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Full Length Article

Do grid-connected solar irrigation pumps help promote groundwater sustainability?: Evidence from India

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ABSTRACT

India's water-energy nexus is complex, with two-thirds of irrigation dependent on groundwater and ~75% of 23 million pumps being electric. Subsidized electricity has driven groundwater over-abstraction, while solar irrigation, though promising, risks exacerbating unsustainable pumping due to near-zero costs. Grid-connected solar pumps offer a solution by enabling farmers to sell surplus energy to the grid, incentivizing sustainable water and energy use. This study assesses the impact of grid-connected solar irrigation on farmers' pumping behaviour in Gujarat, India using empirical data from ~220–240 farmers across two seasons in districts with contrasting aquifers: hard rock (Botad) and alluvial (Anand). Results show irrigation water use in Anand (1753–1961 mm) is 3–4 times higher than in Botad (450–546 mm). In Botad, where shallow aquifers and prevailing cropping pattern and irrigation practices constrain groundwater availability and its use, no significant differences were found between solar and non-solar farmers, as water not energy is the primary constraint. Conversely, in Anand's alluvial aquifers, significant reductions in water use (-608.45 mm in 2021–2022; -556.13 mm in 2022–2023) suggest grid connected solar pumps can influence groundwater conservation through the opportunity cost of energy exports. This reduction may partly reflect shifts in local water markets in Anand, where sellers balance energy exports with water sales, and buyers adapt through efficient irrigation or adjusted irrigation hours in response to higher water prices. The reduction in water use highlights the scheme's potential to incentivise groundwater conservation, demonstrates the scheme's potential as a groundwater management tool in alluvial aquifer settings with sufficient groundwater availability, while highlighting that its conservation impact is highly context-specific. These findings underscore the need to align solar irrigation policies and tariff designs with local hydrogeology to enhance groundwater sustainability and socio-economic benefits.

1. Introduction

Groundwater is critical for global food security, supporting around 40% of the global irrigated land [1,2]. Its significance is particularly pronounced in South Asia, where it drives irrigated agriculture and has played a key role in the region's agriculture and economic progress [3,4]. The South Asia region has about 30 million pumps, abstracting over 350 km^3 annually and irrigating nearly two-thirds of all cultivated land [2–4]. India, the largest groundwater user globally, with approximately 23 million pumps in use, with groundwater's share in irrigation rising from under 30% in the 1950s to 64% today [3–5]. This growth accelerated post-1960s, driven by subsidized electricity and advent of modern drilling and pumping technologies [2,3]. Of these, roughly 76% pumps are electric, mainly concentrated in northwestern and southern states with heavily subsidized power [5,6].

However, intensive groundwater irrigation in India, largely driven by subsidized electricity with limited incentives for efficient water use, has led to widespread overexploitation [3,6,7]. In northwestern and southern peninsular regions, where the groundwater irrigation boom is concentrated groundwater levels have declined rapidly over recent decades. According to the most recent national assessment of the Central Groundwater Board [7], 22% of areas assessed are classified to be in an 'overexploited' or 'critical' state, with the majority located in these regions. This unsustainable use could reduce India's cultivated area by

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20%, and up to 68% in severely depleted zones, threatening food security and farmer livelihoods [8]. Additionally, energy subsidies for irrigation have placed a heavy financial burden on state utilities [6]. Groundwater pumping also contributes significantly to agricultural emissions, with estimated CO_2 outputs of 45.3–62.3 MMT annually - around 10% of India's total emission [9], positioning groundwater irrigation at the heart of the water-energy-food nexus [3,10].

In response to the water-energy-food challenges linked to groundwater irrigation, the Indian government has been promoting solar irrigation [10,11]. Launched in 2019, the flagship program, PM-KUSUM aims to install 34,800 MW of solar capacity by March 2026 through small-scale solar plants and solarization of irrigation pumps [11]. Solar irrigation scaling faces several interconnected challenges, including high upfront infrastructure costs that create significant entry barriers for small and marginal farmers, alongside limited technical skills and maintenance capacity that undermine long-term sustainability [12,13]. Structural constraints such as land scarcity, fragmented land holdings, and policy misalignments (e.g., power subsidies favouring electricity pumps over solar) further hinder widespread deployment [12,13]. Despite these challenges, the pace of solar irrigation adoption is accelerating.

However, while solar irrigation can offer potential co-benefits across a range of domains - water, energy, food, climate, and farmer incomes [10,14,15] - concerns remain about its implications for groundwater sustainability [16,17]. There is a perceived risk that expanding solar irrigation with zero-marginal-cost of pumping, could encourage higher groundwater withdrawal, potentially exacerbating overexploitation, mirroring past trends observed under free or subsidized electricity [16–18].

To address the risk of groundwater overexploitation resulting from solar irrigation expansion, the grid-connected solar irrigation model has been proposed as a strategy to incentivize groundwater conservation [11,19]. In this model, farmers' existing electric grid-connected pumps receive financial support to solarize their irrigation pumps through installation of solar panels [11,19,20]. After solarization, pumps continue to operate on grid power, but these are net metered, accounting for energy generated, energy consumed for pumping, and energy exported to the grid. Since solar panels generate electricity throughout the day, whereas pumps only consume power intermittently when needed, farmers can earn income by exporting unused energy. This built-in incentive is intended to encourage more judicious use of both energy and water. India's flagship solar irrigation program, PM-KUSUM, aims to convert and solarise 1 million grid-connected agriculture pumps under this model [11].

The study is warranted for several reasons. While comprehensive evidence as to whether grid-connected solar irrigation has resulted in incentivising groundwater use is still emerging, there has been no systematic assessment of its impact on irrigation water and energy use. A recent study in Gujarat, India is an exception, finding that solar farmers use less energy than non-solar farmers, based on direct comparisons of average energy use [19]. However, the comparison does not account for potentially significant differences between the two farmer groups, which may have an important influence on the observed outcomes in terms of both observed and unobserved characteristics. Another recent study assessing solar irrigation impact in Gujarat that controlled for difference in farmers group [12] found that solar farmers show significantly slower growth in energy consumption than non-solar farmers indicating more sustainable water use.

Studies such as above [12,19], and others [21], rely heavily on energy use or pumping hours as proxies for irrigation water use, even though there can be significant variation in water abstraction per unit of energy consumed across pump types and regions [22]. Moreover, energy use alone offers limited insight into the actual volume and efficiency of irrigation water use. This study therefore takes a complementary approach, comparing applied water volumes directly to assess how solar adoption has altered farmers' irrigation practices and its implications for groundwater sustainability under the grid-connected solar model.

2. Methods

2.1. Study area

The study is carried out in the western state of Gujarat in India which has implemented grid-connected solar pumps under the state scheme, Suryashakti Kisan Yojana (SKY). In Gujarat, >90 agricultural feeders covering 4500 farmers have been solarised since 2018 with over 75% of farmers' irrigation pumps now being powered by solar energy in those feeders [23]. *Agricultural feeders* are dedicated lines supplying power from a substation exclusively to farmers, allowing electricity providers to regulate supply hours and tariffs separately from domestic or commercial consumers. The state scheme provides 7 INR/unit (kWh) of excess energy sold to the grid [23] creating an incentive structure for farmers to efficiently use water to maximise energy evacuation. The incentive consists of Feed-in-Tariff (FiT) at 3.50 INR/kWh, along with an additional 3.50 INR/kWh as evacuation-based incentive (EBI) for the first seven years to support loan repayment against the capital subsidy and the loan taken by the government on behalf of farmers [19,23].

For this study, data on farmers' groundwater withdrawal was collected from four agricultural feeders located in the two districts of Gujarat: Anand and Botad (Fig. 1). Two agricultural feeders, one solar and one non-solar are selected in each of the districts. In Anand, the Ishnav solar feeder was chosen, with the Pachalipura non-solar feeder serving as its control. These are situated in the villages of Sojitra and Petlad, respectively (Fig. 1). Similarly, in Botad, the Parmeshwar solar feeder was selected, paired with the Gadhaliya non-solar feeder, located in the villages of Ratanpur and Gadhaliya, respectively (Fig. 1). The non-SKY (solar) feeders were selected from the same districts and agro-climatic contexts as the SKY (solar) feeders to maximise comparability in terms of farming systems, groundwater dependence, and irrigation conditions.

The two districts were chosen for their contrasting hydrogeological characteristics. Anand in central Gujarat is underlain by high storage productive alluvial aquifers which are generously recharged by the canal irrigation systems whereas Botad in Saurashtra has hard rock aquifers, with little inter-year storage and highly responsive to both pumping and recharge [24,25].

Feeder-level assignment to the SKY programme was undertaken by the Government of Gujarat and was not random with feeders identified based on administrative and operational considerations. SKY programme implementation proceeded only where >60% of farmers in a feeder agreed to participate. Within SKY feeders, participation in the net-metering component involved an additional layer of farmer self-selection. To avoid selection bias, all farmers with complete data across the monitoring period were included in the analysis and the sample was therefore census-based within the study feeders rather than selectively drawn. All non-SKY farmers in the comparison feeders use electric pumps connected to conventional agricultural feeders; diesel pumps are not present in these feeders.

Hereafter, *solar farmers* refers to farmers within SKY (solar) feeders who have grid-connected solar pumps and can sell surplus energy back to the grid at ₹7/kWh. *Electric farmers*, by contrast, refers to farmers using electric pumps who receive heavily subsidised electricity at approximately ₹0.60/kWh.

2.2. Estimation of farmers' irrigation water use

Irrigation water use through groundwater abstraction, the main source of irrigation, by farmers in the selected feeders was estimated using an energy-based approach [22]. This method involved applying a conversion factor (CF), which represents the volume of groundwater pumped per unit of energy consumed (m^3/kWh). The CF was specifically developed for the selected feeders using data from over 300 pump tests,

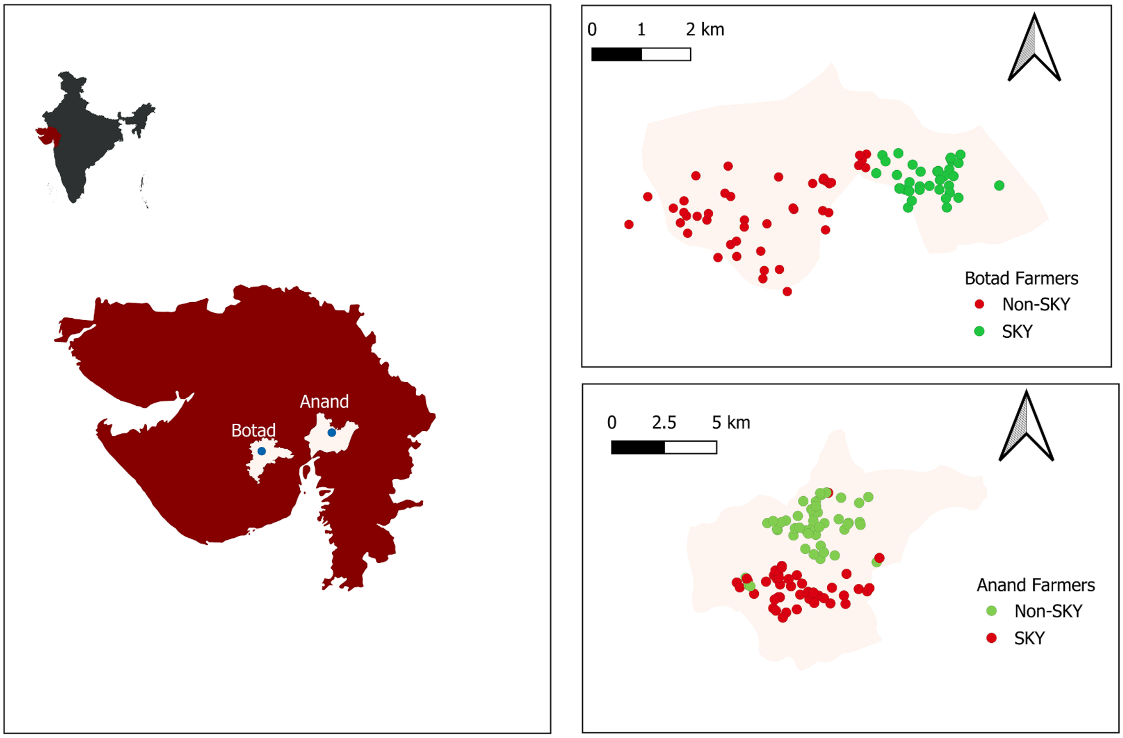

Fig. 1. Location of selected feeders (dedicated power lines that supply electricity specifically to agricultural consumers in an area) and farmers in the districts of Botad and Anand in the state of Gujarat, India.

conducted across two agricultural seasons (2021–22 and 2022–23) [22]. The CFs explicitly account for variations in hydrogeological conditions and pump–well characteristics, including aquifer type, pump horsepower, groundwater depth, and pumping head, rather than assuming uniform pump efficiency across regions. Validation was undertaken through regression-based model testing with datasets (30%) withheld for testing and compared with observed flow measurements. The derived CF was found to provide satisfactory estimates of groundwater abstraction, with an R^2 of approximately 0.92 for alluvial aquifers and 0.69 for hard rock aquifers, when compared with observed groundwater abstraction data [22].

In the hard rock aquifers of Botad, the CF decreases from an average of 6.0 m^3/kWh for 3 HP pumps to 4.7 m^3/kWh for 7.5 HP pumps. In contrast, in alluvial aquifers, which are characterized by higher aquifer transmissivity and flow rates, the CF is higher and decreases from an average of 9.4 m^3/kWh for 10 HP pumps to 4.7 m^3/kWh for 20 HP pumps.

A relationship between the CF and pump technical characteristics was developed for alluvial (Anand) (Eq. (1)) and hard rock (Botad) (Eq. (2)) aquifers, showing that the CF is influenced by multiple factors including pump horsepower, well characteristics, groundwater levels, and pump age [22]. In Anand, CF decreases with increase in pump power (HP), groundwater level depth and tubewell depth. In Botad, CF decreases with groundwater depth and is influenced more by type of pump rather than HP of pump. CF is higher for open-well submersible pumps (similar to centrifugal pumps but submerged in water) as compared to submersible pumps installed vertically at bottom of dugwells.

$$CF_{Anand} = V/E = 13.3 - -0.276 * HP_{pump} - -0.056 * GWL_{depth} - 0.026 * Tubewell_{Depth} \quad (1)$$

$$CF_{Botad} = V/E = 6.307 - 0.118 * GWL_{depth} + 0.973 * Type_{pump} \quad (2)$$

The data on pump HP, tubewell depth and pump type was collected through a pump census. Groundwater levels were collected in selected feeders at multiple points during the monitoring period for Monsoon (July-Oct), Post-monsoon (Nov-Feb), and Pre- monsoon (March-May). The average spatially interpolated groundwater depth for the whole year was used in Eqs. (1) and (2). All grid-connected solar pumps under SKY are net-metered by the utility, with meters recording energy generated, energy consumed for pumping, and energy exported to the grid separately. Similarly, electric pumps are also metered and are billed at subsidised rate. This data on farmers annual energy consumption was collected from energy utilities for the years 2021–22 and 2022–23. The developed CF was then applied to estimate groundwater use in volumetric terms (m^3) of $>$ 200 farmers (241 and 223 farmers in 2021–22 and 2022–23, respectively) in the selected agricultural feeders.

Additionally, agricultural data was collected for all the monitored farmers which included data on farmers land ownership, cultivated area and type of crop for the three agricultural seasons i.e., Kharif (Jun – Oct/ Nov), Rabi (Nov- Feb) and Summary (Feb – May). This was used to estimate gross cropped area (sum of cultivated area across three seasons, in ha) for each year. Additionally, in Anand where water markets prevail, data was collected from farmers on “area of buyers” which is the area they served by selling water. This was added to the gross cropped area for Anand. Thereafter, irrigation water application (in mm) was estimated by dividing estimate groundwater use in volumetric terms (m^3) with the gross cropped area. Data were cleaned for errors/data gaps and only farmers where all data was complete were utilised for comparison.

2.3. *Propensity score matching (PSM) to compare solar and non-solar farmers irrigation water use*

A direct comparison of irrigation water use between solar pump users (treatment group) and non-solar pump users (control group) could lead to biased results due to differences in farm characteristics [26]. Thus, to compare water use of solar and non-solar farmers and evaluate the impact of solar irrigation pumps on irrigation water use, we apply propensity score matching (PSM) using two years of cross-sectional data on farmers' energy consumption and irrigation practices. PSM is a widely used method for estimating the impact in observational studies, particularly when valid instrumental variables factors, influencing solar pump adoption but not irrigation water use, are unavailable [27–29]. PSM mitigates this selection bias by constructing a statistically comparable control group using a conditional probability model based on observed characteristics. This ensures that key factors such as farm size, pump type, well depth, and crop profile are balanced between solar and non-solar farmers, enabling a more reliable comparison. Variable selection for matching was guided by field experience and the broader literature on factors influencing farmer irrigation behaviour, capturing key farm-level characteristics including farm size, pump type, well depth, and crop profile [22]. Farmers with solar pumps (treatment group) are matched to non-solar farmers (control group) based on their propensity score which gives the probability of adopting a solar pump given their observed characteristics.

A key identifying assumption in PSM is that selection into treatment depends only on observed characteristics, meaning all relevant factors influencing both treatment and outcomes must be accounted for. Additionally, the common support or overlap condition must hold, ensuring that for each treated observation, there is a comparable control observation with a similar propensity score [30]. This condition prevents biased estimates by avoiding unmatched treated cases. For the analysis, the common support region is defined as the range between the maximum of the minimum propensity score among solar farmers and the minimum of the maximum propensity score among non-solar farmers. This ensures that treatment observations have comparable counterparts within the propensity score distribution, thereby improving the reliability of the estimated treatment effects. Observations falling outside this common support region are excluded from the analysis to prevent biased estimates due to lack of overlap. To validate these assumptions, the distribution of propensity scores for both groups is examined to ensure sufficient overlap and comparability. Additionally, to assess the quality of matching, we examine the significance of Pseudo R^2 before and after matching and evaluate the mean bias reduction across covariates.

The propensity score (P) is estimated using a logit model incorporating covariates such as land size, pump size, well depth, and crop profile. After estimating propensity scores, we employ nearest neighbour (NN) matching to construct the counterfactual. In NN matching, each treated observation is matched with the closest control observations based on propensity scores (specifically using three and five nearest neighbours) to balance observable characteristics between treated and control groups. This approach allows for intuitive interpretation and minimizes bias by restricting matches to those most similar in observed covariates. To assess the robustness of our estimates, we complement NN matching with kernel matching, which uses weighted averages of all control observations, assigning higher weights to those with propensity scores closest to the treated units and vice-versa. Consistent results across these different matching techniques enhance the credibility of our findings [31].

The impact of solar irrigation on energy use (kWh/HP) and irrigation water application (mm) is then measured as the average difference in outcomes between matched treatment (solar) and control (non-solar) farmer groups. The Average Treatment Effect (ATE) on the Treated on energy use and irrigation water application can be expressed as follows (Eq. (3)):

$$PSM\ Estimator = \frac{1}{|NT|}\sum_{i=1}^{NT}\left(Y_i^T - \sum_{j=1}^{NC} W_{ji} Y_{ji}^C\right) \tag{3}$$

Where Y represents the outcome of interest (energy use or irrigation water application); NT is the number of solar farmers; NC is the number of non-solar farmers and W_{ji} are the matching weights that aggregate the outcomes for the matched non-beneficiaries.

Recognizing that unobserved factors may influence farmers' participation in solar scheme, we assess the sensitivity of our results to potential violations of the key identifying assumption that selection into treatment is based solely on observed characteristics. If unobserved heterogeneity exists, it could simultaneously affect both treatment selection and the outcome variables, leading to biased estimates [32]. To examine the robustness of our findings, we apply the sensitivity analysis Rosenbaum bounds [32], which tests how strongly unobserved factors would have to influence treatment selection to alter the estimated impact. In other words, they help answer: *"How much hidden bias would be required to explain away the observed treatment effect?"* If the results remain robust even when allowing for moderate levels of unobserved bias, we gain greater confidence that our findings are not solely driven by omitted variables.

When implementing Propensity Score Matching (PSM), the estimation of standard errors is a critical consideration due to multiple sources of variability. These include variance from the estimation of propensity scores, the enforcement of common support, and the sequence in which treated individuals are matched. To account for these complexities, we estimate bootstrapped standard errors, which provide a more robust measure of uncertainty [33]. However, PSM only accounts for selection on observable characteristics only and cannot eliminate bias arising from unobserved heterogeneity such as farmer motivation, risk preferences, or unmeasured groundwater conditions that may simultaneously influence both participation in the SKY scheme and water use outcomes. Accordingly, the findings should be interpreted as evidence of behavioural associations between grid-connected solar adoption and groundwater extraction, rather than definitive causal estimates. The Rosenbaum bounds analysis reported provides an indication of how strongly any such hidden bias would need to operate to overturn the observed associations, but cannot fully substitute for randomised assignment or panel identification strategies.

3. Results

3.1. Irrigation water application of solar and non-solar (electric) farmers

Table 1 summarizes the characteristics of monitored data from all farmers across selected districts. Results show that irrigation water application (mm) in Anand is 3 – 4 times higher (1753–1961 mm) compared to Botad (450–546 mm) while energy use by the pump per unit of installed power (kWh/HP) in Anand (948 – 1012 kWh/HP) is twice of Botad (521 - 525 kWh/HP), reflecting differences in cropping patterns, cropping intensity, and aquifer capacity. In Anand, cropping intensity (a measure of how intensively land is cultivated, indicating the number of crops grown per plot per year) is high (246–247%) (Table 1), dominated by water-intensive crops of paddy in the monsoon (kharif) season (~ 90%), followed by tobacco and wheat in the post monsoon (rabi) season (Fig. 2). The district has a well-established water market, with an average farmers gross cropped area (own plots + plots of farmers to whom water is sold) of approximately 6 ha (Table 1). This high cropping intensity and water use are sustained by productive

Table 1
Summary characteristics (mean values) of farmers in Anand and Botad district for the years 2021–22 and 2022–23.

Variable	Anand		Botad	
	21–22	22–23	21–22	22–23
Number of farmers	138	135	102	87
Annual Irrigation application (mm)	1961.8	1777.7	459.0	553.0
Annual Energy use (kWh/HP)	1012.8	948.3	521.2	525.6
Gross Cropped area (ha)	6.1	6.3	3.9	2.6
Cropping intensity (%)	246.2	247.2	154.8	106.9
Monsoon rainfall (mm)[a]	846.5	764.1	790.4	610.5

[a] includes pre-monsoon May month rainfall which helps June sowing.

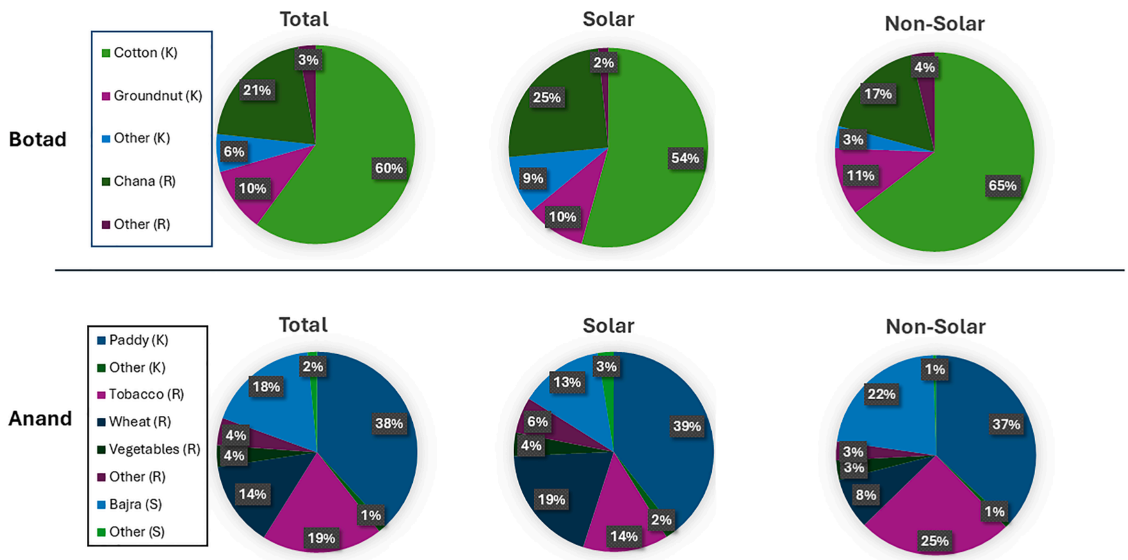

Fig. 2. Average cropping pattern in Anand and Botad for the years 2021–22 and 2022–23. K, R and S in bracket indicates kharif (monsoon), rabi (post monsoon) and summer season, respectively.

alluvial aquifers accessed via medium-depth tubewells (~70 m), typically powered by 10–20 HP pumps. Groundwater levels in Anand are relatively shallow (6–12 m; Fig. 3), recharged by good rainfall in the monsoon and canal network in the northern side reflected in relative shallow groundwater tables (Fig. 3).

In contrast, Botad exhibits lower cropping intensity (107–155%) (Table 1) which is heavily reliant on annual rainfall and shallow hard rock aquifers that is accessed through large-diameter dugwells (~18–20 m deep), restricting access to deeper groundwater reserves. Cropping patterns are dominated by kharif cotton and groundnut, with chana (chickpea) covering most of the rabi area (Fig. 2). In 2021–22, a favorable monsoon (~790.4 mm) with good pre-monsoon in May month rainfall (Table A1) supported moderate cropping intensity (155%) as sufficient groundwater recharge is critical for post monsoon cultivation in the region [23]. However, in 2022–23, poor rainfall (~610.5 mm) significantly reduced cropping intensity (107%), with limited post-monsoon season cropping due to depleted groundwater levels (2–3 m deeper post-monsoon) (Fig. 3).

Table 2 presents a comparison of irrigation water use and other monitored characteristics between farmers in solar and non-solar feeders. There are apparent differences between solar and non-solar feeders. In Anand, the average irrigation water use (mm) is consistently lower in the solar feeder across both years (1443.8 mm in 2021–22 and 1286.6 mm in 2022–23) compared to the non-solar feeder, with application of 2196.3 mm and 1959.9 mm for the respective seasons. These differences also reflect intrinsic variations in cropping

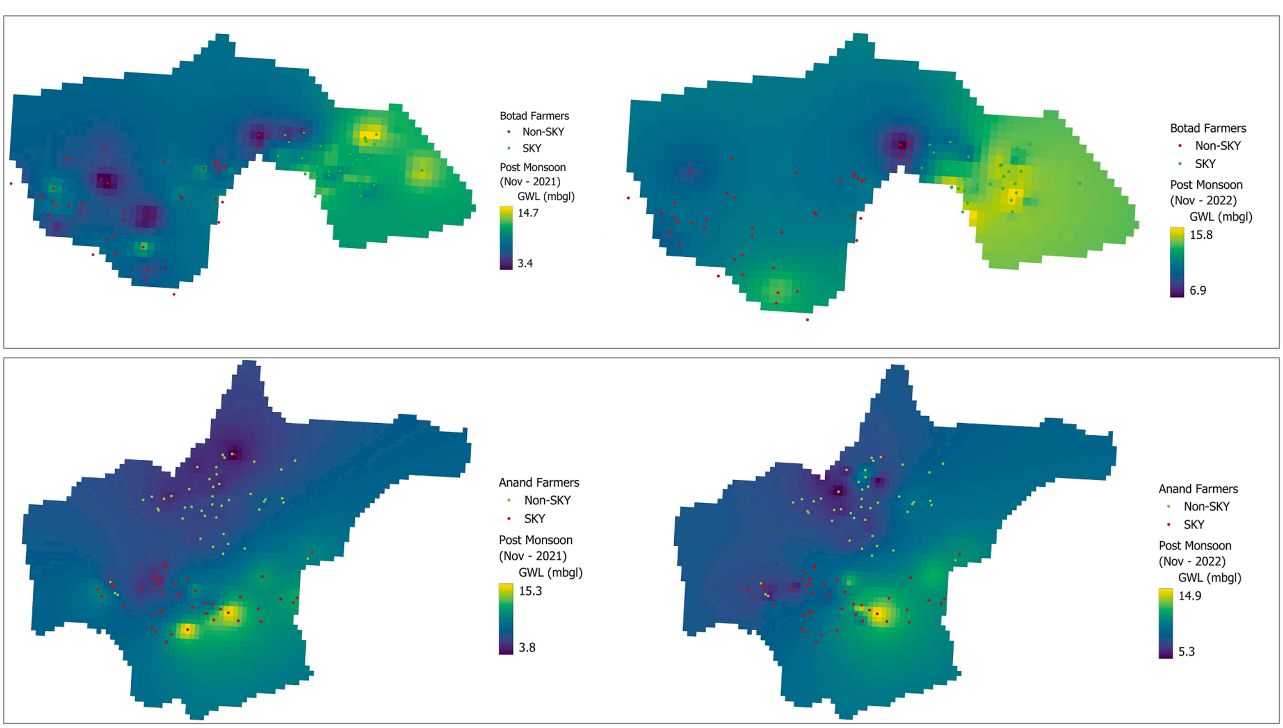

Fig. 3. Post monsoon groundwater level (meter below ground level) for year 2021 and 2022.

Table 2
Summary characteristics of solar and non-solar farmers in Anand and Botad district for the years 2021–22 and 2022–23.

Year	Anand				Botad			
	Solar		Non-Solar		Solar		Non-Solar	
	21–22	22–23	21–22	22–23	21–22	22–23	21–22	22–23
# Farmers	43	41	95	94	51	48	51	39
Gross cropped area (GCA) (ha)	7.2	7.3	5.7	5.9	3.9	2.4	3.9	2.7
Annual Irrigation (mm)	1443.8	1317	2196.3	1978.6	483.8	644.5	436.1	440.3
Annual Energy use (kWh/HP)	999.7	864.2	1018.8	985.0	531.8	542.3	510.6	505.2
Water sold % (area-ha)	65 (4.5)	70.1 (4.7)	75.7 (2.9)	78.7 (2.9)	NA	NA	NA	NA
Groundwater levels (mbgl)	9.2	9.8	6.4	8.1	11.1	13.5	7.2	9.8
Saturated aquifer intersect depth (m) (m)[a]	49.0	48.4	74.1	72.1	10.7	8.3	5.9	3.3
Tube/Dug well depth (m)	58.2	80.5	21.8	13.1				

[a] specific depth interval where a well intersects the aquifer's water-bearing zone (Tube/Dug well depth – GWL).

patterns, pump types, well depths, and groundwater levels.

Although paddy dominates the kharif season in both feeders (occupying over 90% of the cropped area), the rabi season shows divergence: the solar feeder has a more balanced mix of wheat and tobacco, whereas the non-solar feeder is more heavily skewed toward tobacco (Fig. 2). During the summer season, *bajra* (Pearl millet) is the dominant crop in both feeders. A high proportion of farmers engage in water selling in both feeders (ranging from 65% to 79%). However, the area irrigated by buyers is notably larger in the solar feeder (4.5–4.7 ha) than in the non-solar feeder (2.09 ha). As a result, the total gross irrigated area (own use plus sold water) is higher in the solar feeder, averaging 7.2 ha, compared to 5.7–5.9 ha in the non-solar feeder. Groundwater levels are relatively shallow in both feeders, ranging from 4 to 15 m (Fig. 3). However, tube wells in the non-solar feeder are significantly deeper, averaging around 80.5 m, compared to 58.2 m in the solar feeder.

In Botad, during the 2021–22 season, the average irrigation water application was similar for both solar (483.8 mm) and non-solar (436.1 mm) feeders, with an average gross cropped area of 3.9 ha. The cropping patterns across both feeders were also comparable (Fig. 2). However, in the 2022–23 season which had deficit rainfall (Table 1), the gross cropped area declined in both feeders, dropping from 3.9 ha to 2.4 ha in the solar feeder and to 2.7 ha in the non-solar feeder. This reduction reflects a decline in cropping intensity, particularly for the post-monsoon season. Total post-monsoon crop area of all monitored farmers shrank significantly to just 25.0 ha and 135 ha in the solar and non-solar feeders, respectively, compared to 667 ha and 562.5 ha in 2021–22 (Table A2). This suggests the limitations of the underlying hard rock aquifer system, where low rainfall and limited inter-annual groundwater storage provide limited buffering capacity against the effect of the drought condition.

Interestingly, despite the decline in cropped area, irrigation water application in the solar feeder increased to 644.5 mm, while it remained relatively unchanged in the non-solar feeder at 440.3 mm. Energy use (kWh/HP) remained consistent across both years, indicating that the increased water use (per unit of cropped area) in the solar feeder was due to more intensive irrigation of the kharif cotton. In contrast, the stable water use in the non-solar feeder may be linked to shallower dug wells resulting in lower water availability (reflected in lower average depth of well intersecting saturated aquifer of only 3.3 m compared to 5.9 m in Solar feeder) (Table 2). This likely led to early groundwater storage depletion in the wells with low rainfall limiting recovery, possibly resulting in early crop harvesting or reduced yields, though data on harvest timing and yields were not collected. Pump horsepower data further supports these differences in well depth: in the non-solar feeder, the majority of pumps are 3 HP (47.1%) and 5 HP (45.2%), whereas in the solar feeder, most pumps are 5 HP (70.5%) and 7.5 HP (21.8%)

3.2. Impact of solar irrigation on energy and irrigation water use

Since a direct comparison of irrigation water and energy use between solar and non-solar farmers could lead to biased estimates due to underlying differences in farmer characteristics as discussed above (Table 2), propensity score matching (PSM) was employed to ensure a more valid comparison of energy and water use between the two groups. Fig. 4 shows the results of the density plots of the propensity score distributions before and after matching (based on land size, pump size, well depth, and crop profile), providing a visual assessment of the like-to-like comparison of solar and non-solar farmers. Before matching, there were substantial differences in key characteristics between solar and non-solar farmers, as reflected in the divergence in density curves. Specifically, the untreated (non-solar) group is heavily concentrated at lower propensity scores, with peak density around 0.1–0.2, while the treated (solar) group shows a flatter, more dispersed distribution extending across the full propensity score range. This divergence indicates that solar farmers systematically differ from non-solar farmers in their observed characteristics, most notably having larger landholdings, more active well connections, and higher rates of prior water-selling experience which would bias a direct comparison of water and energy use between the two groups.

After matching, the distributions of propensity scores for both groups, solar and non-solar, align closely, indicating that the matching process effectively reduced differences in observed characteristics, thereby improving the comparability of the two groups and strengthening the reliability of these findings when comparing solar and non-solar farmers. The convergence of the two density curves in the matched sample is particularly notable in the 0.1–0.6 propensity score range, where the bulk of observations are concentrated, confirming that the matched pairs are well-balanced in the region of common support most relevant to estimating the treatment effect. The residual minor divergence at the upper tail of the distribution where propensity scores approach 1 is expected given the small number of observations in this range and does not materially affect the overall balance achieved. The close overlap in the matched density curves is particularly encouraging given the moderate sample sizes in each district, suggesting that sufficient common support was achieved despite this constraint. Nonetheless, recognising that observed covariates alone may not fully capture all sources of selection bias, Rosenbaum bounds sensitivity analysis was additionally conducted to assess the robustness of results to potential unobserved heterogeneity.

Impact on Energy use (kWh/HP)

Table 3 presents estimate of the average treatment effect (ATE) for energy use (kWh/HP) across two years (2021–2022 and 2022–2023) for different regions (Whole Sample, Anand, Botad). Standard errors, which account for variability and robustness of estimates, are shown in parentheses. The results show that for energy use (kWh/HP) of solar and non-solar farmers there is no significant differences between solar and non-solar farmers, suggesting that solar irrigation adoption does not alter energy consumption patterns. For the nearest neighbour matching ($n = 5$), results show that solar farmers used 73 and 85 fewer energy units (kWh) per HP than non-solar farmers in 2021–2022 and 2022–2023, respectively but the results are not statistically significant in

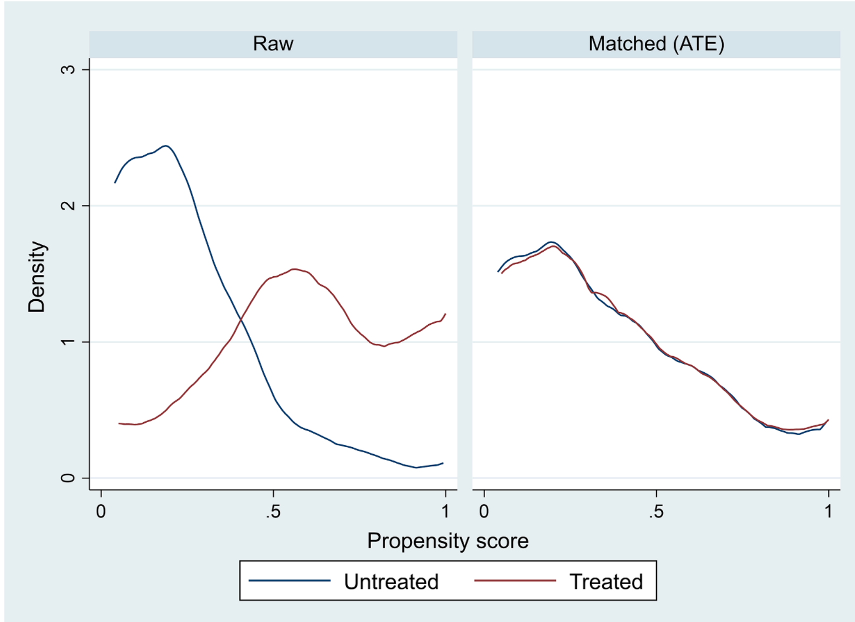

Fig. 4. Before and after matching kernel density plots for propensity score, whole sample.

Table 3
Impact estimates (Average Treatment Effect (ATE) and Rbounds) of solar and non-solar farmers on energy use per unit HP of irrigation pump (kWh/hp) and irrigation water use per gross cropped area (mm/GCA) in Botad and Anand districts, India for nearest neighbour (n = 5) matching. Standard errors in parentheses.

		Energy use per HP (kWh/hp)		
Year		Whole sample	Anand	Botad
2021–2022	ATE	−73.8 (128.6)	−174.6 (231.4)	32.0 (80.6)
	Rbounds[a]	(1–1.1)	(1–3)	(1.3–2)
2022–2023	ATE	−84.8 (137.4)	−120.5 (199.7)	−1.4 (119.0)
	Rbounds	(1–1.4)	(1–1.8)	(1.2–3)
		Water use in (mm/GCA)		
		Whole sample	**Anand**	**Botad**
2021–2022	ATE	−301.8** (158.2)	−608.4** (267.6)	107.2 (95.9)
	Rbounds	(2.1–3)	(1–2.3)	(1.3–3)
2022–2023	ATE	−248.4** (165.1)	−556.1* (305.9)	148.9 (139.8)
	Rbounds	(1–1.6)	(1.2–3)	(1.2–3)
Observation	462	273	189	

**Significant at 5% *Significant at 10%.
[a] Rosenbaum bounds (Γ) indicate the degree of hidden bias required to overturn the result; higher values indicate greater robustness.

both years. Similarly, in both Anand and Botad, average treatment effect (ATE) on energy use per unit HP of the pump remains insignificant. Results under alternative matching algorithms i.e. nearest-neighbor matching (n = 3) and kernel matching yields similar results (Table A3). Overall, results suggest no significant differences in solar and non-solar farmers' energy use (per unit of pump HP).

The robustness of these results is further assessed through sensitivity analysis to account for potential bias from unobserved heterogeneity. The robustness to unobserved heterogeneity, as indicated by the Rosenbaum bounds, varies across districts and years. In 2021–22, the treatment effect in Anand remains robust even if unobserved factors triple the odds of selection into the solar group, while in Botad, it holds even if such factors double the odds. For energy use, the results indicate the Pseudo R^2 values dropped significantly after matching (from 0.206 to 0.021 overall, from 0.347 to 0.03 in Anand and 0.15 to 0.018 in Botad), indicating a well-balanced comparison between treatment and control groups (Table A4). Similarly, p-values increased substantially for the likelihood ratio (LR) chi-square test indicating that the matched samples do not exhibit systematic differences, thus improving comparability. Additionally, for the mean and median bias before and after matching, the results indicating a substantial reduction. This improvement confirms the effectiveness of the matching process in minimizing differences between treatment and control groups.

Irrigation water application

The impact of solar irrigation adoption on irrigation water application (mm) varies across years and regions (Table A4). For the whole sample, matching results for 2021–2022 and 2022–23 indicate that solar farmers applied significantly less water −301.8 mm and −248.4 mm, respectively. The overall reduction is driven by reduction in water use in Anand. Solar farmers in Anand demonstrate significantly lower irrigation water application compared to non-solar farmers, with an ATE of −608.4 mm in 2021–2022 (significant at 5%) and ATE of −556.1 mm in 2022–2023 (significant at 10%). The nearest neighbour matching method (n = 3) and kernel matching presents a similar pattern for reduced water use in Anand for both years, though significance level varies (Table A5).

In Botad, results show solar farmers using slightly more water than non-solar farmers (+107.2 and +149.0 mm in 2021–22 and 2022–23, respectively), though the differences are not statistically significant for both years. The nearest neighbour matching method (n = 3) and kernel matching presents a similar pattern for Botad for both years (Table A5). For 2021–22, the relatively higher Rosenbaum bounds for Botad (1.3 – 3) suggest higher susceptibility to hidden bias compared to Anand where Rosenbaum bounds are relatively low (1 – 2.3) indicating that results in Botad are more sensitive to unobserved heterogeneity. Like energy, sensitivity of these results based on different metrics (Pseudo R^2, likelihood ratio (LR) chi-square test, reduction in mean and median bias) confirms the effectiveness of the matching process in minimizing differences between treatment and control groups.

4. Discussion

Solar irrigation can offer multiple co-benefits across the water-energy-food nexus spectrum, but near-zero pumping costs may pose a risk to groundwater sustainability, especially in the subsidy-driven water stressed ecosystem in India [16]. This study evaluates a grid connected solar irrigation model in India that incentivizes farmers to use less energy (and so water) through energy buyback for surplus electricity generated through solar panels. Using empirical data on energy and irrigation water use from ~ 220–240 farmers over two agricultural seasons, it examines how this solar irrigation model influences irrigation water pumping behaviour among solar farmers compared to non-solar farmers.

First, the findings underscore the importance of considering the underlying hydrogeological conditions when assessing the impacts of irrigation technologies on groundwater use. Results show contrasting patterns of irrigation water use across two districts underlain by different aquifer types i.e. hard rock and alluvial. In areas with hard rock aquifers, limited groundwater storage capacity constrains cropping intensity, resulting in 3–4 times lower irrigation water application compared to Anand (Table 2), which benefits from a high-storage alluvial aquifer. In low-storage aquifer regions, water availability, not energy, is the limiting factor, and constrains farmers cropping practices based on the available water. This is evident in the region's post-monsoon cultivation, which closely aligns with the seasonal groundwater availability [25].

When comparing solar and non-solar farmers, the findings indicate that the impact of solar irrigation on water use is highly context-specific, with a significant reduction in irrigation water application observed in Anand but no significant differences in Botad (Table 3). These differences again likely stem from underlying hydrogeological conditions (alluvial versus hard rock aquifers), as well as variation in cropping patterns and irrigation practices across these two districts. In Anand, where groundwater is relatively abundant, the observed reduction in water use is consistent with the incentive provided under the solar scheme for farmers to sell back surplus energy. Recent study [12] has shown that in central Gujarat region where Anand district is located, > 90% SKY-enrolled farmers evacuated energy to the grid reflecting financial incentives to export electricity.

Interestingly, while the reduction in irrigation water application in Anand is statistically significant, the corresponding energy use estimates, though directionally negative, do not reach significance (Table 3). This apparent divergence is in part methodological as water use in this study is derived from energy consumption using established energy-abstraction conversion equations [22], meaning the two variables are closely related but water use estimates additionally incorporate pump, well and aquifer characteristics that can amplify differences not detectable in raw energy metrics alone. This may mean that changes captured in water application doesn't necessarily translate proportionally into detectable differences in energy per unit HP, especially in a small sample set. Recent study [12] with larger sample size of solar and non-solar farmers has shown solar farmers show significantly slower growth in energy consumption than non-solar farmers.

In addition, use of the CF to estimate water application introduces a degree of uncertainty that should be accounted for when interpreting the magnitude of the observed effect. It is important to note, however, that within each study feeder the CF is derived at the individual pump level, based on pump horsepower, tubewell depth, and local aquifer characteristics, and is independent of whether a farmer has a solar or electric pump. Any unobserved factors influencing the CF would therefore be distributed across both solar and non-solar farmers within the same feeder, rather than acting systematically on one group. This limits the likelihood that the observed divergence between groups is an artefact of differential CF bias. Nonetheless, the divergence between statistically significant water application results and directionally negative but non-significant energy results warrants interpretive caution, and water application findings are indicative of a behavioural response rather than a precise volumetric estimate.

However, the presence of well-established water markets in Anand necessitates a deeper understanding of how these incentives impact such markets. Prior findings [34] indicate that water buyers have been affected, with SKY farmers either reducing water sales or increasing prices. The observed reduction in irrigation water application in Anand may be linked to water seller farmers using irrigation water more rationally and optimizing their operations to maximize earnings from surplus energy sales. It is expected that water buyer farmers have also adopted applying water more efficiently or reducing irrigation hours in response to rising water rates, charged on hourly basis. Recent study [12] has shown that overall in central Gujarat utilities, where Anand is situated, farmers have high evacuation rates (93–94%) but water sellers consume 60 percentage points more energy than non-sellers reflecting water markets are still active with farmers facing competing incentives between using solar energy for irrigation-linked water sales and exporting surplus to the grid. Thus, mechanisms of reduction in irrigation water application observed in Anand in the present study may partly reflect both - a gradual reallocation from sellers towards grid exports and water buyer farmers increasing efficiently or reducing irrigation hours. Nevertheless, the underlying mechanism driving this reduction warrants further investigation over longer term. For example, while in a dynamic market realisation of revenue may make water sellers shift to export or increasing irrigation prices and similarly rising water prices may incentivise efficiency among buyers in the short run but could equally stimulate investment in private wells over time, potentially offsetting any conservation gains at the aquifer level. Thus, assessing how competing market dynamics translate into sustained groundwater conservation over the longer term requires further research requires longitudinal data on both water market transactions and groundwater levels that extend well beyond the two-season window of the present study.

In contrast, the absence of a significant association in Botad is consistent with the constraints imposed by its hard rock aquifer system and underlying crop specific irrigation incentives and rainfall conditions. The underlying low storage aquifer system in Botad inherently limits groundwater storage and constrains cropping intensity [25]. Our results show that cropping intensity in Botad remained low across both years, reinforcing the role of water availability as a key limiting factor (Table 1). In such settings, water availability rather than energy acts as the binding constraint. This is further influenced by underlying crop-specific irrigation incentives and rainfall conditions. Botad's cropping system is dominated by kharif cotton and groundnut, primarily rainfed crops requiring only supplementary irrigation during rainfall deficits. Under conditions of rainfall uncertainty, the marginal benefit of an additional unit of irrigation water can be very high, and farmers may rationally prioritise protective irrigation over exporting surplus electricity despite the opportunity cost created by grid-connected solarisation. In this sense, climatic stress and high marginal returns to irrigation can offset or even dominate the energy-export incentive. This effect was further amplified by below-average rainfall during 2022–23 (610.5 mm compared to 790.4 mm in 2021–22), which reduced groundwater recharge and sharply contracted post-monsoon cultivation with cropped area reducing from 667 ha (solar feeder) and 562.5 ha (non-solar feeder) in 2021–22 to just 25 ha and 135 ha respectively in 2022–23, substantially narrowing the window within which incentive-driven savings could emerge statistically. These findings are consistent with recent companion study assessing energy use changes showing that pumping energy savings during kharif are often limited [12]. The relatively higher Rosenbaum bounds for Botad further indicate greater sensitivity of the results to unobserved heterogeneity. Thus, aquifer conditions, crop-specific irrigation demand, the marginal productivity of water and energy, and rainfall variability together contribute for the Botad non-result. More clear contribution and explanation would require the estimation of marginal productivity of energy in the study region.

4.1. Implications for groundwater management and policy

Overall, the results of this study indicate that grid-connected solar irrigation can help alleviate concerns about its likely negative impact on groundwater. However, its effectiveness in promoting groundwater conservation is strongly influenced by the local context, particularly the characteristics of the underlying aquifer, cropping practices and Feed-in-Tariff (FiT) incentive provided. Results show that in regions such as Botad, underlain by hard rock aquifer systems, hydrological, agronomic, and climatic conditions together impact farmer behaviour in ways that reduce solar irrigation risks to groundwater systems. In such regions limited groundwater storage constrains cropping intensity, rainfed crop dominance means irrigation is largely supplementary, and climatic stress raises the marginal returns to each unit of water applied which lead farmers to prioritise protective irrigation over energy-export incentives. In such contexts, grid-connected solar pumps can serve as an alternative income stream during periods of low irrigation demand, reinforcing earlier propositions that solar power can offer livelihood alternatives beyond crop production [10]. This is supported by the energy use data, which show that farmers in Botad used only half the energy for pumping as compared to those in Anand.

In contrast in regions such as Anand lying above an alluvial aquifer without significant water constraints, the incentives provided by the grid-connected solar model can influence change pumping behaviour of farmers in favour of reduced water application, demonstrating its potential as a tool for managing groundwater overexploitation under similar contexts. However, the effectiveness of this mechanism is dependent on the attractiveness of the feed-in tariff. Under national PM-KUSUM solar scheme, tariffs in many states remain considerably lower than those offered under SKY scheme in Gujarat [35], that may potential weaken the behavioural incentive that makes grid-connected solar potentially useful as a groundwater management instrument. An appropriately calibrated tariff must account for local cropping systems, prevailing electricity prices, and the degree of groundwater stress if it is to meaningfully influence farmer pumping behaviour, crop choices, and the adoption of water-positive agricultural practices.

This underscores the need for groundwater management policies and incentive structures that are explicitly differentiated by hydrogeological and agro-climatic context. In regions such as Botad, where shallow hard rock aquifers and cropping patterns impose binding limits on groundwater availability, policy efforts such as grid connected solar should be prioritizing income-enhancing incentives that discourage the use of available energy in post monsoon season for accessing deep groundwater through deep bore drilling (high-energy pumping with limited water returns), practices that have become increasingly evident in recent years [36]. In contrast, in alluvial aquifer systems such as Anand, akin to aquifers in Northwest India facing acute depletion, results suggest appropriate feed-in tariff–based incentives can be more effective in moderating pumping behavior by encouraging energy exports over excessive irrigation use. At the same time, such differentiated approaches require context-specific tariff designs that provide sufficiently strong incentives for electricity export rather than groundwater-intensive cultivation, thereby aligning farmer income objectives with groundwater sustainability. Recent study [12] have shown that while the SKY scheme is profitable in the long run, many farmers particularly in MGVCL (the region encompassing Anand) do not earn positive net income during the first seven years due to high loan instalments relative to energy export earnings. Their simulation further demonstrates that extending the loan repayment period from 7 to 10 years could nearly double farmer net income from energy sales, indicating meaningful scope to strengthen repayment terms and interest subvention as a lever for both financial inclusion and groundwater conservation.

While results suggest that grid-connected solar irrigation can help alleviate groundwater concerns, successful scaling remains contingent on addressing several institutional and equity challenges. Research on solar irrigation schemes in India has highlighted recurring constraints including high upfront capital costs, reliance on subsidies, and institutional and infrastructure gaps [12,13,37]. For example, capital constraints and risk aversion limit participation among marginal farmers, who constitute over 80% of India's farming population but remain significantly underrepresented in solar irrigation schemes [12,37]. Additionally, grid instability, voltage fluctuations causing inverter tripping, and variable DISCOM capacity introduce disparities in scheme performance and farmer earnings across regions [13,37]. Feed-in tariffs under the national scheme have also declined, reducing farmer incentives to export surplus power over groundwater-intensive cultivation, with viability demonstrated only in specific agro-institutional contexts [13,16]. Addressing these constraints through improved financing mechanisms, strengthened grid infrastructure, and context-specific tariff design is therefore essential to ensure that grid-connected solar irrigation delivers both livelihood and groundwater sustainability outcomes at scale.

Taken together, these findings point to several priorities for future research. Longitudinal studies tracking groundwater levels, water market dynamics, and farmer behaviour over multiple seasons are needed to assess whether the short-term water use reductions observed here translate into sustained aquifer-level conservation particularly in alluvial regions where water markets are active and groundwater depletion is acute. Research is also needed on the long-term performance of grid-connected solar models, including operation and maintenance challenges, farmer behavioural adaptation over time, and the design of feed-in tariffs that remain effective incentives across changing agro-climatic and institutional contexts. Comparative evidence on alternative solar irrigation models would further help identify the most suitable configurations for different hydrogeological settings. Finally, the implications of solar irrigation for broader agricultural productivity outcomes including crop diversification, yield stability, and livelihood resilience merit systematic investigation as these schemes scale under national programmes such as PM-KUSUM

5. Conclusion

This study evaluated a grid-connected solar irrigation model in India designed to incentivize reduced energy and water use through surplus electricity buyback, using empirical data from approximately 220–240 farmers across two districts with contrasting aquifer systems over two agricultural seasons. The findings demonstrate that the impact of solar irrigation on groundwater use is strongly context-dependent, shaped primarily by underlying hydrogeological conditions. In Botad, where underlying hard rock aquifers and prevailing cropping pattern and irrigation practices constrain groundwater availability and its use, water rather than energy acts as the primary limiting factor, leaving limited scope for measurable savings from solar incentives. In this setting, grid-connected solar pumps offer livelihood benefits as an alternative income stream during low irrigation demand periods. In Anand, where a high-storage alluvial aquifer supports intensive irrigation, feed-in tariff incentives appear to meaningfully moderate pumping behaviour, with solar farmers applying significantly less irrigation water than non-solar farmers. This suggests that under the right hydrogeological and institutional conditions with appropriately calibrated tariff that incentivises energy export, grid-connected solar irrigation can potentially serve as an effective tool for managing groundwater overexploitation with direct relevance to similarly water-stressed alluvial systems across India, including the critically depleted aquifers of northwest India.

These findings carry broader implications for sustainable groundwater management at national scale. India's groundwater crisis is spatially heterogeneous, and solar irrigation policy must reflect this. In alluvial, water-stressed regions, grid-connected solar schemes coupled with strong export tariffs and supportive financing can moderate unsustainable pumping. In hard rock regions where available water is a constraint, policy should prioritise income-enhancing incentives that discourage energy-intensive deep drilling. These findings offer valuable policy insights for India and other regions adopting solar irrigation in water-stressed and intensively irrigated areas. They highlight the importance of designing nuanced policy instruments, including attractive incentives, to ensure groundwater sustainability while maximizing the benefits of solar irrigation.

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CRediT authorship contribution statement

Mohammad Faiz Alam: Conceptualization, Methodology, Data curation, Investigation, Visualization, Writing – original draft. **Deepak Varshney:** Methodology, Data curation, Investigation, Writing – original draft, Visualization. **Paul Pavelic:** Conceptualization, Supervision, Writing – review & editing. **Alok Sikka:** Conceptualization, Supervision, Writing – review & editing. **Sunderrajan Krishnan:** Writing – review & editing, Conceptualization. **Meru Dodiya:** Investigation, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.nexus.2026.100746.

Data availability

Data will be made available on request.

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