral change. In contrast, farmers in "Bad Experience" sites show increased water and electricity consumption, along with higher volumes of water sold and more cultivation of high value crop. Cultivating high value crops such as horticulture crops normally requires more water or access to instant cash which can be realized through selling water. However, establishing causality is challenging: it is unclear whether higher water use led to negative experiences. They rated experience as bad since they increased the water consumption first which violated the financial assumption of the policy,

[10]We have 37 sites as clusters and since our identification requires to compare the cluster-wise sample, the heterogeneity analysis requires to identify cluster in the category of interest.

hence lower than expected income and violated trust in the policy. Or the dissatisfaction with the policy prompted them to neglect the "opportunity cost mechanism" and increase the water consumption since they have more hours of electricity available. Claiming dissatisfaction with the policy is a good proxy to understand the implementation challenges that would have violated the underlying goals of the policy.

We identify two possible drivers of bad experiences: (i) Physical system failures, such as non-functional SKY systems; and (ii) Financial misunderstandings, where farmers' expectations about consumption and income did not align with reality.

In our sample, only 40 out of 1,447 surveyed farmers reported non-functional systems—34 of whom are concentrated on a single feeder, with the remaining 6 spread across five feeders—the physical system failures are unlikely to fully explain the negative experiences. However, we are unable to rule out the potential metering issues as claimed by the farmers. It is more plausible that farmers did not have clear understanding of the financial assumptions underlying SKY or they assumed they would receive relief from increased bills through political negotiations. This caused increased consumption and lower-than-expected income.

Table 7: Heterogeneity analysis

Subsample:	log(Groundwater Irrigation Metric) (1)	log(Cropping Intensity) (2)	High Value Crop (3)	High Water Crop (4)	Increased Water Consumption (5)	Increased Electricity Consumption (6)	Increased Water Selling (7)
				Overall Experience			
Good	−0.015	−0.079	−0.035	0.035	0.037	0.084	0.027
(N = 1102, S = 18)	(0.094)	(0.045)	(0.065)	(0.058)	(0.064)	(0.058)	(0.030)
Bad	−0.007	−0.044	**0.079***	0.034	**0.064*****	**0.125*****	**0.077****
(N = 1115, S = 19)	(0.082)	(0.033)	**(0.039)**	(0.029)	**(0.021)**	**(0.032)**	**(0.031)**

*p<0.1; **p<0.05; ***p<0.01

Note: Treatment effect estimates are using PDS-LASSO estimates with site fixed-effect and standard errors clustered at the site-level. p-values are derived through the clustered standard errors. N indicates the sample size and S indicates number of sites (clusters) assigned to the specific groups. There are total 37 clusters and 2217 sampled observation between adopters and ineligible farmers.

Overall, the findings support the narrative that farmers either misunderstood or disregarded the financial assumptions underlying the SKY policy, increasing their electricity consumption to facilitate water sales. Importantly, the water being sold may not be limited to agricultural use. It could also be serving household needs, industrial consumption, or peri-urban water supply, as observed during fieldwork. Unfortunately, the survey did not capture specific data on peri-urban water markets or off-farm water supply, limiting further analysis of these dynamics.

6 Limitations

While this study is the first known attempt to understand the role of grid-connected solar irrigation on groundwater use, it certainly has limitations. This section discusses limitations related to the SKY policy itself, the study design, and the survey instrument.

6.1 SKY policy limitations

SKY was a pilot policy that appeared to be an ideal setting to test behavioral responses to electricity pricing for irrigation at scale. However, fieldwork revealed significant challenges in its implementation. If we classify the primary stakeholders into three distinct groups—(1) planners (e.g., the Ministry of New and Renewable Energy), (2) implementers (such as DISCOMs and installation contractors), and (3) adopters (farmers)—it becomes apparent that planners and implementers operated on one side, while farmers remained on the other, with minimal or, in some cases, no meaningful consultation or information exchange between two sides.

Fieldwork revealed that many SKY adopters faced financial losses and technical issues, which, together with limited understanding of the policy's pricing mechanism, undermined its intended design. Farmers often relied on rough estimates of expected income rather than the concept of marginal opportunity cost, and the critical assumptions about functional systems, consistent solar efficiency, and timely maintenance rarely held true. Given these constraints, it is unsurprising that farmers showed little behavioral change or groundwater reduction within the first few years. Furthermore, most systems were operational for less than two years and most farmers received only one or two bills with significant delays and limited adoption of real-time monitoring tools. Thus, their limited exposure and experience made it difficult to interpret price signals or adjust pumping and irrigation practices accordingly. Furthermore, the treatment was not uniform. During SKY deployment, many farmers engaged in complementary practices such as oversizing their solar capacities, upgrading motors, or adopting micro-irrigation technologies (see Table 6). For example, almost third of the farmers changed their pump sets when adopted SKY.

6.2 Measurement error

The survey required farmers to report details about their agricultural and irrigation practices. In most parts of Gujarat, standard units are not used for measuring area, production, or yield. Enumerators often had to rely on local conversion factors provided by respondents. Despite training, this introduces a risk of measurement or enumeration error. Additionally, farmers facing grievances were often unwilling to engage, leading enumerators to rush through sections of the survey. We accept that the Groundwater Irrigation Metric (GWIM) used in our analysis is not a robust estimate of actual groundwater extraction, but a noisy proxy. The noisiness of the variable is evident in the large confidence intervals for the GWIM parameter (Table 4). It also does not capture non-irrigation uses of water. Nevertheless, it remains the best available proxy in the absence of direct measurement of groundwater withdrawal, pump operation hours, or electricity consumption.

6.3 Sampling bias

The survey aimed to sample approximately half of the SKY feeders in each DISCOM. Enumerators had access to list of adopters and non-adopters within each selected feeder and sought to achieve at least 90 percent coverage of those lists. Ineligible farmers were sampled using snowball methods from nearby areas. While the resulting sample is considered representative of SKY adopters, the lack of random assignment in the policy limits claims about broader representativeness for all Gujarat farmers. Findings may not be generalizable to other regions of Gujarat or India, especially those with different demographic compositions, socio-economic status and political influence, or agro-climatic conditions.

7 Conclusion & Way Forward

This study offers a distinct opportunity to understand the groundwater impacts of grid-connected solar irrigation in the context of an innovative program, *Suryashakti Kisan Yojna (SKY)*. The policy piloted in Gujarat presented two critical avenues of inquiry: first, the opportunities and challenges of promoting grid-connected solar irrigation; and second, whether the opportunity cost mechanism can incentivize farmers to reduce groundwater consumption, thereby contributing to sustainable groundwater management alongside renewable energy transition. Given the limited contextual understanding and scarce observational data, the study employs a novel evaluation approach that combines household surveys with stakeholder engagement.

The analysis highlights significant implementation barriers associated with grid-connected solar irrigation programs. While the policy intent behind the SKY policy was commendable, its implementation faced operational challenges that led to mixed experiences among farmers. One key insight concerns the misalignment between policy design and farmer comprehension. Programs like SKY are primarily led by state electricity departments and energy ministries, which have traditionally been trained to focus on improving access to reliable irrigation electricity. For these agencies, groundwater sustainability is, at best, a secondary priority. They often lack both the incentives and the capacity to educate farmers about groundwater conservation or to provide the critical information and support needed. These efforts would cost substantial resources and require sustained engagement.

We find that the farmers did not comprehend or were not interested in adhering to the marginal opportunity cost framework embedded in the SKY. Instead, they perceived the policy's subsidies, loans, and feed-in tariffs as mechanisms for enhancing income or expanding irrigation, rather than for conserving groundwater. As a result, farmers were unlikely to alter their extraction behavior in short-term, a finding supported by the empirical evidence, which suggests minimal short-term change in groundwater use for irrigation but increased electricity consumption and water sold.

The study was conducted soon after the implementation and reflects the short-term effects. However, there may be significant learning effects over time leading to better financial understanding of the new incentives. We can not say if groundwater conservation would improve over time.

The majority of farmers reported additional income from selling electricity, which could improve household welfare by investing in education or farm infrastructure. Notably, one-third of respondents upgraded their pump sets, indicating some level of technological investment. This study fills a critical gap in the literature by documenting the outcomes and limitations of Gujarat's SKY policy and offers lessons for similar initiatives in other Indian states. One major shortcoming was the lack of field-testing for SKY's financial assumptions and the insufficient communication and engagement with stakeholders. These issues undermined grievance redressal mechanisms and created mistrust. Negative early experiences, often shared through peer networks, have fostered skepticism—not only toward SKY, but also toward solar technology in general—thereby jeopardizing future adoption.

Given the policy's technical and institutional limitations and the low salience of electricity pricing, expecting major shifts in groundwater use during 2021–2022 may have been premature. While electricity consumption data offer useful behavioral insights, they can miss key nuances such as pump oversizing, adoption of new irrigation technologies, or substitution of groundwater with surface water sources (e.g., canals or check dams), as farmers may invest additional income from SKY to extract water through their own pipelines from faraway surface water sources. As India and many other emerging economies pursue their ambitious agendas to scale up solar irrigation, the critical question is no longer whether to promote Solar Irrigation Pumps (SIPs), but how to promote them in ways that safeguard groundwater resources. In this context, grid-connected solar irrigation offers theoretical advantages over off-grid systems, which risk either underutilization of energy or incentivizing unchecked groundwater extraction due to the zero marginal cost of electricity. However, these theoretical benefits must be rigorously tested through field-based evaluations. This is particularly important across the Global South, where SIPs are increasingly viewed as instruments of climate resilience.

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A Types of SIPs

Figure 4: Three major pathways of solar irrigation adoptions

(A) Utility-scale Feeder Tail-end Decentralized Solar Plants

- Renewable Energy-based Power Plants (REPP) by
  - individual farmers
  - group of farmers
  - cooperatives
  - *panchayats* (village council)
  - Farmer Producer Organizations (FPO)
  - Water User Associations (WUA)

  on barren/fallow land.
- Energy produced is directly evacuated to the grid.
- Needs large scale initial investment.
- **PM-KUSUM Target:**
  Setting up 10,000 MW (of individual capacity of 500 kW to 2 MW)

(B) Off-grid Standalone Pumps for Irrigation

- Individual farmers supported to install standalone SIPs.
- For farmers without access to reliable source of energy for irrigation purposes.
- Energy generated can only be used for running pump set on field.
- Eg: Decentralized distribution of solar pumps in different states.
- **PM-KUSUM Target:**
  Setting up 1.75 million stand-alone SIPs (Subsidy for capacity up to 7.5 HP)

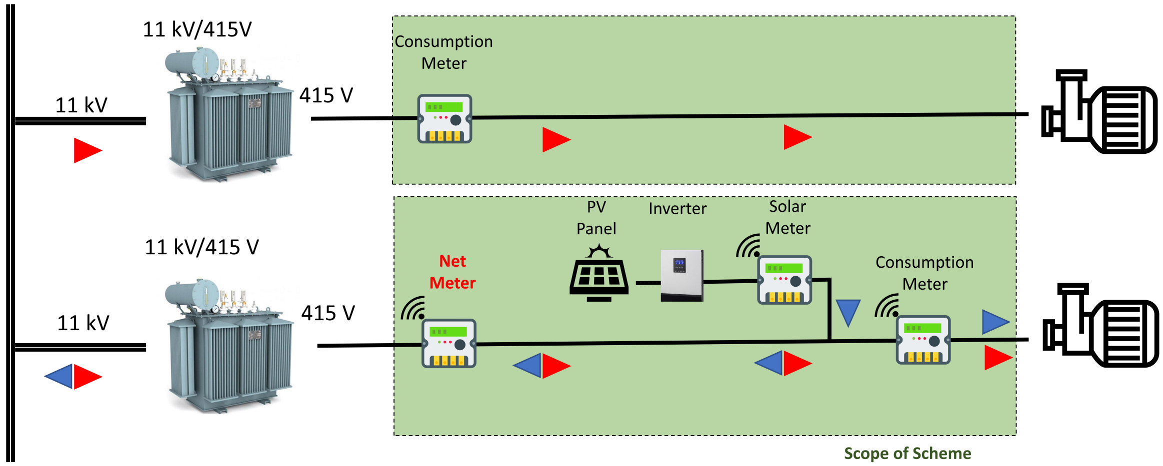
(C) Grid-connected Farm Level Pumps

- Decentralized farm level units owned by farmers.
- Energy generated is first used for irrigation and surplus energy is evacuated to grid for monetary returns.
- Eg: Gujarat's *Suryashakti Kisan Yojana* (SKY)
- **PM-KUSUM Target:**
  Setting up 1 million Grid Connected (Subsidy for capacity up to 7.5 HP.)

**SKY Scheme (Gujarat) did not have a cap on the capacity.*

Note: The figure illustrates the three common solar irrigation deployment strategies—feeder-level solarization, off-grid solar pumps, and grid-connected individual solar pumps—each with distinct technical and operational models.

Figure 5: Electrical Schema of he SKY Scheme



Note: The figure illustrates electrical circuit diagram of grid-connected irrigation pump connection before and after the implementation of the SKY Scheme.

B SKY Financial Estimates

The following scheme document was shared with the farmers to help them understand the estimated cost and benefits from adopting the grid-connected solar irrigation pumps through SKY scheme.

Figure 6: Estimated income for the farmers through the SKY

ખેડૂતને થનાર આવકની અંદાજિત ગણતરી

(5, 10, 20 hp)

સૂર્યશક્તિ કિસાન યોજના

सत्यमेव जयते

Government of Gujarat

Energy & Petrochemicals Department

સોલાર સિસ્ટમ ક્ષમતા (એસી)	5 kW	>5-9 kW	>9-20 kW	>20-50 kW	>50-100 kW	>100-150 kW
સોલાર સિસ્ટમ (એસી) ના ભાવ રૂ પરૃતિ કીવો (જીઅસટી સાથે)	52,091	51,975	50,295	45,149	41,999	41,474

Sr.	HEAD	(Unit)	Metered	Un-metered	Metered	Un-metered	Metered	Un-metered
1	**કરારીત વીજ ભાર**	**(hp)**	**5**		**10**		**20**	
2	**સૌર ઊર્જા સિસ્ટમની ક્ષમતા**	**(kW)**	**6.25**		**12.5**		**25**	
3	એક કિલોવોટ દીઠ પરૃોજેકટ ખર્ચ	(Rs./KW)	51,975		50,295		45,149	
4	સૌર ઊર્જા સિસ્ટમનો પરૃોજેકટ ખર્ચ	(Rs.)	3,24,844		6,28,688		11,28,724	
5	5%ના દરે ખેડૂત નો ફાળો	(Rs.)	16,242		31,434		56,436	
6	ખેડૂત દ્વારા હાલમાં ભરવામાં આવતા વીજ બિલ ભરવા માથી મુક્તિ ને લીધે થતી બચત	(Rs./ year)	2,400	3,325	4,800	8,075	9,600	16,150
7	સૌર ઊર્જાના વેંચાણથી ખેડૂતને થતી આવક (રૂ. ૩.૫૦ પરૃતિ યુનિટ)	(Rs./ year)	24,500		49,000		98,000	
8	રાજ્ય સરકાર તરફથી સબસિડી રૂપે વધારાનો લાભ (લોનના ૭ વર્ષના સમયગાળા દરમ્યાન – રૂ. ૩.૫૦ પરૃતિ યુનિટ)	(Rs./ year)	21,875		43,750		87,500	
9	ખેડૂતને કુલ ફાયદો (૭ વર્ષ દરમ્યાન) (6+7+8)	(Rs./ year)	48,775	49,700	97,550	1,00,825	1,95,100	2,01,650
10	સરળ વાર્ષિક હપ્તો	(Rs./ year)	37,163		71,924		1,29,129	
11	**ખેડૂતને ચોખ્ખો ફાયદો. (લોનના ૭વર્ષ દરમ્યાન) (9-10)**	**(Rs./ year)**	**11,612**	**12,537**	**25,626**	**28,901**	**65,971**	**72,521**
12	**ખેડૂતને ચોખ્ખો ફાયદો (લોનના ૭ વર્ષ પછી) (6+7)**	**(Rs./ year)**	**26,900**	**27,825**	**53,800**	**57,075**	**1,07,600**	**1,14,150**

*અંદાજિત આંકડાકીય માહિતી

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Note: The information brochure shared with farmers while promoting the SKY scheme in Gujarat. The information is in the local language, Gujarati

To better understand, consider this illustrative example for a farmer with a 10 hp pump described.[11] First, the farmer with a 10 hp pump is allowed 12.5 kW solar panel capacity. The hardware and installation cost under the government tendering process is INR 628,688. The farmer pays 5% (INR 31,434) upfront; a subsidy from the Ministry of New and Renewable Energy (MNRE) covers; 30% (INR 188,606.4); and the remaining 65% (INR 408,647.2) is a loan taken by the farmer and repaid through evacuation based incentives and feed-in-tariff. If a farmer uses 600 kWh/hp/year, it yields an annual consumption of 6,000 kWh. The solar panels are expected to produce 6 kWh energy for each kW capacity per day, or 75 kW/day. Assuming

[11] When SKY was launched, the scheme document circulated provided similar information with a 10 hp pump example (Government of Gujarat, 2018) [A leaflet shared with the farmers is available in Appendix B].

sufficient sunshine for 300 days/year, the system would generate 22,500 kWh. Some electricity generated will be lost due to operation and maintenance issues (assume 2,500 kWh). Based on the above example and assumptions, we calculated net evacuation at 14,000 kWh. There are two components to the price earned per unit evacuated: (1) the feed-in-tariff (INR 3.5/kWh) on all kWh evacuated (INR 49,000); (2) the EBI (INR 3.5/kWh) on the first 12,500 kWh evacuated (INR 43,750). Finally, there is an annual loan installment the farmer must pay, calculated as 17.6% of the total INR 408,647.2 loan, of INR 71,924.

C Survey Data Compilation

C.1 Quantitative data : deriving Groundwater Irrigation Metric (GWIM)

The outcome variable of interest needs to reflect the total irrigation water requirements. The survey data captures the season-wise farmer-level crops cultivated, with (1) range of irrigation applied, (2) water consumption type of the crops, (3) micro-irrigation application, and (4) area under the crop. Since we are interested in comparing the total irrigation requirements of the treated with that of control farmers, we need to develop a single metric that can incorporate different crops and their irrigation requirements into a single metric. The metric needs to capture the difference in irrigation requirements of the treated and control group farmers.

We start with the following considerations:

1. **Assigning area weights**: Farmers can use a mix of crops for each season, and each crop can have different irrigation needs noted in the survey. To develop a single metric at the farmer level, we need to take a cultivated-area weighted average of the mean irrigation applied for each crop in a season. This gives season-wise irrigation requirements for the farmers.

$$Irrigation_{fsm} = \sum_{c}[(a_{fsmc}/A_{fs}) * Irrigation_{fsmc}] \implies Irrigation_{fsm} = \sum_{c}[(w_{fsmc}) * Irrigation_{fsmc}] \quad (5)$$

Here, f stands for farmer, s indicates season and c is for the crop. m indicates the min or maximum irrigation requirements. w_{fsc} indicates weights assigned to each crop based on the percentage of area under the crops in each season. We have compiled similar data for current cropping year and pre-solarization, (for, non-solar farmers the reference year was 2018).

2. **Incorporating micro-irrigation**: Farmers have indicated if they are using any micro-irrigation technique for each crop. Micro-irrigation is expected to reduce the water consumption for each irrigation applied. The respondents have indicated one of three choices. 1) No micro-irrigation, 2) Partial use, 3) Full utilization of micro-irrigation. Thus Eq. 1 needs to be modified to incorporate the micro-irrigation factor.

$$Irrigation_{fsm} = \sum_{c}[w_{fsmc} * M_{fsmc} * Irrigation_{fsmc}] \tag{6}$$

We assume that micro-irrigation usage will reduce irrigation water consumption by half. Thus, the water consumption shall be half. If there is partial micro-irrigation consumption, we assume that half of the time (50 percent), they use micro-irrigation. Thus, the water saved shall be half as compared to full micro-irrigation use. Hence, we assume there will be a 25 percent water saving.

Hence, M_{fsmcp} takes up the following value:

$$M_{fsmcp} = \begin{cases} \mathbf{0.50}, & \text{if micro-irrigation = "Full"} \\ \mathbf{0.75}, & \text{if micro-irrigation = "Partial"} \\ \mathbf{1}, & \text{Otherwise} \end{cases}$$

3. **Mean of minimum and maximum irrigation applied**: We have crop-wise minimum and maximum irrigation requirements reported by the respondents. The respondents have reported the range of irrigation they need to apply for each crop. e.g. For Crop (C), the x Acre of land parcel is irrigated for n to m number of times. We take an average of the range to have

$$Irrigation_{fs} = (Max\_Irrigation_{fs} + Min\_Irrigation_{fs})/2 \tag{7}$$

For *Kharif* season, the survey separately collected irrigation requirements for "good" and "bad" rainfall year. Thus, we take mean of these two to create the *Kharif* season Irrigation demand.

$$Irrigation_{f\textbf{Kharif}} = \frac{(Irrigation_{f\textbf{Kharif(Good Rainfall)}} + Irrigation_{f\textbf{Kharif(Bad Rainfall)}})}{2} \tag{8}$$

4. **Compiling the seasonal data into farmer-level data**: Given that we want a metric of irrigation water usage at the farmer level, we take a season-wise weighted average of the seasonal irrigation applied ($Irrigation_{fs}$). there can be some parcels of land not cultivated during different seasons. Thus, for the seasons cultivated, there can be different cultivated areas. We take the seasonal cultivated area and divide it by the net cultivated area to find the weights for each season.

$$Irrigation_f = \sum_s [A_{fs} * Irrigation_{fs}] \tag{9}$$

   Where A_{fsp} is the area cultivated in each season divided by the maximum area in three seasons [in case of Y1] or land managed by the farmer [in case of Y2].

5. **Incorporating Percentage of groundwater in total irrigation** The survey asked farmers to indicate amount of groundwater used in their overall irrigation water consumption. If farmers are using mix of groundwater and surface-water, they were asked to estimate percentage groundwater in this mix. Thus, for estimating impact on groundwater, we need to incorporate factor *Perc_GW* variable.

$$GWIM_f = Perc\_GW * Irrigation_f \tag{10}$$

C.2 Quantitative data : deriving Cropping Intensity (CI)

Cropping Intensity (CI) help to identify how extensively the land is cultivated. We use this factor to compare the additional cultivation seasons or increased area under cultivation for the SKY Adopters. The indicator is derived by taking a ratio of sum of total cultivated area across the seasons and dividing it by the total land managed by the family.

$$CI_f = \sum_s [A_{fs}] / [Land\ Managed] \tag{11}$$

If a family managed 10 acre land. Cultivated 10 acre in *Kharif* (Monsoon-season), 10 acre in *Rabi* (Winter-season), and 3 acre in *Summer*, then the Cropping intensity would be $(10 + 10 + 3)/10 = 2.3$.

C.3 Likert-scale data

During the survey, farmers were asked how strongly they feel their agriculture and irrigation practices have changed since 2018. They were asked to rate the following 5 agriculture practices on Likert Scale, indicating (a) Strongly Disagree, (b) Disagree, (c) Maybe/ No Change, (d) Agree, (e) Strongly Agree.

1. Switched to high-value crops (P1)
2. Switched to high water consuming crops (P2)
3. Irrigation Water Consumption Increased (P3)
4. Electricity Consumption Increased (P4)
5. Water sold/provided to neighbors increased (P5)

We use the practice in each of the 5 cases as binary outcome variables to compare the SKY Adopters and Off-grid farmers with their respective counterfactual groups. For this, the Likert scale is combined to make binary variables as follows:

$$Practice_i(P_i) = \begin{cases} 1, & \text{if "Agree" or "Strongly Agree"} \\ 0, & \text{Otherwise.} \end{cases}$$

D Demographic Variables

These variables are categorical variables and we transform them into continuous hierarchy for checking marginal effects. Table 8 lists the variables, categories, and assigned values.

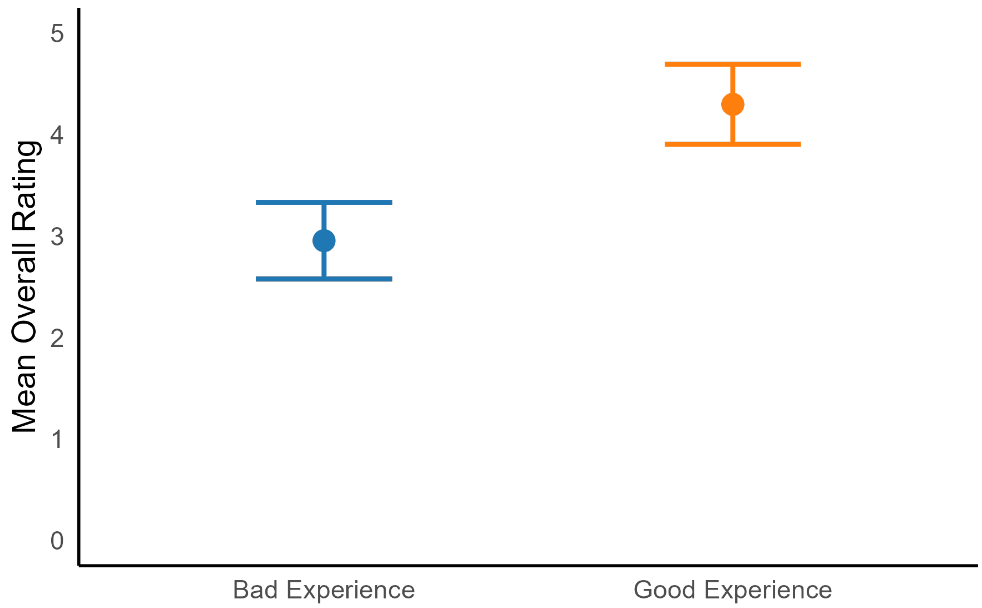
Table 8: Categorical variables and assigned numerical and binary values

Variable	Category	Numerical (1)	Binary (2)	SKY adopters (3)	SKY non-adopters (4)	Ineligible
Annual Income	<50,000	1	0	78	25	27
	50,000-1,00,000	2	0	434	234	255
	1,00,000-2,50,000	3	0	569	232	280
	2,50,000-5,00,000	4	1	267	80	175
	5,00,000-10,00,000	5	1	74	9	27
	>10,00,000	6	1	24		4
Farm Mechanization	Does not require Bullock/Tractor	1	1	16	7	5
	Use of Bullock	2	1	31	25	11
	Rented	3	0	453	207	241
	Owns a Tractors	4	0	946	342	512
Highest Education	No Formal Education	0	0	68	21	39
	Primary School Level (Class 1-7)	1	0	363	215	206
	Secondary School Level (Class 8-10)	2	0	564	195	209
	High School or Diploma (Class 12/PTC/Diploma)	3	1	290	117	227
	College Under Graduate Degree (BA/BSc/B.Com)	4	1	139	26	82
	College Post Graduate Degree (MA/MBBS)	5	1	19	4	2
	PhD or Equivalent	6	1	2		1
Housing Type	Own a hut (Non-Pukka)	1	1	79	25	24
	Pukka (Brick & Concrete Structure) (Selfmade)	2	0	538	201	305
	Rented Pukka house (Well-built)	3	0	6	3	1
	Own Pukka house (Well-built)	4	0	818	347	439
	Do not own a house		1	6	4	1
Ration Card	Antyoday	1	1	38	8	
	BPL Card active user	2	1	127	64	137
	BPL Card holder but not active user	3	0	2	2	5
	APL Card holder	4	0	1255	499	625
	No Ration Card		0	25	8	3

Note: The table outlines the conversion of categorical variables used in the analysis to corresponding numeric or binary indicators for inclusion in regression models. These assignments are based on the ranked nature or binary presence of the attribute in question.

E Source of Heterogeneity

Figure 7: Heterogeneity in SKY Experiences



Note: The figures indicate the classification of groups and difference in observed variables of interest based on the heterogeneity definition. The error bars in solid and dashed lines indicate 95 % and 90 % confidence intervals respectively.

F Matching-based Estimation

Table 9: Matching-based estimators | Non-SKY control

	log(Groundwater Irrigation Metric)	log(Cropping Intensity)	High Value Crop	High Water Crop	Increased Water Consumption	Increased Electricity Consumption	Increased Water Sold
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
SKY Adopters	0.048	−0.064	0.019	0.035	0.036	**0.094****	**0.061****
	(0.122)	(0.034)	(0.054)	(0.032)	(0.048)	**(0.026)**	**(0.019)**
SKY adopters	1,447	1,447	1,447	1,447	1,447	1,447	1,447
Matched Ineligible	380	380	380	380	380	380	380
R^2	0.668	0.281	0.314	0.313	0.331	0.323	0.253
Adjusted R^2	0.384	0.444	0.123	0.110	0.133	0.146	0.172

*p<0.1; **p<0.05; ***p<0.01

Note: The estimates are derived using the Mahalanobis matching method with site-fixed effect estimates.

Table 10: Matching-based estimators | Non-SKY control (Matched within site)

	log(Groundwater Irrigation Metric)	log(Cropping Intensity)	High Value Crop	High Water Crop	Increased Water Consumption	Increased Electricity Consumption	Increased Water Sold
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
SKY Adopters	0.044	−0.064	0.024	0.048	0.042	**0.101****	**0.063****
	(0.134)	(0.035)	(0.051)	(0.028)	(0.047)	**(0.028)**	**(0.019)**
SKY adopters	1,237	1,237	1,237	1,237	1,237	1,237	1,237
Matched Ineligible	330	330	330	330	330	330	330
R^2	0.680	0.287	0.308	0.301	0.319	0.320	0.248
Adjusted R^2	0.413	0.414	0.078	0.062	0.116	0.159	0.191

*p<0.1; **p<0.05; ***p<0.01

Note: The estimates are derived using the Mahalanobis matching method with site-fixed effect estimates. 210 SKY Adopters could not be matched within the same site.

G Data & Code

Sharing data publicly is restricted due to Internal Review Board (IRB) restrictions or personal data sharing. Analysis code is available on request.