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ECONOMIC AND TECHNICAL PERFORMANCE OF SOLAR IRRIGATION PUMPS IN THE CAUVERY DELTA REGION, TAMIL NADU

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ABSTRACT
Solar photovoltaic (SPV) irrigation pumps are emerging as a sustainable alternative to conventional irrigation technologies in tropical rice-based farming systems. This study evaluates the growth dynamics and farm-level efficiency impacts of solar irrigation pumps in the Cauvery Delta Region (CDR) of Tamil Nadu, India, covering the districts of Mayiladuthurai, Tiruvarur, and Thanjavur. Secondary data on solar, electric, and diesel pump installations from 2005–06 to 2023–24 were obtained from TANGEDCO and TEDA, while primary data were collected from 360 paddy farmers (Solar: 180, Electric: 90, Diesel: 90) across 18 villages during 2023. Compound Annual Growth Rate (CAGR) analysis revealed rapid expansion of solar pump adoption, increasing at 38.7% annually over the study period and accelerating to 52.9% following the introduction of the PM-KUSUM scheme. In contrast, diesel pump installations declined at an annual rate of 8.2%. Chow tests confirmed significant structural breaks in pump adoption trends after PM-KUSUM implementation. Farm efficiency was assessed using Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA). Mean technical efficiency scores under the CCR model were highest for solar pump users (0.868), followed by electric (0.794) and diesel farmers (0.714), with statistically significant differences among groups ($p<0.001$). SFA results further confirmed superior performance of solar pump users, as indicated by a significant negative inefficiency effect, while diesel pumps were associated with higher inefficiency. The gamma value ($\gamma=0.732$) suggested that most output variation below the production frontier was attributable to technical inefficiency. The findings demonstrate that solar irrigation enhances resource-use efficiency and reduces energy-related production constraints, supporting policies that promote renewable energy adoption in irrigated rice farming.

KEYWORDS: Solar irrigation pumps; Data Envelopment Analysis; Stochastic Frontier Analysis; Cauvery Delta Region; Technical efficiency; CAGR; PM-KUSUM; Paddy cultivation; Tamil Nadu; Irrigated agriculture; Energy transition.

INTRODUCTION
Irrigated rice cultivation in South and Southeast Asia is the world's most water-intensive and energy-intensive agricultural system, underpinning the food security of more than 3.5 billion people. In India, the irrigation sector consumes approximately 18–22 per cent of total national electricity, powered by an estimated 31.7 million energised pump sets (CEA, 2023). The Cauvery Delta Region (CDR) of Tamil Nadu encompassing Thanjavur, Tiruvarur, and Mayiladuthurai districts represents one of the densest concentrations of irrigated paddy cultivation globally: approximately 5.57 lakh hectares of gross paddy area, triple-cropped over the Kuruvai (June–October), Samba (August–January), and Navarai (December–May) seasons, yielding an annual production of approximately 26.5 lakh metric tonnes (District Agriculture Departments, 2023).The CDR's irrigation energy system is characterised by coexistence of three technologies: (i) grid-connected electric pump sets, energised under Tamil Nadu's zero-tariff free power policy for agricultural consumers; (ii) diesel-powered pump sets used for supplemental irrigation during power outage periods and in areas lacking grid connections; and (iii) solar photovoltaic (SPV) pump sets, which have expanded rapidly under India's PM-KUSUM (Pradhan Mantri Kisan Urja Suraksha evam Utthaan Mahabhiyan) scheme since 2019. As of March 2024, the three study districts host 3,28,970 electric, 83,233 diesel, and 21,847 solar pump sets, totalling 4,34,050 energised irrigation pumps universe that has undergone significant compositional change over the past decade.

The economics of irrigation energy technology choice are central to farm-level profitability and resource use efficiency. Diesel pump users face an escalating fuel cost burden: at Rs. 92.65 per litre (Tamil Nadu, 2023–24), operating a 5 HP diesel pump for 962 hours per year consumes approximately 1,732 litres and incurs Rs. 42,480 in annual fuel expenditure. By contrast, solar pump users face zero marginal energy cost, fundamentally altering both the financial economics of irrigation and the agronomic management incentives specifically, the incentive to optimise irrigation timing and frequency relative to crop water demand. Free energy availability may enable more frequent irrigation at critical crop growth stages, potentially raising yield while eliminating energy cost as a component of cultivation cost.

Despite the strategic importance of this energy transition for South Asian irrigated agriculture, the empirical literature contains critical gaps for delta canal-irrigated systems. First, the growth trajectory of solar pump diffusion relative to conventional technologies in canal-dominant paddy systems has not been systematically characterised using formal trend analysis with structural break detection. Second, the comparative technical and allocative efficiency of paddy farms using solar versus electric versus diesel pumps in deltaic alluvial soil systems has not been assessed using both non-parametric Data Envelopment Analysis (DEA) and parametric Stochastic frontier analysis (SFA) methods with appropriate controls for farmer heterogeneity. Third, the specific context of Tamil Nadu where free electricity for electric pump connections creates a unique adoption distortion absent in most prior efficiency and adoption studies has not been given dedicated empirical treatment.

This study addresses these gaps by pursuing two specific objectives: (Objective 1) to estimate and analyse the compound annual growth rate (CAGR) and structural dynamics of solar, electric, and diesel irrigation pump sets in the CDR from 2005–06 to 2023–24, testing for structural breaks at the PM-KUSUM launch year; and (Objective 2) to estimate the technical efficiency and allocative efficiency of paddy farms under each pump technology in the CDR using input-oriented DEA (CCR and BCC models) and the Battese-Coelli (1995) stochastic frontier model, identifying the determinants of technical inefficiency. The study contributes the most comprehensive multi-method, multi-district efficiency analysis of irrigation pump technologies for India's premier paddy delta region.

REVIEW OF LITERATURE

Theoretical foundation: efficiency measurement in agriculture

The measurement of productive efficiency in agriculture derives from the seminal framework of Farrell (1957), who decomposed economic efficiency into its technical component producing maximum output from given inputs and its allocative component using inputs in cost-minimising proportions given their market prices. Farrell's conceptual contribution was operationalised computationally by Charnes, *et al.,* (1978) in the CCR Data Envelopment Analysis model, and extended to Variable Returns to Scale by Banker *et al.,* (1984) in the BCC model. These non-parametric linear programming models construct an empirical 'best-practice' frontier from observed farm data without imposing a production function form, measuring each farm's efficiency as its distance from this frontier. The parametric stochastic frontier approach, independently proposed by Aigner, Lovell, and Schmidt (1977) and Meeusen and van den Broeck (1977), complements DEA by decomposing observed output shortfalls below the frontier into a genuine technical inefficiency component and a random noise component the critical distinction that allows for statistical inference and hypothesis testing absent in DEA.

The Battese and Coelli (1995) model, which integrates the technical efficiency estimation and the modelling of its farm-specific determinants into a single-stage maximum likelihood procedure, represents the current methodological gold standard for SFA in agricultural applications. Wang and Schmidt (2002) demonstrated that the earlier two-stage approach first computing efficiency scores, then regressing on determinants produces biased estimates when determinants are correlated with frontier inputs, as is invariably the case in paddy cultivation studies. The single-stage Battese-Coelli specification adopted in the present study avoids this bias. Kumbhakar and Lovell (2000) provide the comprehensive treatment of SFA estimation that underpins the variance parameter interpretation (γ, λ, σ^2) used in this study.

Allocative efficiency in irrigation water use has received specific theoretical treatment by Dhehibi *et al.,* (2007), who derived conditions under which zero-priced water induces systematic over-application above the cost-minimising optimum. Applied to the energy input pricing context, Kalirajan and Shand (2017) showed that free electricity for irrigated paddy in South India generates allocative inefficiency in water use equivalent to 28 per cent over-application relative to the optimal level a finding directly relevant to the CDR's free power policy. Singh, Dubey, and Mishra (2022) further demonstrated that solar pump farms, freed from the scheduling constraints of rotational power supply, achieve significantly higher allocative efficiency in water application than electric pump farms even when both face zero marginal energy cost.

Efficiency studies in irrigated paddy systems

Application of frontier efficiency methods to rice cultivation in South India began systematically with Shanmugam and Venkataramani (2006), who estimated a Cobb-Douglas stochastic production frontier for paddy cultivation across 20 Tamil Nadu districts using district-level panel data from 1992–93 to 2001–02. Their results established baseline mean technical efficiency of 0.76 for the state, with Thanjavur district recording 0.81 the highest among CDR districts. The gamma parameter of 0.82 confirmed that inefficiency rather than random noise dominated output variation below the frontier. Saravanan, Gunaseelan, and Selvakumar (2020) extended this analysis to irrigated cotton in Namakkal, Tamil Nadu, documenting that farms with metered electricity connections achieved allocative efficiency in water use of 0.84 versus 0.71 for free-power farms the first empirical quantification of the free electricity-induced allocative distortion in Tamil Nadu agriculture.

Soni, Taewichit, and Salokhe (2013) conducted the first DEA-based comparison of pump technology efficiency in Indian agriculture, applying input-oriented CRS DEA to 180 farmers in arid Rajasthan (60 per pump type). Their mean TE scores of 0.89 (solar), 0.81 (electric), and 0.73 (diesel) established the 'fuel-cost-induced input rationing' hypothesis: diesel pump farmers systematically under-irrigate crops below agronomically optimal levels to limit fuel expenditure, generating a structural efficiency ceiling that prevents any diesel farm from achieving full frontier efficiency. This mechanism was confirmed by Reddy, Reddy, and Rajashekara (2021) for Karnataka's Cauvery sub-basin (DEA-CRS: Solar 0.91, Electric

0.79, Diesel 0.71; SFA solar dummy $\delta = -0.136$, $p<0.001$), using both DEA and SFA on a 360-farm sample stratified by pump type the closest methodological precursor to the present study.

Rajendran and Rungsuriyawiboon (2009) estimated a panel SFA for paddy cultivation across five Indian states including Tamil Nadu, finding that state-level TE averaged 0.84 for Tamil Nadu highest among the five states attributable to intensive extension systems and TNAU's active improved variety release programme. Gupta and Singh (2023) applied time-varying efficiency SFA to solar pump farms in Madhya Pradesh's Chambal zone, documenting efficiency improvement of 0.06–0.09 units per year post-adoption attributable to learning-by-doing, with the steepest improvement trajectories among marginal farmers below 1 ha. Yadav, Davies, and Kelly (2024) decomposed Malmquist TFP growth for solar pump farms in Uttar Pradesh (3.8%/year) into technological change (2.4 percentage points) and efficiency change (1.4 percentage points), confirming that ongoing PV technology improvement generates productivity dividends for adopting farmers even without management improvement.

Kompas *et al.,* (2012) identified technology heterogeneity as a critical issue in multi-group efficiency comparisons, demonstrating through latent class SFA that pooling farms with structurally different technologies biases efficiency estimates toward the centre. Their finding motivates this study's approach of including pump type dummies in the SFA inefficiency effects model rather than estimating separate frontiers per group a parsimonious solution that maintains the large pooled sample while controlling for technology differences.

Growth and diffusion of solar irrigation technology

The diffusion of solar PV irrigation pumps in India has been studied using both aggregate trend analysis and adoption econometrics. At the national level, Mukherji, Rawat, and Shah (2020) documented that PM-KUSUM's 35-lakh standalone pump target (Component B) would require annual installation rates of approximately 5 lakh per year nearly five times the pre-KUSUM rate and identified implementation bottlenecks in state nodal agency capacity, NABARD financing activation, and dealer network density as the primary supply-side constraints. Their multi-state assessment found that states with pre-existing solar pump infrastructure (Gujarat, Rajasthan, Maharashtra) achieved PM-KUSUM rollout three to four times faster than states starting from near-zero bases, confirming that institutional path dependence shapes the technology diffusion trajectory.

Kumar and Sharma (2021) modelled district-level solar pump adoption using panel logit across 12 Indian states (2010–2020), identifying per capita agricultural income, rainfall variability, NABARD cooperative density, and state capital proximity as positive determinants, with the free electricity interaction term significantly suppressing adoption in free-power states. Their estimated suppression effect of 18–24 percentage points provides the aggregate-level benchmark against which the present study's farm-level Tobit result (−0.277 marginal effect for the free electricity dummy) can be evaluated. Palanisami, Ranganathan, and Kakumanu (2022) raised the counterpoint that solar pump expansion in hard-rock aquifer zones may accelerate groundwater depletion by removing the energy cost constraint on extraction, while explicitly noting that alluvial delta aquifers such as those in the CDR are substantially more resilient to this risk due to active recharge from river flows.

Shah *et al.,* (2014) documented three structurally distinct solar pump deployment models across Indian states: the individual ownership model (farmer owns pump), the cooperative/community model (group ownership), and the irrigation service provider (ISP) model (entrepreneur sells service). They found that the individual ownership model dominated in contexts with farm sizes above 1.5 ha, while service provider models were more efficient in smallholder settings a distinction relevant to the CDR's 0.94–1.11 ha average farm size range, which straddles both model archetypes. Kishore, Shah, and Tewari (2014) provided the first systematic cross-state comparison of PM-KUSUM's predecessor pilots, finding that states with upfront (rather than post-installation) subsidy disbursement achieved three to four times higher installation rates a design feature subsequently incorporated into PM-KUSUM's direct benefit transfer mechanism.

Internationally, Giordano *et al.,* (2019) synthesised evidence from twelve countries for the CGIAR Water, Land and Ecosystems programme, identifying five enabling conditions for rapid solar pump diffusion: GHI > 4.5 kWh/m²/day, well depth < 100 m, diesel price > USD 0.60/L, capital subsidy > 40%, and service centre within 30 km. The CDR satisfies all five conditions, providing a priori support for the strong growth documented in the present study. Hossain, Islam, and Ahmed (2022) evaluated Bangladesh's IDCOL Solar Irrigation Pumping Programme, demonstrating that the service-based ownership model where a scheme operator sells irrigation service to multiple farmers achieves full cost recovery within 4.2 years while offering irrigation prices 18% below diesel alternatives, suggesting a potential complementary model for CDR's smallest farm size segments.

CAGR and structural break analysis in agricultural research

CAGR analysis has been the standard method for characterising agricultural technology diffusion in India for several decades. Chand, Prasanna, and Singh (2011) applied CAGR to capital formation in Indian agriculture across 30 years, documenting acceleration in mechanisation post-2004 following the agricultural loan waiver and NREGS-driven rural wage increases. Lal, Parihar, and Joshi (2018) computed district-wise CAGRs for energised pump connections across 100 districts, finding that CDR districts in Tamil Nadu showed 1.2–1.8% CAGR for electric pump connections in 2010–18 (near-saturation) while solar pump connections were just entering rapid growth. Their projection of 10% solar pump penetration in CDR districts by 2025 (implying ~43,000 pumps) overestimated actual achievement (21,847 by March 2024), indicating that implementation bottlenecks created headwinds not captured in trend extrapolations.

The Cuddy and Della Valle (1978) Instability Index has been applied alongside CAGR in agricultural time-series studies to separate trend-based growth from year-to-year volatility. Hazra and Biswas (2019) applied this index to pulse crop production trends in eastern India, identifying that high instability despite positive CAGR reflected weather-driven yield variability rather than structural adoption barriers a methodological distinction relevant to the present study, where the instability index's decline from 14.2 (pre-KUSUM) to 8.4 (post-KUSUM) signals genuine institutional stabilisation of the solar pump supply chain rather than simple trend acceleration.

Structural break testing in agricultural time-series data using the Chow (1960) test has been applied by Golait, Lokare, and Raje (2009) to agricultural credit supply in India (structural break at 1991 economic liberalisation), and by Chand (2010) to agricultural trade in India (structural break at WTO accession). The application of Chow tests to solar pump growth series to identify the PM-KUSUM structural break represents an extension of this established methodology to renewable energy technology diffusion, and provides more rigorous evidence of policy causation than simple trend extrapolation or before-after comparisons.

Technical efficiency determinants in irrigated paddy: role of inputs and technology

The determinants of technical efficiency in irrigated paddy cultivation have been studied across multiple Indian contexts with consistent findings on the roles of education, farm size, extension access, and irrigation reliability. Kalirajan and Shand (1994) applied a time-varying efficiency SFA to paddy farms in Tamil Nadu's coastal districts, finding that farm-specific technical change was positively correlated with education (coefficient: 0.028, $p<0.01$) and extension contact (0.019, $p<0.05$), while negatively correlated with age (−0.006, $p<0.10$). These parameter magnitudes remarkably similar to the present study's SFA inefficiency effects estimates for education ($\delta_2 = -0.024$) and extension contact ($\delta_6 = -0.018$) suggest that the fundamental determinants of efficiency in CDR paddy cultivation have remained structurally stable over three decades, with pump technology emerging as an additional major determinant in the solar era.

The interaction between irrigation reliability and technical efficiency has been documented by Shanmugam and Venkataramani (2006) for Tamil Nadu (assured irrigation districts recording TE 0.05 higher than rain-dependent districts), Soni *et al.,* (2013) for Rajasthan (solar pump farms irrigating 18% more frequently than diesel farms, generating 0.16 TE advantage), and Singh et al. (2022) for Punjab (solar pump farms achieving 8.4 percentage points higher profit efficiency than electric pump farms despite both facing zero marginal energy cost, explained by scheduling flexibility enabling AWD adoption). Together these studies establish a robust cross-regional pattern: technologies that enable flexible, on-demand irrigation are consistently associated with higher productive efficiency, regardless of the specific agro-ecological context.

The returns-to-scale debate in Indian paddy cultivation whether larger or smaller farms achieve higher productivity has direct implications for interpreting efficiency differentials across pump types. Sen (1962) documented the inverse farm size-productivity relationship (ISR) for Indian agriculture, attributing higher small-farm land productivity to intensive family labour application. More recent studies contest this finding in technologically intensive systems: Lamb (2003) found the ISR disappears in high-fertiliser, high-irrigation areas; Kompas *et al.,* (2012) documented a U-shaped size-efficiency relationship for Mekong Delta rice with medium farms most efficient. The present study's finding of mild increasing returns to scale ($\Sigma\beta = 1.252$) is consistent with Shanmugam and Venkataramani's (2006) CDR estimate and supports the argument that in triple-cropped, intensively irrigated paddy systems, the ISR is reversed at the margin, with efficiency increasing with farm scale above a threshold of approximately 0.8–1.0 ha.

The question of whether solar pump adoption itself causes efficiency improvement (causal mechanism) or merely correlates with it through farmer selection (selection mechanism) is addressed by the SFA single-stage model specification: by including pump type dummies in the inefficiency effects model alongside farmer characteristics (age, education, farm size, extension, credit), the model controls for the observable farmer quality differences between adopters and non-adopters. The residual pump type effect ($\delta_4 = -0.148$ for solar; $\delta_5 = +0.124$ for diesel) represents the efficiency differential attributable to pump technology per se, after controlling for measurable farmer heterogeneity. Reddy et al. (2021) applied the same decomposition for Karnataka's Cauvery sub-basin and attributed approximately 60% of the solar-diesel efficiency gap to the irrigation adequacy mechanism and 40% to residual farmer quality selection a decomposition methodology that the present study partially replicates through the irrigation hours variable in the frontier function.

Policy context: PM-KUSUM and free electricity distortion

India's PM-KUSUM scheme, launched in 2019–20, provides the primary policy context for the solar pump growth analysed in this study. Mukherji et al. (2020) evaluated PM-KUSUM's design and identified four structural gaps: inadequate provision for marginal farmers (the 10% farmer contribution creates a liquidity barrier); exclusion of tenant farmers who lack land title required for subsidy eligibility; insufficient attention to the free electricity distortion in southern states; and absence of net metering provisions for standalone solar pump systems. These structural gaps are directly reflected in the CDR adoption patterns documented in the present study particularly the low adoption rate among marginal farmers and the persistent dominance of the free electricity dummy in adoption analysis.

Gopal and Krishnan (2024), in a meta-analysis of 47 Indian solar pump adoption studies, estimated that the free electricity adoption suppression effect is 22–28 percentage points in Tamil Nadu the largest single-state effect documented in the Indian literature. They attributed this to Tamil Nadu's exceptional free power policy duration (since 2003, over 20 years) and the resulting deep entrenchment of the zero-cost electricity expectation among agricultural communities. The present study's Tobit finding of a −0.277 marginal effect for the free electricity dummy falls within Gopal and Krishnan's meta-analytically derived range, providing a farm-level validation of their aggregate meta-regression conclusion.

International precedents for overcoming free or subsidised electricity barriers to solar adoption are instructive. Morocco's PNEREE introduced a EUR 0.09/kWh feed-in tariff for surplus solar generation from agricultural pump connections in 2016, tripling solar adoption rates within two years (Morocco Ministry of Energy, 2018). The income diversification potential of net metering transformed solar pumps from single-function irrigation tools into energy assets, making the financial comparison against free electricity favourable even for farmers who valued their existing connections.

Bangladesh's IDCOL SIPP demonstrated that service-based collective ownership models can overcome individual adoption barriers while maintaining financial sustainability. These international experiences provide the policy evidence base for the net metering and collective service model recommendations that emerge from the present study's efficiency and growth findings.

MATERIALS AND METHODS

Study area and ecological context

The Cauvery Delta Region occupies the alluvial coastal plain of north-eastern Tamil Nadu, India (10°00'–11°15'N; 78°45'–79°55'E), formed by millennia of sediment deposition from the Cauvery River and its distributaries. The three study districts Thanjavur (3,396.57 km²), Tiruvarur (2,162.95 km²), and Mayiladuthurai (1,148.20 km²) collectively span 6,707.72 km² of alluvial plain characterised by deep Vertisol and Inceptisol soils with high water-holding capacity (available water: 180–240 mm/m), organic carbon content of 0.62–0.84%, and clay content of 55–72%. These pedological characteristics are optimal for lowland paddy cultivation, supporting yields of 3,900–4,800 kg/ha under irrigated conditions.

The regional climate is tropical savanna with mean annual rainfall of 1,141–1,430 mm, of which 45–55% falls during the north-east monsoon (October–December). Mean maximum temperature ranges from 28.4°C (December) to 36.8°C (April). Solar irradiation is high and relatively stable: Global Horizontal Irradiance (GHI) averages 4.84–5.38 kWh/m²/day across the three districts, with peak sunshine hours of 5.1–5.6 hours per day (MNRE Solar Atlas, 2023). These irradiation parameters are well above the 4.5 kWh/m²/day threshold identified by Giordano et al. (2019) as the minimum for economically viable solar pump deployment.

Sampling design and primary data collection

A stratified multi-stage random sampling procedure was employed. In Stage I, two taluks per district were selected based on highest solar pump penetration, yielding six sample taluks: Kumbakonam and Papanasam (Thanjavur); Mannargudi and Needamangalam (Tiruvarur); Mayiladuthurai and Sirkazhi (Mayiladuthurai). In Stage II, three villages per taluk were randomly selected from the Tamil Nadu Energy Development Agency TEDA solar pump installation register, yielding 18 sample villages. In Stage III, 60 solar, 30 electric, and 30 diesel pump farmers per district were randomly selected from stratified lists, yielding the final sample of 360 farm households (Solar: n=180; Electric: n=90; Diesel: n=90).

Primary data were collected through structured interview schedules administered in Tamil by trained field investigators during July–December 2023. The schedule covered: socioeconomic profile; pump characteristics (type, HP, installation year, cost); crop cultivation data following CACP methodology (cost A1 through C2 for paddy across all three seasons); irrigation parameters (frequency, duration, water source); energy consumption (diesel litres consumed, electricity units); and detailed input-output data at the farm level. All data were cross-validated: energy data were verified against pump workshop records; paddy yield data were cross-referenced with TNAU crop cutting experiment results for the same taluks.

Table 1: Sampling design and sample distribution across study districts and pump types

District	Taluks (n=2)	Villages (n=3/taluk)	Solar Farms	Electric Farms	Diesel Farms	District Total
Thanjavur	Kumbakonam; Papanasam	6	60	30	30	120
Tiruvarur	Mannargudi; Needamangalam	6	60	30	30	120
Mayiladuthurai	Mayiladuthurai; Sirkazhi	6	60	30	30	120
CDR TOTAL		18	180	90	90	360

Note: Source: Authors' primary survey, 2024–25.

Secondary data for growth analysis

Eighteen years of annual pump set installation data (2005–06 to 2023–25) were obtained from TANGEDCO district office records (electric and diesel pump connections) and TEDA Tamil Nadu quarterly progress reports (solar pump installations). Data for Mayiladuthurai district for the pre-2021 period were reconstructed from erstwhile Nagapattinam district records (Mayiladuthurai taluk data). All secondary data were cross-validated across two independent sources; discrepancies were resolved by reference to original administrative orders and ground-truthed against TEDA installation verification reports.

Analytical methods

Objective 1: CAGR and structural break analysis

Compound Annual Growth Rate (CAGR) was computed for three temporal periods: the full study period (2005–06 to 2024–25; n=18 years); the pre-PM-KUSUM period (2005–06 to 2018–19; n=13 years); and the post-PM-KUSUM period (2019–20 to 2024–25; n=5 years). The point estimate formula is:

$$\mathbf{CAGR\ (\%) = [\ (V_n / V_0)^{(1/n)} - 1\ ] \times 100 \quad ...(1)}$$

where V_0 is the initial year value, V_n is the terminal year value, and n is the number of years. To test statistical significance and derive confidence intervals, exponential growth trend models were estimated by ordinary least squares (OLS):

$$\ln(Y_t) = \alpha + \beta \cdot t + \varepsilon_t \quad ...(2)$$

where Y_t is the number of pump sets in year t, β is the growth coefficient, and $\varepsilon_t \sim N(0, \sigma^2)$. CAGR = (e^β – 1) × 100. Statistical significance of β was assessed by t-test; 95% confidence intervals for CAGR were computed by exponential transformation of the confidence interval for β. The Cuddy-Della Valle (1978) Instability Index was computed as:

$$I = CV \times \sqrt{(1 - R^2)} \quad ...(3)$$

where CV is the coefficient of variation of the detrended series and R^2 is the goodness-of-fit of the exponential trend. A higher instability index indicates greater year-to-year volatility above the underlying trend. To test for structural change in the growth series at the PM-KUSUM announcement year (2018–19), Chow (1960) tests were applied:

$$F = [(RSS\_R - RSS\_U) / k] / [RSS\_U / (n - 2k)] \quad ...(4)$$

where RSS_R is the restricted residual sum of squares (single pooled equation), RSS_U is the unrestricted RSS (sum of two sub-period residual sums), k is the number of parameters (2 for the linear trend model), and n is total observations. Under H_0 of no structural break, F ~ F(k, n–2k). A significant F-statistic rejects the null of parameter stability, confirming PM-KUSUM-induced structural change in the growth trajectory.

Objective 2: Data Envelopment Analysis (DEA)

Data Envelopment Analysis (DEA) is a non-parametric linear programming method for measuring productive efficiency, originally developed by Charnes, Cooper, and Rhodes (1978). The input-oriented CCR model for decision-making unit (DMU) j_0 minimising the proportional reduction in inputs feasible for the observed output solves:

$$\text{Min } \theta \text{ s.t. } \sum\lambda_j\, y_{ji} \geq y_{i0} \ \ \forall i; \ \ \sum\lambda_j\, x_j^{\varphi} \leq \theta\, x^{\varphi}_0 \ \ \forall j; \ \ \lambda \geq 0 \quad ...(5)$$

where θ ∈ (0,1] is the efficiency score for DMU j_0; y_i and x_j are output and input vectors; and λ is the intensity vector identifying the efficient reference set. DMUs with θ = 1 are on the efficient frontier; θ < 1 implies proportional input reduction of (1–θ)×100% is feasible. The Variable Returns to Scale (VRS) extension (BCC model; Banker, Charnes, and Cooper, 1984) adds the convexity constraint Σλ = 1, yielding separate CRS and VRS efficiency scores. Scale efficiency (SE) is:

$$SE = TE(CRS) / TE(VRS) \quad ...(6)$$

SE = 1 implies operation at the most productive scale size (MPSS). SE < 1 indicates scale inefficiency from either increasing returns (farm too small: Σλ > 1 in dual) or decreasing returns (farm too large: Σλ < 1). The DEA model for this study uses eight inputs: (X_1) irrigated land area (ha); (X_2) seed cost (Rs./ha); (X_3) fertiliser cost (Rs./ha); (X_4) pesticide cost (Rs./ha); (X_5) total labour person-days per hectare; (X_6) irrigation water applied (pump-hours per ha per season); (X_7) energy cost for irrigation (Rs./ha; zero for solar and electric); (X_8) machine labour cost (Rs./ha). Output Y_1 is gross value of crop output (Rs./ha). All values are normalised per hectare of irrigated area to control for farm size effects. DEA computations were performed using DEA-SOLVER. Kruskal-Wallis tests and pairwise Mann-Whitney U tests with Bonferroni correction assessed statistical significance of efficiency differences.

Objective 2: Stochastic Frontier Analysis (SFA)

To complement the non-parametric DEA with a parametric approach that accommodates random disturbances, the Battese-Coelli (1995) single-stage stochastic frontier model was estimated. The Cobb-Douglas production frontier is:

$$\ln Y_i = \beta_0 + \Sigma_j\, \beta_j \ln X_{ij} + v_i - u_i \quad ...(7)$$

where Y_i is gross crop output value per hectare for farm i; X_{ij} are the j input quantities; β_j are production elasticities; $v_i \sim N(0, \sigma_v^2)$ is symmetric random noise; and $u_i \geq 0$ is a one-sided non-negative technical inefficiency term following a truncated-normal distribution $u_i \sim N^+(\mu_i, \sigma_u^2)$, where $\mu_i = \delta' Z_i$ is the inefficiency effects model. Technical efficiency for farm i is:

$$TE_i = E[\exp(-u_i) \mid \varepsilon_i] \quad ...(8)$$

The inefficiency effects model specifies μ_i as a linear function of farm-specific variables:

$$u_i = \delta_0 + \delta_1\, Age + \delta_2\, Education + \delta_3\, Farm\_size + \delta_4\, Solar\_D + \delta_5\, Diesel\_D + \delta_6\, ExtContact + \delta_7\, CreditAccess + \omega_i \quad ...(9)$$

where Solar_D and Diesel_D are dummy variables for pump type (reference: Electric); positive δ implies higher inefficiency; negative δ implies lower inefficiency. Variance parameters: $\sigma^2 = \sigma_u^2 + \sigma_v^2$; $\gamma = \sigma_u^2/\sigma^2$ (share of inefficiency in total variance); $\lambda = \sigma_u/\sigma_v$. The Cobb-Douglas functional form was confirmed over translog by a non-significant likelihood ratio test (LR = 18.4, df = 28, p = 0.863). Model estimated by Maximum Likelihood in FRONTIER (Coelli, 1996), validated in Stata. The null hypothesis γ = 0 (OLS is adequate; all variation is noise) was tested using the likelihood ratio test with mixed chi-square critical values (Kodde and Palm, 1986).

RESULTS

Socioeconomic characteristics of sample farms

Solar pump farmers were, on average, 2.8 years younger (46.3 ± 8.4 years vs. 49.1 ± 9.2 years for electric) and had 1.3 more years of formal schooling (8.7 ± 2.9 vs. 7.4 ± 3.1 years). Mean farm size was significantly larger for solar farms (1.24 ± 0.68 ha) compared to electric (1.08 ± 0.52 ha) and diesel (0.94 ± 0.44 ha) farms (ANOVA F = 12.4, p<0.001). Solar farmers had higher institutional credit access (62.2% vs. 44.4% electric vs. 32.2% diesel) and more frequent extension contact (4.8 ± 2.1 times/year vs. 2.4 ± 1.4 for diesel). Annual pump operating hours were highest for solar farms (1,128 ± 142 hrs/year), intermediate for electric (1,082 ± 118), and lowest for diesel (962 ± 138) confirming the a priori expectation that diesel fuel costs constrain pump operation below the agronomically optimal level.

Table 2: Socioeconomic profile of sample farmers by pump type (n=360), 2023–24

Characteristic	Solar (n=180)	Electric (n=90)	Diesel (n=90)	F, χ² (p)
Age (mean ± SD, years)	46.3 ± 8.4	49.1 ± 9.2	47.8 ± 8.7	F=3.82** (0.022)
Education (mean ± SD, years)	8.7 ± 2.9	7.4 ± 3.1	6.9 ± 2.8	F=12.64*** (<0.001)
Farm size (mean ± SD, ha)	1.24 ± 0.68	1.08 ± 0.52	0.94 ± 0.44	F=12.41*** (<0.001)
Irrigated area (mean ± SD, ha)	1.19 ± 0.62	1.04 ± 0.49	0.88 ± 0.41	F=11.82*** (<0.001)
Annual pump op. hours (mean ± SD)	1,128 ± 142	1,082 ± 118	962 ± 138	F=38.24*** (<0.001)
Irrig. frequency Samba (no./season)	17.8 ± 2.8	16.2 ± 2.6	14.1 ± 2.9	F=42.18*** (<0.001)
Institutional credit access (%)	62.2	44.4	32.2	χ²=24.6*** (<0.001)
PM-KUSUM awareness (%)	84.4	48.9	37.8	χ²=64.2*** (<0.001)
Extension contact freq. (mean/yr)	4.8 ± 2.1	3.2 ± 1.8	2.4 ± 1.4	F=44.92*** (<0.001)
Free elec. connection (%)	48.3	100.0	0.0	—

*Note: ** p<0.05; *** p<0.01. ANOVA for continuous variables; Chi-square for proportions. Source: Primary survey, 2024–25.*

Objective 1: Growth dynamics of irrigation pump sets

CAGR estimates by pump type and sub-period

Table 3 presents the CAGR estimates for all three pump types across the three study districts for the full study period (2005–06 to 2023–24) and the two sub-periods delineated by the PM-KUSUM launch year (2018–19).

Table 3: CAGR of irrigation pump sets by type, district, and period

Pump Type / Period	Thanjavur (%)	Tiruvarur (%)	Mayiladuthurai (%)	CDR CAGR (%)	95% CI Lower	95% CI Upper	Instability Index	R²
SOLAR PUMP SETS								
Full period (2005–2023–24)	37.2	39.1	41.8	38.7***	34.2	43.4	18.4	0.982
Pre-PM-KUSUM (2005–2018–19)	26.8	28.4	30.2	28.4***	24.1	32.8	14.2	0.978
Post-PM-KUSUM (2019–2023–24)	50.8	52.4	55.6	52.9***	46.2	59.8	8.4	0.991
Chow F (structural break)	—	—	—	F=18.42***	—	—	—	—
ELECTRIC PUMP SETS								
Full period	1.9	1.7	1.8	1.8*	1.2	2.4	4.2	0.948
Pre-PM-KUSUM	2.1	1.9	2.0	2.0**	1.4	2.6	3.8	0.961
Post-PM-KUSUM	1.2	1.1	1.4	1.2*	0.6	1.8	5.1	0.918
Chow F (structural break)	—	—	—	F=4.84*	—	—	—	—
DIESEL PUMP SETS								
Full period	−2.1	−2.4	−2.5	−2.3***	−3.1	−1.5	6.8	0.936
Pre-PM-KUSUM	1.2	1.4	1.6	1.4*	0.6	2.2	8.4	0.884
Post-PM-KUSUM	−7.8	−8.4	−8.4	−8.2***	−10.4	−6.2	5.2	0.962

Chow F (structural break)	—	—	—	F=22.18***	—	—	—	—

*Note: * p<0.10; ** p<0.05; *** p<0.01. Chow F tests H_0: no structural break at 2018–19. CAGR from exponential trend model [Eq. 2]. Instability index from Cuddy-Della Valle (1978) [Eq. 3]. Source: TANGEDCO & TEDA; authors' computation.*

Solar pump sets demonstrated the most striking growth trajectory in CDR history, recording a CDR-wide CAGR of 38.7% over the full study period the highest growth rate of any irrigation energy technology in the region across the 18-year data series. This growth was not linear: the pre-PM-KUSUM CAGR of 28.4% accelerated dramatically to 52.9% in the post-PM-KUSUM. The Chow F-statistic of 18.42 (p<0.001) confirms a highly significant structural break in the solar pump growth series at the PM-KUSUM launch year a level of structural change not observed in any previous agricultural technology diffusion study for the CDR. The instability index declined from 14.2 (pre-KUSUM) to 8.4 (post-KUSUM), indicating that the PM-KUSUM institutional framework has created a more stable, predictable adoption environment.

Mayiladuthurai recorded the highest solar CAGR (41.8% full period; 55.6% post-KUSUM), a counterintuitive finding for the newest of the three districts (formed in January 2021). This likely reflects: (i) the fresh institutional momentum and priority target allocation assigned to the newly formed district administration; (ii) the district's superior solar irradiation (GHI: 5.38 kWh/m²/day vs. 4.84 in Thanjavur); and (iii) the smaller electric pump base, meaning that the free electricity distortion is proportionately less dominant in Mayiladuthurai than in the older districts.

Diesel pump sets exhibit a trajectory that is the mirror image of solar growth: from a modest positive CAGR of 1.4% pre-KUSUM (consistent with agricultural expansion), they declined sharply to 8.2% CAGR post-KUSUM (Chow F = 22.18, p<0.001). This sharp reversal confirms that PM-KUSUM-driven solar adoption is actively displacing diesel irrigation technology not merely adding to the overall pump inventory. The compound effect of 52.9% annual solar growth and 8.2% diesel decline implies that the CDR is undergoing a rapid and irreversible energy transition in agricultural irrigation.

Electric pump sets, insulated by the free electricity policy from direct economic competition with solar, show low but positive growth (1.8% CAGR full period), reflecting continued growth in new agricultural power connections as irrigation intensity increases. The slight deceleration post-KUSUM (1.2% vs. 2.0% pre-KUSUM) may reflect saturation of new connection demand in the most intensively irrigated taluks.

Objective 2: Technical efficiency analysis

DEA efficiency score distributions

Table 4 presents the distributional statistics of DEA efficiency scores by pump type under both CRS (CCR model) and VRS (BCC model) assumptions. The Kruskal-Wallis test confirms that efficiency score distributions differ significantly across all three pump type groups for both CRS (χ^2 = 84.2, p<0.001) and VRS (χ^2 = 76.4, p<0.001) specifications

Table 4: DEA efficiency score statistics by pump type CCR (CRS) and BCC (VRS) models

Statistic	Solar CRS	Solar VRS	Solar SE	Electric CRS	Electric VRS	Diesel CRS	Diesel VRS	Overall CRS
n (farms)	180	180	180	90	90	90	90	360
Mean	0.868	0.912	0.952	0.794	0.842	0.714	0.774	0.802
Std. deviation	0.074	0.061	0.042	0.091	0.079	0.108	0.094	0.098
Minimum	0.642	0.724	0.812	0.514	0.608	0.412	0.514	0.412
25th Percentile	0.824	0.874	0.924	0.742	0.792	0.648	0.712	0.724
Median	0.884	0.924	0.962	0.812	0.854	0.724	0.784	0.814
75th Percentile	0.924	0.964	0.982	0.854	0.904	0.784	0.844	0.874
Maximum	1.000	1.000	1.000	1.000	1.000	0.984	1.000	1.000
% Fully efficient (TE=1.0)	18.9	28.3	—	11.1	16.7	0.0	7.8	12.5
Kruskal-Wallis χ^2 (p)	84.2 (<0.001)***	76.4 (<0.001)***	—	—	—	—	—	—
Mann-Whitney Solar vs Diesel	z=9.82 (<0.001)***	—	—	—	—	—	—	—
Mann-Whitney Solar vs Electric	z=5.42 (<0.001)***	—	—	—	—	—	—	—

*Note: *** p<0.001. SE = Scale Efficiency = TE(CRS)/TE(VRS). Mann-Whitney U with Bonferroni correction. DEA-SOLVER Pro 14.0. Source: Primary survey, 2024–25.*

The DEA results reveal a clear and statistically robust efficiency hierarchy: Solar > Electric > Diesel, consistent across both CRS and VRS model specifications. Solar pump farms achieve a mean CRS efficiency of 0.868, implying that these farms could, on average, produce the same gross crop output using only 86.8% of their current inputs if they managed resources with the efficiency of the best-practice farms in the dataset. The 15.4 percentage point CRS efficiency advantage of solar over diesel farms (0.868 vs. 0.714) is economically substantial: it represents an average potential input savings of Rs. 9,400–12,800 per hectare per season that diesel farms are forgoing through suboptimal resource management.

The scale efficiency analysis reveals that 9.2% of solar farms operate under increasing returns to scale (IRS), 72.3% under constant returns (CRS), and 18.5% under decreasing returns (DRS). By contrast, 28.4% of diesel farms operate under IRS, indicating that these farms are predominantly below the Most Productive Scale Size (MPSS) consistent with the smaller average farm size of diesel users (0.94 ha) and suggesting that scale economies in irrigation management could be unlocked by consolidating smaller diesel pump farms into collective arrangements.

The finding that no diesel pump farm achieves full CRS efficiency (TE = 1.0) is particularly noteworthy. It implies that diesel farms, as a group, do not include any 'best-practice' operations that could serve as efficiency benchmarks for the technology the best-practice frontier is entirely defined by solar and electric pump farms. This result is consistent with the 'fuel-cost-induced input rationing' mechanism: diesel pump farmers systematically under-irrigate their crops below the agronomically optimal level to limit fuel expenditure, creating a structural efficiency floor below which no diesel farm can rise regardless of management quality.

Stochastic Frontier Analysis results

Table 5 presents the MLE results of the Battese-Coelli (1995) SFA model for the pooled sample (n=360). The likelihood ratio test for $\gamma = 0$ yields LR = 84.2 ($p<0.001$), strongly rejecting the null hypothesis that OLS is adequate and validating the SFA framework. The gamma parameter ($\gamma = 0.7318$) indicates that 73.2% of the composite error variance is attributable to technical inefficiency (u_i) rather than random noise (v_i) confirming that genuine farm-level management differences, rather than random weather or measurement error, dominate the observed output variation below the stochastic frontier.

Table 5: MLE estimates of Stochastic Frontier model (Cobb-Douglas, n=360)

Variable / Parameter	Coefficient	Std. Error	t-ratio	p-value	Output elasticity
A. FRONTIER PRODUCTION FUNCTION					
Constant (β_0)	3.842	0.284	13.53	0.000	—
ln(Land area, ha) [β_1]	0.348	0.042	8.29	0.000	0.348
ln(Seed cost, Rs/ha) [β_2]	0.124	0.031	4.00	0.000	0.124
ln(Fertiliser cost, Rs/ha) [β_3]	0.218	0.038	5.74	0.000	0.218
ln(Pesticide cost, Rs/ha) [β_4]	0.092	0.026	3.54	0.000	0.092
ln(Labour, person-days/ha) [β_5]	0.192	0.047	4.09	0.000	0.192
ln(Irrigation hrs/ha) [β_6]	0.143	0.028	5.11	0.000	0.143
ln(Energy cost, Rs/ha) [β_7]	0.087	0.019	4.58	0.000	0.087
ln(Machine cost, Rs/ha) [β_8]	0.048	0.018	2.67	0.008	0.048
Sum of elasticities ($\Sigma\beta$)	1.252	—	—	—	Mild IRS
B. INEFFICIENCY EFFECTS MODEL ($\mu_i = \delta' Z_i$)					
Constant (δ_0)	0.582	0.092	6.33	0.000	—
Age (years) [δ_1]	0.008	0.003	2.67	0.008	+ve inefficiency
Education (years) [δ_2]	−0.024	0.007	−3.43	0.001	−ve inefficiency
Farm size (ha) [δ_3]	−0.062	0.018	−3.44	0.001	−ve inefficiency
Solar pump dummy (δ_4)	−0.148	0.029	−5.10	0.000	Solar lowers ineff.
Diesel pump dummy (δ_5)	0.124	0.032	3.88	0.000	Diesel raises ineff.
Extension contact freq. [δ_6]	−0.018	0.006	−3.00	0.003	−ve inefficiency
Institutional credit [δ_7]	−0.042	0.021	−2.00	0.046	−ve inefficiency
C. VARIANCE PARAMETERS					
$\sigma^2 = \sigma_u^2 + \sigma_v^2$	0.0842	0.0121	6.96	0.000	—
$\gamma = \sigma_u^2/\sigma^2$	0.7318	0.0482	15.18	0.000	73.2% = inefficiency
$\lambda = \sigma_u/\sigma_v$	1.651	—	—	—	Ineff. > noise
Log-likelihood	148.62	—	—	—	—
LR test: H_0: $\gamma=0$ (OLS adequate)	$\chi^2=84.2$***	—	—	p<0.001	SFA justified

*Note: Reference pump category: Electric. IRS = Increasing returns to scale. Estimated using FRONTIER 4.1 *** p<0.001; ** p<0.01. Source: Primary survey, 2024–25.*

All eight production frontier parameters (β_1 through β_8) are positive and highly significant ($p<0.01$), confirming that each input contributes positively to gross crop output in CDR paddy cultivation. The largest output elasticities are for land ($\beta_1 = 0.348$), fertiliser ($\beta_3 = 0.218$), and labour ($\beta_5 = 0.192$), collectively accounting for 75.8% of total output variation

explained by inputs. The irrigation hours elasticity ($\beta_6 = 0.143$) is particularly noteworthy in the solar pump context: since solar pump farms apply significantly more irrigation hours per hectare (24.8 hrs/ha/season) than diesel farms (21.4 hrs/ha/season), the incremental crop output from solar adoption can be partially quantified through this elasticity relationship.
The inefficiency effects model provides the study's central finding on pump technology efficiency: the solar pump dummy coefficient ($\delta_4 = -0.148$, $p<0.001$) confirms that solar pump farms are significantly less technically inefficient than the reference category (electric pump farms), after controlling for age, education, farm size, extension contact, and credit access. Translated into efficiency score terms, the solar pump effect is equivalent to raising technical efficiency by approximately 11–14 percentage points above the electric pump baseline. The diesel pump dummy ($\delta_5 = +0.124$, $p<0.001$) indicates that diesel pump farms are significantly more technically inefficient than electric farms establishing a clear and statistically robust efficiency ranking of Solar > Electric > Diesel for CDR paddy cultivation.
The returns to scale estimate ($\Sigma\beta = 1.252$) indicates mild increasing returns in CDR paddy production: a 10% proportional increase in all inputs would increase output by 12.52% on average. This implies that the predominant small farm sizes in the CDR (0.94–1.11 ha) are below the optimal production scale, and that institutional arrangements enabling scale economies such as farmer producer organisations, consolidated solar pump service schemes, or group cultivation could amplify the efficiency gains from solar pump adoption.
The mean predicted technical efficiency scores from the SFA model confirm the DEA hierarchy: Solar farms 0.891 (± 0.062); Electric farms 0.836 (± 0.074); Diesel farms 0.762 (± 0.089). The narrower standard deviation of SFA efficiency scores for solar farms (0.062) compared to diesel farms (0.089) confirms that solar pump adoption not only raises average efficiency but also reduces inter-farm efficiency variance suggesting that the technology acts as a management equaliser, enabling farmers of varying management capacity to achieve more similar output levels by removing the energy cost constraint on irrigation decision-making.

Table 6: Frequency distribution of DEA-CRS technical efficiency scores by pump type

TE-CRS Score Interval	Solar (n=180) %	Electric (n=90) %	Diesel (n=90) %	Overall (n=360) %
Below 0.50 (Highly inefficient)	0.0	1.1	4.4	1.4
0.50 – 0.60	0.0	2.2	8.9	3.1
0.60 – 0.70	2.2	5.6	17.8	7.2
0.70 – 0.80	8.3	16.7	27.8	16.1
0.80 – 0.90	28.9	37.8	28.9	31.9
0.90 – <1.00 (Near-efficient)	41.7	23.3	10.0	27.8
1.00 (Fully efficient)	18.9	11.1	0.0	12.5
Cumulative % with TE ≥ 0.80	89.4	72.2	38.9	72.2

Note: Source: Primary survey; DEA-SOLVER. Differences across pump types: Kruskal-Wallis $\chi^2=84.2$, $p<0.001$.

DISCUSSION

The findings of this study contribute to a growing literature on the economics of solar irrigation in tropical paddy systems, while providing the most comprehensive empirical evidence base specifically for India's Cauvery Delta Region. Three themes merit extended discussion: the mechanisms underlying solar pump efficiency superiority; the significance of the structural break evidence for energy transition policy; and the broader implications for paddy-based agricultural systems globally.
The efficiency advantage of solar pump farms over both electric and diesel counterparts confirmed by both DEA (CRS differential: Solar 0.868 vs. Diesel 0.714, $p<0.001$) and SFA (solar inefficiency dummy: $\delta_4 = -0.148$, $p<0.001$) aligns with and extends prior findings from comparable studies. Soni *et al.* (2013) found mean DEA TE of 0.89 (solar) vs. 0.73 (diesel) in Rajasthan; Reddy et al. (2021) found 0.91 vs. 0.71 in Karnataka's Cauvery sub-basin. The present study's CDR-specific estimates (0.868 vs. 0.714) are slightly below the Karnataka estimates, consistent with the CDR's more complex multi-season irrigation management and the moderating effect of free electricity which raises the electric pump baseline efficiency above that observed in states without free power policies compressing the overall efficiency spread.
The mechanism driving the efficiency differential is what we term 'energy-cost-induced input rationing': diesel pump farmers face Rs. 167 per hour in marginal irrigation energy cost and therefore systematically apply fewer irrigation events per season (mean: 14.1 Samba events vs. 17.8 for solar farms; difference: 3.7 events, $p<0.001$ by t-test). This rationing is rational at the individual farm level given fuel prices but produces collectively suboptimal outcomes: the primary survey documents that diesel farmers skip irrigation at the panicle initiation, heading, and grain-filling stages of paddy the three periods of maximum crop-water-stress sensitivity (Bouman *et al.,* 2007) more frequently than solar farmers. The resulting yield shortfall (3,912 kg/ha for diesel vs. 4,412 kg/ha for solar Samba season, a 12.8% difference) is not attributable to soil, variety, or management differences (controlled in the SFA model) but to the irrigation adequacy differential created by pump energy economics. Solar pump adoption eliminates this rationing mechanism by setting the marginal cost of irrigation to zero.
The structural break evidence from the CAGR analysis (solar: Chow F = 18.42, $p<0.001$; diesel: Chow F = 22.18, $p<0.001$) provides the clearest empirical confirmation yet available that PM-KUSUM has functioned as a genuine energy transition accelerant in Indian delta agriculture not merely as a subsidy programme that supplements existing technology. The post-KUSUM solar CAGR of 52.9% far exceeds any prior trajectory documented for agricultural technology adoption in the CDR, including Green Revolution variety adoption in the 1970s and drip irrigation expansion in the 2010s. The

simultaneous sharp diesel contraction (−8.2% CAGR post-KUSUM) confirms that the transition is substitutive rather than additive.

The declining instability index of solar pump growth (from 14.2 pre-KUSUM to 8.4 post-KUSUM) indicates that the diffusion process is becoming more stable and predictable a signature of the 'early majority' phase of the Rogers (2003) S-curve, where institutional infrastructure (vendor networks, dealer density, administrative processing capacity, service centres) has matured sufficiently to support sustained, consistent year-on-year adoption. If this stability persists, projections based on the current post-KUSUM CAGR suggest that solar pumps could reach 15% of CDR pump inventory by 2027 and 30% by 2030, at which point they would displace sufficient diesel consumption to avoid approximately 1,10,000 tonnes CO_2 annually from the three-district area alone.

The finding that no diesel pump farm achieves full DEA efficiency (TE = 1.0) is unprecedented in the India irrigation efficiency literature to the authors' knowledge, and has important theoretical implications. It suggests that the energy cost constraint is not merely a quantitative moderator of efficiency reducing efficiency scores by a fixed amount but a structural determinant that prevents any diesel pump farm from reaching the production possibility frontier, regardless of the farm operator's management quality. This is consistent with the theoretical prediction of Soni et al. (2013) that 'fuel-cost-induced input rationing' creates an irreducible efficiency ceiling for diesel farms. Solar adoption, by removing this structural ceiling, enables farms to approach the true production frontier defined by available soil resources, crop genetic potential, and agronomic management a potential that is demonstrably being realised by 18.9% of solar pump farms that achieve TE = 1.0 in this study.

The mild increasing returns to scale ($\Sigma\beta = 1.252$) observed in the production frontier have specific implications for solar pump adoption economics: they imply that the efficiency gain from solar adoption is positively correlated with farm size larger farms realise proportionately greater efficiency improvements because they have more flexibility to schedule irrigation across a larger spatial area and can fully utilise the installed pump capacity. This creates a potential equity concern: if the efficiency and income gains from solar adoption are disproportionately captured by larger farmers, the technology may deepen within-community inequality rather than reducing it. This concern is mitigated but not eliminated by the PM-KUSUM 90% subsidy for small and marginal farmers (< 2 ha), which ensures adoption access across the farm size distribution.

CONCLUSION

This study provides robust empirical evidence from 360 farm households and 18 years of secondary data for two core conclusions on solar photovoltaic irrigation pump sets in the Cauvery Delta Region of Tamil Nadu:

(1) Solar pump installations are undergoing a historically unprecedented growth trajectory, with a CAGR of 52.9% post-PM-KUSUM confirmed by Chow test as a structurally distinct acceleration from the pre-KUSUM baseline of 28.4%. This growth is simultaneously driving diesel pump contraction at −8.2% per annum, confirming that PM-KUSUM is catalysing a genuine energy transition in CDR irrigation rather than merely expanding the technology portfolio.

(2) Solar pump farms demonstrate significantly higher technical efficiency than electric and diesel farms. The Battese-Coelli SFA confirms that the solar pump adoption reduces technical inefficiency by 14.8 percentage points relative to electric farm baseline, controlling for all farmer and farm characteristics. The elimination of energy-cost-induced input rationing is identified as the primary causal mechanism: solar pump farms apply 3.7 additional irrigation events per Samba season compared to diesel farms, translating into a 12.8% yield advantage.

For irrigated paddy systems globally, these findings suggest that solar pump adoption represents a technology with the unusual property of simultaneously improving farm-level economic efficiency, reducing energy costs, and generating substantial environmental co-benefits through CO_2 avoidance. Policy frameworks that enable rapid, equitable diffusion of solar irrigation through deep capital subsidies for small and marginal farmers, zero-interest credit products, dense after-sales service networks, and awareness campaigns are among the highest-return interventions available for raising productivity and incomes in canal-command deltaic agriculture. The structural break evidence establishes a clear causal role for PM-KUSUM in accelerating this transition, providing strong justification for continuation and deepening of the scheme with particular attention to the free electricity distortion that continues to limit adoption among Tamil Nadu's 3.29 lakh electric pump farm households.

Author Contributions

Conceptualisation, data collection, analysis, and writing: Research Scholar. Supervision, review, editing: Thesis Supervisor. Both authors read and approved the final manuscript.

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