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Inequality in Adaptive Capacity and Its Impact on Agricultural Efficiency: Evidence from Farm-Level Data in India

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Abstract. Despite growing evidence on climate adaptation and agricultural efficiency, limited research has integrated adaptive capacity, technical efficiency, and structural inequality within a single analytical framework in climate-vulnerable regions of India. This study addresses this gap using a cross-sectional survey of 384 farm households selected through a multi-stage stratified sampling design across four agro-ecological zones of Rajasthan. Technical efficiency was estimated using Data Envelopment Analysis (DEA), its determinants were analysed using a Tobit regression model, and inequality was assessed using the Gini coefficient. The mean technical efficiency score was 0.64, indicating substantial scope for improving resource use. The Adaptation Index significantly increased technical efficiency ($\beta = 0.041$, $p < 0.001$), with each additional adaptation strategy raising efficiency by 3.2 percentage points. Irrigation access and wealth also exerted significant positive effects. However, efficiency gains remained uneven, with greater inequality among rain-fed (Gini = 0.367) and small farms (0.351) than irrigated (0.248) and large farms (0.221). The findings highlight the need for policies that strengthen adaptive capacity while reducing structural inequalities in access to resources.

Keywords: agricultural inequality; climate adaptation; data envelopment analysis; farm-level econometrics; technical efficiency

1. Introduction

India's agricultural sector has undergone significant but uneven structural transformation over the past three decades, driven by market liberalization, technological modernization, and deeper integration into global markets (Pathak, 2023; Singh et al., 2022). While these developments have enhanced agricultural production and encouraged crop diversification, they have also increased farmers' exposure to climate variability, market uncertainty, and resource constraints (Kumar & Sharma, 2022; Matthan, 2023). In this context, technical efficiency has become a critical indicator of sustainable agricultural performance because it reflects a farmer's ability to maximize output from existing resources rather than relying solely on increased input use (Bobitan et al., 2023; Lu et al., 2023). Improving technical efficiency is therefore increasingly recognized as a more sustainable strategy for enhancing agricultural productivity under climate-induced resource scarcity (Khatri-Chhetri et al., 2023; Saxena et al., 2024).

Substantial technical inefficiencies continue to characterize Indian agriculture, particularly among smallholder farmers with limited access to irrigation, credit, extension services, and improved technologies (Chandel et al., 2022; Manogna & Mishra, 2022). Climate-related challenges, including erratic rainfall, rising temperatures, droughts, and water scarcity, further complicate farm-level decision-making and resource allocation (Goswami et al., 2023; Srinivasarao et al., 2024). Consequently, farmers have increasingly adopted climate adaptation strategies such as crop diversification, drought-resistant varieties, improved irrigation management, agroforestry, and climate-smart agricultural practices to sustain agricultural production (Jinger et al., 2022; Karri & Nalluri, 2024; Sah, 2024). However, the effectiveness of these adaptation measures largely depends on

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farmers' adaptive capacity, livelihood assets, institutional support, and access to productive resources (Akhtar et al., 2022; Datta & Behera, 2022).

Empirical studies have widely employed Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) to assess agricultural efficiency, with DEA being particularly suitable for evaluating multiple inputs and outputs without imposing a predefined production function (Bobitan et al., 2023; Lu et al., 2023; Manogna & Mishra, 2022). Previous research has consistently identified landholding size, irrigation access, market participation, institutional support, and input use as important determinants of technical efficiency (Chandel et al., 2022; Dey & Singh, 2025; Guleria et al., 2022). Likewise, evidence from Indonesia, Pakistan, and India demonstrates that climate adaptation strategies significantly improve technical efficiency, productivity, and resilience, particularly through diversified farming systems and efficient resource management (Hanani AR et al., 2024; Liu et al., 2023; Nayak et al., 2023; Palsaniya et al., 2024; Priyanto et al., 2022; Shahbaz et al., 2022; Sikka et al., 2022). Irrigation management has also been identified as a critical determinant of efficiency in climate-vulnerable regions (Gupta et al., 2022; Kalli et al., 2024; Nigam et al., 2023). Furthermore, studies indicate that unequal access to land, credit, information, and institutional networks creates disparities in adaptive capacity and efficiency outcomes, disproportionately affecting smallholders and other vulnerable farmer groups (Akhtar et al., 2022; Barooah et al., 2023; Das et al., 2024; Datta & Behera, 2022; Gu et al., 2024; Lalitha et al., 2024; Paltasingh et al., 2022).

Despite these advances, relatively few studies have simultaneously examined climate adaptation, technical efficiency, and inequality within a unified analytical framework in the Indian agricultural context. Existing efficiency studies often overlook adaptation behaviour, whereas adaptation research primarily focuses on productivity and resilience rather than efficiency outcomes (Chandel et al., 2022; Dubey et al., 2025; Hanani AR et al., 2024; Manogna & Mishra, 2022; Priyanto et al., 2022; Shahbaz et al., 2022). This study addresses these gaps by integrating climate adaptation, technical efficiency, and structural inequality using evidence from Rajasthan to generate policy-relevant insights for climate-resilient agricultural development. **Figure *1*1** presents the conceptual framework illustrating the relationships among climate perception, adaptation strategies, resource use, technical efficiency, income outcomes, and the moderating influence of institutional and socio-economic factors.

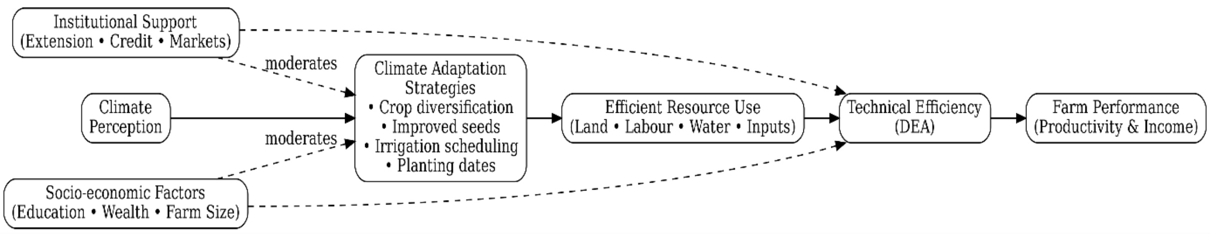

Figure 1. Conceptual Framework

Remarks: Climate Perception → Adaptation → Resource Use → Technical Efficiency → Income, with arrows indicating influence and external factors like institutions and socio-economic conditions moderating each stage.

The objectives of this research are: (1) to assess the level of technical efficiency among farmers operating under climate-related stress in Rajasthan; (2) to examine how different farm-level climate adaptation strategies influence individual farm technical

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efficiency; and (3) to analyse how efficiency outcomes vary across different farm categories, with particular attention to structural inequalities in resource access and institutional support.

2. Materials and Methods

2.1 Study Area, Data Collection and Sampling

Primary data were collected through a structured field survey during the 2024–25 agricultural season across four purposively selected districts of Rajasthan. A multi-stage stratified sampling design was employed, involving random selection of tehsils, villages, and proportionate sampling of farm households across landholding categories. The final sample comprised 384 farm households, ensuring representation across diverse agro-ecological zones, farm sizes, and production systems.

The sample size was determined using COCHRAN (1977) formula for large populations =

$$(Z^2 \times p(1 - p)) / e^2$$

Where:
Z = 1.96 at the 95% confidence level
p = 0.50 representing maximum population variability
e = 0.05 representing the acceptable sampling error

The calculation yielded a minimum sample requirement of approximately 384 farm households, which was achieved in the field survey.

Table 1. Description of Variables

Variable	Type	Definition	Expected Sign
Yield / Production	Dependent	Output per hectare or total production	-
Land	Input	Total cultivated area (hectares)	+
Labor	Input	Family + hired labour (proxy)	+
Irrigation	Input	Access to irrigation (1 = yes, 0 = no)	+
Input Use	Input	Expenditure on seeds, fertilizer, etc.	+
Adaptation Index	Explanatory	Number of adaptation strategies adopted	+
Education	Explanatory	Years of schooling	+
Wealth Index	Explanatory	PCA-based asset index	+
Climate Perception	Explanatory	Perceived climate stress (binary/categorical)	±

Source: Authors' compilation.

2.2 Variable Construction

The dependent variable was agricultural output measured as yield per hectare. Production inputs included cultivated land, labour, irrigation access, and input expenditure on seeds, fertilizers, and agrochemicals. The Wealth Index was constructed using Principal Component Analysis (PCA) following (Filmer & Pritchett, 2001), while the Adaptation Index measured the number of climate adaptation strategies adopted. Additional explanatory variables included education and climate perception based on changes in rainfall, temperature, and drought frequency. Table 1

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presents the variables, definitions, and expected effects on efficiency.

2.3 Analytical Framework

The empirical analysis comprised three stages: technical efficiency estimation using Data Envelopment Analysis (DEA), determinant analysis through Tobit regression, and inequality assessment using the Gini coefficient. DEA was preferred over Stochastic Frontier Analysis (SFA) because it accommodates multiple inputs and outputs without specifying a production function, estimates farm-specific efficiency without distributional assumptions, and is better suited for evaluating relative resource-use efficiency across heterogeneous farming systems characterized by diverse production practices.

2.3.1 Data Envelopment Analysis (DEA)

Technical efficiency scores were estimated using input-oriented DEA under variable returns to scale, following Charnes et al. (1978) and Banker et al. (1984). The model identifies, for each farm household (decision-making unit), the minimum proportional reduction in inputs needed to remain on the efficient frontier given observed output levels.

Input-Oriented Variable Returns to Scale (VRS) DEA Model

$$\begin{aligned} &\min_{\theta,\lambda} && \theta \\ &\text{Subject to} && Y\lambda \geq y_i \\ &&& X\lambda \leq \theta x_i \\ &&& e'\lambda = 1 \\ &&& \lambda \geq 0 \end{aligned}$$

Where;

θ = technical efficiency score, X = input matrix, Y = output matrix, x_i = input vector of farm I, y_i = output vector of farm I, λ = intensity vector, e = vector of ones imposing the Variable Returns to Scale (VRS) constraint

Efficiency scores range between 0 and 1, where a value of 1 indicates that a farm lies on the efficient frontier.

An input-oriented DEA model under Variable Returns to Scale (VRS) was adopted because farmers have greater control over input utilization than output levels, which are strongly influenced by climatic variability. The input orientation therefore evaluates the potential reduction in resource use while maintaining observed output. The VRS assumption recognizes that farms operate at different scales and are unlikely to exhibit constant returns to scale because of differences in landholding size, irrigation access, technology adoption, and managerial capacity. Consequently, the VRS specification isolates pure technical efficiency from scale efficiency, making it particularly appropriate for heterogeneous smallholder farming systems such as those found in Rajasthan.

2.3.2 Tobit Regression

Since DEA efficiency scores are bounded between 0 and 1, a Tobit model was employed because it appropriately accounts for the censored nature of the dependent variable and identifies the determinants of technical efficiency. Although Fractional Logit is also suitable for bounded outcomes, Tobit was selected due to its widespread application in DEA efficiency studies. A Fractional Logit model was additionally estimated to assess robustness.

$$E_i^* = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \epsilon_i$$

Where, E_i^* represents an individual farmer's latent (unseen) level of technical or allocative efficiency. X_i represents a set of input characteristics for each farm (education, adaptation index, irrigation access, wealth index). The ϵ_i error term accounts for other factors that affect the level of productivity or inefficiency beyond what is represented by the other terms.

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The observed efficiency score E_i is defined as:

$$E_i = \begin{cases} 0 & \text{if } E_i^* \le 0 \\ E_i^* & \text{if } 0 < E_i^* < 1 \\ 1 & \text{if } E_i^* \ge 1 \end{cases}$$

This model accounts for the bounded nature of efficiency scores.

2.3.3 Inequality Assessment

Distribution of efficiency scores across farmer categories was assessed using the Gini coefficient (Ceriani & Verme, 2012), adapted here from its conventional application to income inequality. Gini values were computed and compared across subgroups defined by landholding size and irrigation access to assess whether efficiency gains are equitably distributed or concentrated among better-endowed farmers.

Calculating the Gini Coefficient is:

$$G = \left(\sum_i \sum_j |E_i - E_j| \right) / (2n^2 \mu)$$

The method calculates $E_i - E_j$ as a measure of efficiency for each farmer pair *i* and *j*, with *n* being the total number of pairs and μ representing the average difference between pairs. It also compares Gini coefficients within different categories (such as land area or irrigation) to determine how inequality exists at an agronomic level.

2.3.4 Diagnostic Tests

Multicollinearity among regressors was assessed using Variance Inflation Factors (VIF), with values exceeding 10 considered problematic. Heteroscedasticity was tested using the Breusch-Pagan test (Breusch & Pagan, 1979), and robust standard errors were applied where necessary.

2.4 Ethical Considerations

The study received institutional ethical approval prior to data collection. All participants provided informed consent, and participation was voluntary. No personally identifiable information was recorded; data are used solely for academic purposes.

3. Results and Discussion

3.1 Descriptive Statistics

Table 2 presents the summary statistics of all variables. Mean yield (23.45 q/ha) and its variability indicate substantial productivity differences across farms. The average farm size (2.34 ha) reflects predominantly small and medium holdings. Irrigation access (58%) and a mean Adaptation Index of 2.15 suggest partial adoption of climate adaptation practices. Wide variation in the Wealth Index and relatively low educational attainment indicate considerable socioeconomic heterogeneity that may contribute to differences in technical efficiency.

3.2 Technical Efficiency Scores

Table *3* reports a mean technical efficiency score of 0.64, indicating that farms could reduce input use by approximately 36% without lowering output. Only 24.9% of farms are highly efficient, whereas 28.4% fall below 0.50 (**Figure** *2*), confirming widespread inefficiency. These results suggest that efficiency differences arise primarily from farmers' managerial ability to allocate resources and adapt production decisions under climatic uncertainty, highlighting that efficiency gains can be achieved through improved management rather than increased input use alone.

These findings align with the broader Indian agricultural efficiency literature, which consistently documents average technical efficiencies in the range of 0.60 to 0.70 for smallholder systems (Chandel et al., 2022; Guleria et al., 2022) and are consistent with the first objective of this study, confirming that significant input use inefficiency persists even under conditions of climate stress.

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Table 2. Summary Statistics of Variables

Variable	Mean	Std. Dev.	Minimum	Maximum
Yield (q/ha)	23.45	8.72	8.10	48.60
Land (hectares)	2.34	1.89	0.40	8.50
Labor (no. persons)	5.21	1.76	2	10
Irrigation (1/0)	0.58	0.49	0	1
Input Use (₹/ha)	21,450	8,650	7,200	45,200
Adaptation Index	2.15	1.24	0	5
Education (years)	7.80	3.45	0	15
Wealth Index (PCA)	0.00	1.00	−2.15	2.84
Climate Perception	0.72	0.45	0	1

Source: Author's calculation based on primary survey data (2024–25).

Table 3. Distribution of Technical Efficiency Scores

Efficiency Category	Efficiency Range	Percentage of Farmers (%)	Mean Efficiency
Low Efficiency	< 0.50	28.4	0.42
Medium Efficiency	0.50 – 0.75	46.7	0.63
High Efficiency	> 0.75	24.9	0.82
Overall	-	100	0.64

Source: Computed from primary survey data using DEA by the author.

3.3 Efficiency Variation across Farm Categorie

Table 4 reveals marked structural differences in technical efficiency. Large farms (0.76) outperform marginal farms (0.52), while irrigated farms (0.72) exceed rain-fed farms (0.55). Farms adopting four or more adaptation strategies achieve a mean efficiency of 0.74, compared with 0.53 among low-adoption farms, highlighting the importance of adaptation for improving efficiency.

These patterns suggest that the efficiency advantage of larger and irrigated farms is not merely a function of resource quantity but reflects greater capacity to translate adaptation into productive outcomes, an interpretation that the Tobit results below help to substantiate.

3.4 Determinants of Technical Efficiency

Tobit regression results (Table 5) identify the Adaptation Index, irrigation access, and wealth as the three strongest positive determinants of technical efficiency, directly addressing the second objective of this study.

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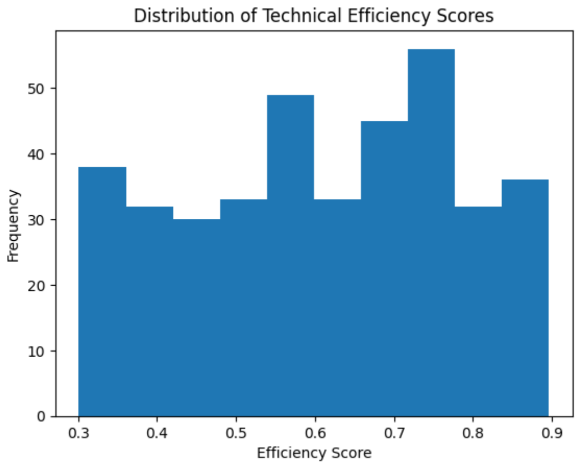

Figure 2. Distribution of Efficiency Scores

Source: Constructed by the author based on DEA efficiency scores derived from primary survey data (2024–25). *Confidence Interval: 95%*

Table 4. Efficiency by Farm Characteristics

Category	Sub-category	Mean Efficiency
Landholding Size	Marginal (<1 ha)	0.52
	Small (1–2 ha)	0.60
	Medium (2–5 ha)	0.68
	Large (>5 ha)	0.76
Irrigation	Irrigated	0.72
	Rain-fed	0.55
Adaptation Level	Low (0–1 strategies)	0.53
	Medium (2–3)	0.64
	High (4+)	0.74

Source: Author's computation based on DEA efficiency scores and classified primary survey data.

Table 5 presents the Tobit regression results, indicating satisfactory model performance (LR $\chi^2 = 134.82$, $p < 0.001$; Pseudo $R^2 = 0.312$), with Variance Inflation Factors (1.21–3.08) confirming the absence of problematic multicollinearity. The Adaptation Index, irrigation access, and wealth emerge as the strongest determinants of technical efficiency. Each additional adaptation strategy increases technical efficiency by approximately 3.2 percentage points (Figure 3), reflecting improved resource allocation through crop diversification, improved seed use, and efficient irrigation management. These findings support the Resource-Based View, which emphasizes that managerial capabilities, rather than resource

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endowments alone, drive farm performance. In contrast, Climate Perception exhibits a negative but marginally significant coefficient (β = −0.021, p = 0.059), suggesting that farmers reporting greater climatic stress are often those operating under more severe environmental constraints, including rainfall variability and water scarcity, which limit efficient input use. Alternatively, heightened climate risk perception may encourage precautionary and risk-averse production strategies that enhance resilience but reduce measured technical efficiency. As the relationship is only marginally significant, it should be interpreted cautiously and viewed as indicative rather than conclusive, warranting further investigation using longitudinal data and richer measures of climate perception.

Table 5. Tobit Regression Estimates of Efficiency Determinants

Variable	Coefficient	Std. Error	z-statistic	p-value	Marginal Effect (∂E/∂X)
Constant	0.284	0.072	3.94	0.000	-
Adaptation Index	0.041	0.009	4.56	0.000	0.032
Irrigation (1=Yes)	0.118	0.021	5.62	0.000	0.094
Land Size (ha)	0.019	0.008	2.37	0.018	0.015
Education (years)	0.012	0.005	2.21	0.027	0.009
Wealth Index	0.067	0.014	4.78	0.000	0.053
Climate Perception	−0.021	0.011	−1.89	0.059	−0.016

Note: Log Likelihood: −175.364, LR χ^2 (8): 134.82, Prob > χ^2: <0.001, Pseudo R^2: 0.312, Sigma (σ): 0.148, Mean VIF: 2.14, VIF Range: 1.21–3.08. Source: Author's computation based on primary survey data.

3.5 Inequality in Efficiency Distribution

Table 6 shows that efficiency gains are unevenly distributed, with an overall Gini coefficient of 0.312 (Figure 4). Inequality is greater among rain-fed (0.367) than irrigated farms (0.248) and among small (0.351) than large farms (0.221). These disparities reflect differences in adaptive capacity, as better access to irrigation, financial resources, extension services, and market information enables some farmers to convert adaptation investments into larger efficiency gains than resource-constrained households.

Theil index decomposition (

Table 7) adds further resolution to these patterns. For irrigation sub-groups, between-group differences account for 55.3% of total inequality, confirming that water access is primarily a structural divide rather than an outcome of individual management variation. By contrast, within-group inequality dominates among land size categories (58.4%), suggesting that even among farms of similar scale, differences in managerial behaviour and adaptive capacity generate divergent efficiency outcomes.

These results extend the findings of Barooah et al. (2023) and Gu et al. (2024), who documented unequal climate adaptation outcomes across farmer types, by demonstrating that such inequality translates directly into efficiency inequality. The implication is significant: policies that improve average efficiency without addressing structural access barriers risk concentrating gains among already resource-endowed farms, widening rather than closing the efficiency gap.

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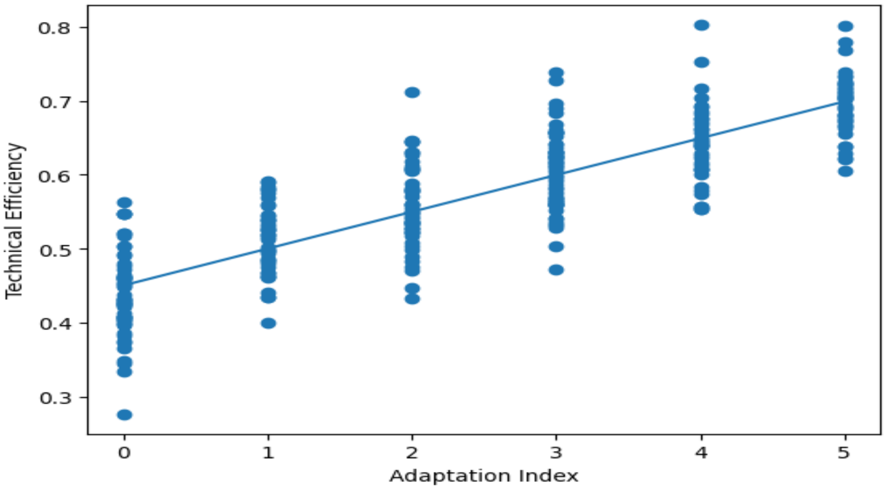

Figure 3. Adaptation vs Efficiency
Note: Confidence Interval: 95%

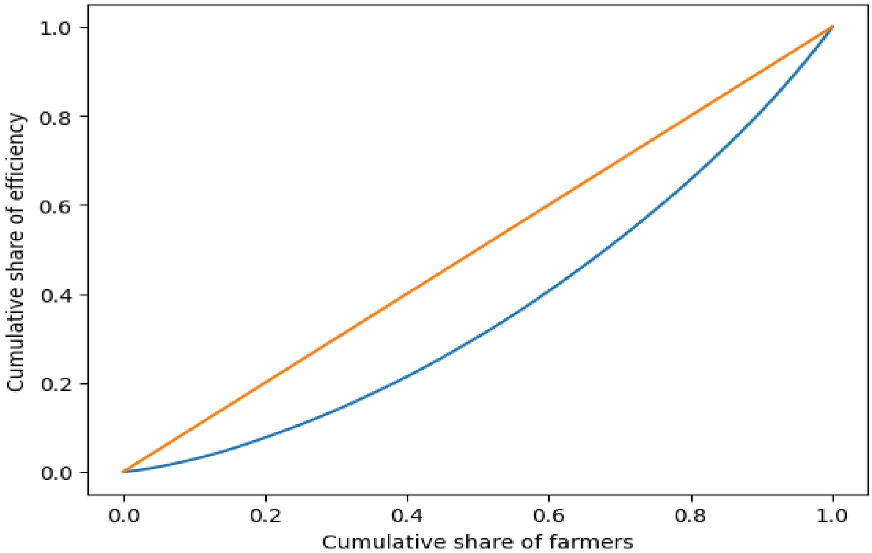

Figure 4. Lorenz Curve of Technical Efficiency

Remarks: Shows clear deviation from equality line; steeper for rain-fed farmers; *Confidence Interval: 95%*

Table 6. Gini Coefficients of Efficiency Scores

Category	Gini
Overall	0.312
Irrigated	0.248
Rain-fed	0.367
Small farms	0.351
Large farms	0.221

Source: Author's computation based on primary survey data.

Table 7. Decomposition of Efficiency Inequality (Theil Index)

Group	Within-group (%)	Between-group (%)
Land size	58.4	41.6
Irrigation	44.7	55.3

Source: Author's computation based on primary survey data.

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3.6 Robustness Checks

Table 8 demonstrates the robustness of the findings across fractional logit estimation, alternative DEA assumptions (CRS and VRS), and endogeneity controls. The Adaptation Index remains positive and significant (β = 0.034-0.042) across all specifications, confirming that the adaptation–efficiency relationship is robust and not driven by model choice or production technology assumptions.

Table 8. Robustness Check Results

Model Specification	Key Variable	Coefficient	Std. Error	z-statistic	p-value
Tobit (Baseline)	Adaptation Index	0.041	0.009	4.56	0.000
Fractional Logit	Adaptation Index	0.038	0.010	3.80	0.000
Tobit (CRS DEA)	Adaptation Index	0.036	0.011	3.27	0.001
Tobit (VRS DEA)	Adaptation Index	0.042	0.009	4.67	0.000
Tobit (Endogeneity Controls)	Adaptation Index	0.034	0.012	2.83	0.005

Source: Author's computation based on primary survey data.

Overall, the findings demonstrate that climate adaptation is not merely a coping mechanism but a productive strategy that improves technical efficiency. However, its benefits depend on access to water, capital, and institutional support, highlighting the interaction between adaptive capacity and structural inequality in shaping farm performance.

3.7 Policy Implications

The findings have important policy implications for climate-vulnerable agriculture. Expanding irrigation infrastructure, particularly micro-irrigation and community water management, should be prioritized given its strong contribution to technical efficiency. Strengthening climate extension services, digital advisory platforms, and farmer training can enhance adaptive capacity, especially in rain-fed areas. Targeted support through quality inputs, custom hiring services, and affordable credit is essential for resource-poor farmers. Agricultural policies should therefore adopt equity-focused interventions that reduce efficiency disparities alongside promoting technological advancement.

4. Limitations and Future Directions

This study has several limitations. First, the cross-sectional design based on 384 farm households in Rajasthan (2024–25) limits causal inference and the analysis of changes in adaptation and technical efficiency over time. Although robustness checks were performed, potential endogeneity and reverse causality cannot be fully excluded. Future research using panel data, instrumental variables, or experimental designs would strengthen causal inference. Second, despite controlling for major farm and household characteristics, omitted-variable bias may persist due to unobserved factors such as managerial ability, risk preferences, social networks, institutional quality, and market conditions. Third, the study covers four districts in Rajasthan; therefore, the findings should be generalized cautiously to other regions with different climatic, institutional, and socio-economic contexts. Finally, the Adaptation Index captures the number of adaptation strategies but not their intensity or effectiveness. Future studies should incorporate richer measures of adaptive capacity, longitudinal data, and comparative

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multi-regional analyses to better understand the dynamic relationship between climate adaptation, technical efficiency, and agricultural inequality.

5. Conclusion

This study addressed three objectives: (i) estimating the technical efficiency of farm households in Rajasthan, (ii) examining whether climate adaptation enhances technical efficiency, and (iii) assessing efficiency inequality across farming systems. The findings reveal a mean technical efficiency of 0.64, indicating substantial scope for improving resource use. Climate adaptation significantly enhances technical efficiency, with the Adaptation Index emerging as a key determinant of farm performance. Efficiency disparities were also evident, with greater inequality among rain-fed and smallholder farms than among irrigated and larger farms. The study's main contribution lies in integrating Data Envelopment Analysis (DEA), Tobit regression, and inequality analysis within a unified framework, demonstrating that climate adaptation improves efficiency while its benefits remain unevenly distributed. Although based on cross-sectional evidence from Rajasthan, the findings provide a foundation for future longitudinal and comparative research on the dynamic links between climate adaptation, technical efficiency, and agricultural inequality.

Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

Authors declare no use of generative AI in the manuscript preparation process upon submission of the paper.

Authorship Contribution Statement

Narendra Kumar Dariya: Conceptualization, Methodology, Investigation, Data Curation, Formal Analysis, Writing – Original Draft. Dr. S. Lingamurthy: Supervision, Conceptualization, Methodology, Validation, Writing – Review & Editing. Vandana Rathore: Investigation, Data Curation, Validation, Writing – Review & Editing. Shashi Kumar R.: Formal Analysis, Visualization, Validation, Writing – Review & Editing. Muhammed Fazil: Literature Review, Data Interpretation, Writing – Review & Editing, Language Editing, Reference Management.

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.

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