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Assessing role of water user associations in enhancing efficiency of rice (*Oryza sativa*) production: Insights from the Nagarjuna Sagar Project command area of Andhra Pradesh

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ABSTRACT

Addressing the rice (*Oryza sativa* L.) yield gap is one of the most necessary steps in sustaining food security. The survey was carried out during 2021–22 to investigate the sources of technical efficiency in rice farming within the Nagarjuna Sagar Project Command area (NSP) of Andhra Pradesh, India. Utilizing Data Envelopment Analysis (DEA) with a double bootstrap approach, the study analysed the primary data collected from 112 Water User Association (WUA) participants and 86 non-participants across the Kanapparu, Muppalla, and Nadenla villages in Muppalla, and Nadenla blocks of the NSP command area of Guntur district. The estimates of average technical efficiency (TE) of 0.69 indicated that farming households can reduce inputs by 31% without altering output levels. Key factors influencing technical efficiency were obtained by double bootstrap estimation revealing participation in Water User Associations (WUAs) enhances the technical efficiency of rice farming. Fixation of water charges and the equitable distribution of irrigation water were found to be key factors associated with the higher level of participation in WUA.

Keywords: DEA Bootstrap, NSP command area, Rice farming, Technical efficiency, Water user association

Rice (*Oryza sativa* L.) is vital to the livelihoods of farming communities in southern India, covering approximately 23.3% of the country's cropped area and contributing 43% of total food grain production and 46% of overall cereal production (Agricultural Statistics at a Glance 2022). Improvement in rice productivity growth over a while, attributed to the widespread adoption of hybrids, higher chemical fertiliser usage, and improved agricultural practices indicated by the increase in yield from 1740 kg/ha in 1990–91 to 2240 kg/ha in 2010–11 (Obianefo 2021). However, productivity varies because of the yield gap (Paul *et al.* 2020, Nayak *et al.* 2024). Andhra Pradesh is the fourth-largest rice producer, historically known as the "Rice Bowl of India". In the state, it is cultivated in more than 22 lakh hectares during *kharif* and *rabi* seasons across 13 districts. The state features diverse soil types, from coastal sands to fertile deltaic alluviums, with red clay as the dominant type. The primary rice varieties cultivated in the state are MTU-1156, MTU-1153, MTU-1121, RNR-15048, NLR-34449, MTU-1064, MTU-1075, NLR-33892, MTU-1061, UMA, NLR-30491, RGL-2537, MTU-1001, and ADT-39.

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The Nagarjuna Sagar Project (NSP) command area in Andhra Pradesh pertains to the region irrigated by the NSP, a multipurpose initiative on the Krishna River. It features two main canals, the Jawahar Canal on the right bank and the Lal Bahadur Canal on the left bank, together irrigating around 22 lakh ha across 13 districts of Andhra Pradesh. To harness the benefit of the project, an institutional innovation has been set up in the form of a Water User Association (WUA). In the NSP command area the district Guntur has 54 WUAs cover 2,49,434 ha served by the Jawahar canal. They handle water distribution, maintain field channels, collect water charges, resolve conflicts, and promote water conservation practices. Understanding the potential benefit of the NSP in enabling paddy cultivation for higher productivity will help the researcher and policymakers to decide to scale up such institutions further to benefit the farming community. With this background, the study examined the role of WUA in improving the efficiency of rice farms and investigated the correlates of farmers' participation in such institutions.

MATERIALS AND METHODS

The survey was carried out during 2021–22, focused on the Nagarjuna Sagar Project (NSP) command area (16°34′32″N 79°18′42″E) in Andhra Pradesh which included part of the Guntur and Prakasam districts, encompassing 22 blocks with a total geographical area of 0.873 mha. We selected the Kanapparu, Muppalla and Nadenla villages in Muppalla and Nadenla blocks of Guntur district for the study. According to the irrigation profile of Guntur district, there are 368 WUAs in Guntur district, covering 4,99,231 acres, established under the Andhra Pradesh Farmers' Management of Irrigation System Act 1997, responsible for the operation, maintenance, and management of the irrigation system within their jurisdiction. The stage of groundwater development in the district is 19%, with all the mandals classified as safe. One hundred ninty eight farmers were selected through multistage random sampling, and 112 farmers were WUA participants from three tanks, and 86 were non-participants. Using the breadth of existing literature as a guide, data on output and inputs as well as other socio-economic indicators were gathered and presented in Table 1. Output was measured as rice yield in quintals per hectare (q/ha). Inputs considered under study include seed (X_1); expenditure spent for purchasing seeds for raising nursery, equipment (X_2); Total spending on equipment for land preparation, Fertiliser (X_3); Total expenditure on NPK fertiliser, Chemicals, Harvesting and Transportation (X_4); Cost for pesticides, harvesting, and transportation and Irrigation charges (X_5); Total amount spent on waterman services and irrigation fee. Data were gathered on various socio-economic factors specific to each farmer, which are used to understand the relationships or factors influencing their technical efficiencies. These include the education level of the farm decision maker (binary) (Z_1), years spent by farmers on rice cultivation (Z_2), and membership in WUA and its activities (binary) (Z_3). Additional variables include the number of adult family members (Z_4), land area under rice cultivation (acres) (Z_5), and days of water availability categorised as 1, 2 and 3 for head, middle and tail, respectively (Z_6). Access to formal credit was also noted (binary), along with binary indicators for whether the farmland is located in Kanapparu (Z_8), Muppalla (Z_9) and Nadenla (Z_{10}).

In rice production, technical efficiency is the potential of a farmer to optimise yields with a specific set of resources. The degree of technical efficiency reflects how far a farmer is from achieving optimal output, with the maximum possible output for the available inputs and technology depicted by the production frontier (Alam and Murshed-e-Jahan 2008, Alam 2011, Nielsen 2011). Input-oriented Data Employment Analysis (DEA) model is used, which aims to reduce the input usage while maintaining the current output level. Since it is important for the rice farmers in the study area, where cost reduction is vital due to financial constraints. The input-based technical efficiency index for the j^{th} farm, among N farms, is calculated using the VRS DEA framework, TE_j, is defined as follows:

$$TEj = \widehat{\theta}_j = \frac{\min\{\theta_j}{y_j} \leq Y_\lambda; \theta_j X_j \geq X\lambda \textstyle\sum_{j=1}^{n} \lambda_j = 1;\ \theta_j > 0;\ \lambda_j \geq 0, j = 1; \ldots, N \quad (1)$$

Where y_j and x_j represent the output and input vectors of the j^{th} farm; Y and X are the output and input matrices of the sample. The linear combination of the j^{th} farm's peers is specified by the technical efficiency value, k, which ranges from 0 to 1. This is a vector of constant weights and $\sum_{j=1}^{n} \lambda_j = 1$ is used for assuming the VRS (Coelli *et al.* 2005). The Scores of efficiency derived from equation are used to describe the origins of farm level efficiency (1) for individual farm, expurgated between zero and one, and are frequently regressed using Tobit regression on the specific farm variables (Nguyen and Fisher 2014).

The modified double bootstrap approach for input-oriented VRS DEA efficiency, developed by Simar and Wilson (2007), was used to achieve more accurate efficiency estimations.

Step 1: Employ (1) for the calculation of the DEA input-oriented technical efficiency in each of the rice farms under the research. Next, compute the j^{th} technical score.

Step 2: When $\hat{\delta}$ >1, use maximum likelihood to estimate $\hat{\beta}$ of β and $\widehat{\sigma_J}$ of σ in the shortened regression of $\hat{\delta}$ on Z_j, where Z_j is the vector of socio-economic and farm characteristic variables of rice farms in Table 1.

Step 3: Repeat the following four steps (i–iv) L1 to yield a set of bootstrap estimates.

$B_J = \{\widehat{\delta_{1b}^{*}}\}_{b=1}^{L1}$: For each j = 1, …, N, ε_j is drawn from N 2(0, $\widehat{\sigma_J}$:

(i) For each j = 1, …, N, compute: $\delta^{*} = Z_j\hat{\beta} + \varepsilon_j$
(ii) Construct a pseudo data set (Xj*, yj*) where xj* = $(\widehat{\delta_J}/\delta_j^{*})$ xj and yj = y:
(iii) Using the pseudo data set and (1), calculate pseudo efficiency estimates $\widehat{\sigma_J} = 1/\widehat{\theta_J^{*}}$ for all j= 1, …, N.

Step 4: For each j = 1, … , N, calculate the bias-corrected estimator $\widehat{\delta_J} = \widehat{\delta_J}$ – bias $(\widehat{\delta_J})$ where the bias term is bias $\widehat{\delta J} = (\frac{1}{L1} \Sigma_{b=1}^{L1} \delta_{ib}^{*}$: Simar and Wilson (2000) provide the calculation of the technical efficiency scores' confidence intervals.

Step 5: Regress $\widehat{\delta_J}$ on Zj to calculate estimates $\hat{\beta}$ and ε, adopting shortened maximum likelihood.

Step 6: To create a set of bootstrap estimates $= \{(\widehat{\widehat{\beta^{*}}}, \widehat{\widehat{\sigma^{*}}})\text{b}\}_{b=1}^{L2}$, repeat steps steps (i–iii) L2 times.

(i) For each j = 1, …, N, e_j is drawn from N (0, $\widehat{\widehat{\sigma_\varepsilon}}$)
(ii) For each j = 1, …, N, compute $\delta_j^{**} = Z_j\hat{\beta}_j + \varepsilon_j$
(iii) Regress δ_j^{**} on Zj to yield estimates $\widehat{\beta^{*}}$ *and* $\widehat{\sigma_\varepsilon^{*}}$, and adopting truncated maximum likelihood

Step 7: Confidence intervals for β and σ_ε are constructed using the bootstrap estimates $(-b_{\frac{\alpha}{2}} \leq \widehat{\widehat{\beta_j^{*}}} - \widehat{\widehat{\beta}}_J \leq -a_{\frac{\alpha}{2}}) \sim 1\text{-}\alpha$ K and the estimates, $\hat{\beta}$ and $\widehat{\widehat{\sigma}}$ produced in Step 5. The Pr () ~ 1-α is used to create the (1- α) percent confidence interval of the jth element of vector β. This means that the estimated confident interval β_j is $[\widehat{\widehat{\beta}}_J + a_{\frac{\alpha}{2}}^{*}, \widehat{\widehat{\beta}}_J + b_{\alpha/2}^{*}]$ for. This is the equivalent method functional to construct confidence intervals for the efficiency scores.

The identified constraints faced by farmers' factors/problems were ranked using Garrett's ranking technique, which helped to determine the greatest substantial factors prompting their participation in WUA. Farmers were asked to rank various problems and outcomes based on their impact. These rankings were then converted into score values by applying the subsequent formula:

$$\text{Per cent position} = 100\ (R_{ij} - 0.5)/\ N_j$$

Where R_{ij}, Rank given for the i^{th} factor (i = 1, 2….5) by the j^{th} individual (j = 1, 2, 3…...240) and N_j, Number of constraints ranked by j^{th} individual.

The estimated percent positions were converted into scores using Garrett's Table. The scores for each factor were summed, and the total and mean scores were calculated. Factors with the maximum mean values were identified as the most significant.

RESULTS AND DISCUSSION

Critical aspects of rice farming, including input costs, technical efficiency and other variables, are given in Table 1. The average rice yield in the area is 24.3 q/acre. The average cultivation costs per acre are as follows: seed (₹937), land preparation (₹3,351), fertilisers (₹6,429), chemicals (₹28,212), and irrigation (₹2,250). Socio-economic variables indicated that the average experience of the sample decision-makers was recorded as 12.5 years, with 17% holding a college degree or higher education. Most of the sample farmers had participated in a WUA. The average household size was observed to be 4.53, and farm sizes ranged from 0.18 to 6 acres. Further, Simar and Wilson's (2002) test for returns-to-scale is performed to test the hypothesis of the nature of rice production technology in Guntur district. The cutoff value of test statistics, 0.927 indicates, a rejection of the null hypothesis of Constant Returns to Scale allows us to choose the DEA model with the assumption of Variable Returns to Scale.

The estimated efficiency levels for both conventional DEA and double bootstrapping approaches are represented in Table 2. The conventional DEA model indicated an average technical efficiency of 0.77, suggesting that tank-irrigated rice farming households can reduce inputs by 23% without affecting their output levels. To address potential biases in the initial estimates, we employed the double bootstrap, as outlined by Simar and Wilson (2007). The average bias-corrected estimate from the double bootstrap is 0.69. Additionally, the 95% confidence interval for technical efficiency using this method is 0.10, indicating lower statistical variability. This adjustment considers socio-economic and farm characteristic variables in addition to input and output data. These results are consistent with the findings of Balcombe *et al.* (2008), who have used a similar methodology in rice farming in Bangladesh. Using the double bootstrap method, the bias-corrected

Table 1 Descriptive statistics variables considered for estimating technical efficiency of rice farming in the NSP command area

Particulars	Description	Unit	Mean	SD	Minimum	Maximum
Output (Y)	Total quantity of rice produced/ha/year	q	24.3	10.5	18.4	42.5
Inputs (X)						
Seed (X_1)	Total quantity of seed used to raise nursery	₹	937	1611	500	9900
Land preparation (X_2)	Total amount spent on equipment	₹	3351	1782	1857	8730
Fertilisers (X_3)	Total quantity of fertiliser used NPK converted	₹	6429	2946	1200	16000
Chemicals, Harvesting & Transportation (X_4)	Total amount spent on pesticides, on harvesting and transport	₹	28212	19006	15714	42000
Irrigation charges (X_5)	Total amount spent on waterman and irrigation fee	₹	2250	1860	511	18250
Socio-economic and farm characteristic variables						
Education (Z_1)	Level of education of the farm decision-maker (1 = college or higher, 0 = otherwise)	Dummy	0.17	0.37	0	1
Experience (Z_2)	Years spent by farmers on rice cultivation	Years	12.5	4.32	3	24
WUA participation (Z_3)	Member in water user association & its activities (1 = yes, 0 = no)	Dummy	0.72	0.5	0	1
Household size (Z_4)	Number of adult family members	No	4.53	0.5	2	8
Farm size (Z_5)	Land under rice cultivation	acre	0.76	0.62	0.18	6
No of days of water availability (Z_6)	Head-1; Middle-2; Tail-3	No	85.02	54.46	55	230
Access to formal credit (Z_7)	Finance accessibility (1 = yes, 0 = no)	Dummy	0.24	0.43	0	1
Kannaparu (Z_8)	Tank where farm land is located (1 = yes, 0 = no)	Dummy	0.19	0.39	0	1
Muppalla (Z_9)	Tank where farm land is located (1 = yes, 0 = no)	Dummy	0.3	0.46	0	1
Nadendla (Z_{10})	Tank where farm land is located (1 = yes, 0 = no)	Dummy	0.32	0.47	0	1

SD, Standard deviation.

technical efficiency's 95% confidence interval was between 0.64 and 0.74. It implies that the 'average' farm could potentially reduce inputs by 26–36% by enhancing technical efficiency. In conclusion, the reliability of our findings has been improved by employing bias-corrected metrics and bootstrapping interval estimates of technical efficiency. These results provided policymakers with a stronger basis for decision-making regarding interventions and improvements in tank-irrigated rice farming practices.

The dependence of efficiencies derived from conventional and double bootstrap Data Envelopment Analysis (DEA) methods arises due to the nature of the bootstrap procedure. To compare the estimates comprehensively, we applied statistical tests, including the paired difference t-test, the two-sample Kolmogorov-Smirnov test, and Kruskal-Walli's rank sum test (Bogetoft and Otto 2010) and the results are presented in Table 2. These assessments showed that on average, the technical efficiency calculated using the conventional DEA method was statistically considerably higher than that estimated from the double bootstrap method. This finding aligned with similar trends in agricultural studies by Latruffe *et al.* (2008) and Olson and Vu (2009). Additionally, Table 2 revealed substantial biases in the uncorrected estimates. Specifically, the conventional DEA estimate of 0.77 indicated that, given a certain output, an average farm could reduce its input by 23% if technical efficiency were improved to 1. In contrast, the bias-corrected estimate of 0.69 suggested an expected input reduction of 31% using the double bootstrap method. These statistical tests and bias corrections enhance our understanding of the efficiency estimates, emphasizing the importance of using robust methodologies for accurate assessments in rice farming under tank irrigation. Evidently, the double bootstrap method indicates a significantly higher percentage of input savings compared to conventional DEA approaches for rice farming households. From a policy perspective, the efficiency estimates indicate a significant potential for improving the technological efficiency of rice farming in Andhra Pradesh. This promising outlook should inspire optimism and encourage further exploration of the factors that influence technological efficiency. The study's findings, captured through Tobit Regression (Table 3), revealed that farm size had a significant positive impact on technical efficiency at the 95% confidence level. Larger

Table 2 Conventional DEA and bootstrap TE estimates

	Mean	Median	SD	Minimum	Maximum
Conventional TE	0.77	0.72	0.14	0.4	1
Corrected TE (double bootstrap)	0.69	0.69	0.12	0.36	0.94
Higher bound double	0.74	0.76	0.16	0.41	1.07
Lower bound double	0.64	0.63	0.12	0.31	0.91

Comparing conventional DEA and double bootstrap TE estimates

Indicator	Mean		t-Ratio	Two-sample Kolmogorov Smirnov test	Kruskal-Wallis
	Conventional TE	Corrected TE double bootstrap			
TE	0.77	0.69	29.975***	0.185**	35.982**

rDEA package- 'R studio', double bootstrap DEA model with L_1= 2000 interactions for the first loop and L_2= 2000 for the second loop of Algorithm 2. DEA, Data Envelopment Analysis; TE, Technical efficiency.

Table 3 Determinants of technical efficiency score: Double bootstrap estimation

Variables	Coefficients	SE	Lower 90% CI	Upper 90% CI	Lower 95% CI	Upper 95% CI	Lower 99% CI	Upper 99% CI
Intercept	1.2493***	0.271	1.0864	1.4158	1.0632	1.4438	0.9788	1.4280
Education (Z_1)	- 0.0101	0.592	- 0.0784	0.058	- 0.1321	0.0893	- 0.1298	0.1224
Experience (Z_2)	- 0.0006	0.289	- 0.0019	0.0072	- 0.0097	0.0068	- 0.0124	0.0100
WUA participation (Z_3)	- 0.0315*	0.364	- 0.0542	0.0728	- 0.0652	0.0894	- 0.0774	0.1240
Household size (Z_4)	0.0492	0.527	0.0078	0.1196	0.0321	0.2435	0.0477	0.1734
Size of the farm (Z_5)	0.2123***	0.264	0.2628	0.2310	0.2875	0.1128	0.3238	0.0928
Location of farm land from tank (Z_6)	0.0019***	0.224	0.0012	0.0032	0.0008	0.0052	0.0006	0.0027
Access to credit (Formal) (Z_7)	- 0.0864**	0.297	- 0.1694	0.0197	- 0.1981	0.0043	- 0.1962	0.0324
Kannaparu (Z_8)	- 0.1158**	0.358	- 0.2486	0.0714	- 0.2891	0.0221	- 0.3204	0.0251
Muppalla (Z_9)	0.0070	0.282	0.0892	0.0738	0.1125	0.1104	0.1270	0.1464
Nadendla (Z_{10})	0.0742	0.311	0.0320	0.1618	0.0283	0.2012	0.0876	0.2286

Table 4 Friedman test for difference mean ranks towards the participation of farmers

Activities	Mean score	Rank
Farmers Participation in WUA meeting	4.53	VII
Labour contribution towards tank repair and maintenance work	3.8	IX
Supervise the small construction work in the tank structure	5.14	V
Work as a committee member in WUA	4.4	VIII
Consult WUA officers for repair work	6.93	III
Regular inspection on field channel	6.26	IV
Distribution of Irrigation water, sharing and scheduling	7.02	II
Contribution of money for WUA functioning	3.42	X
Fixing of water charges	8.4	I
Get inputs from WUA at low cost	5.1	VI
Test Statistics		
N: 112		
Chi-Square: 132.36		
Df: 9		
Asymp. Sig: $p<0.001$		

farms make better use of inputs, benefiting from economies of scale (Iliyasu *et al.* 2015, Long *et al.* 2020). The study also identifies a positive relationship between technological efficiency and the availability of official credit for operating expenses, a statistically significant estimate at the 5% level. However, factors such as education, experience, and household size could not explain the variation in technical efficiency among rice farms.

The involvement of farmers is the most important action needed to harness the benefits of WUA. Due to the diversity among farmers, active participation is critical and for any bottom-up approach member engagement is crucial for effective operation and long-term sustainability. The farmers who have enrolled in the WUA were asked to list the top 10 participation activities and to rate them by using a 5-point Likert's scale (from 5=strongly agree, 4=agree, 3=neutral, 2=disagree, 1=strongly disagree). The Friedman test (Simar and Wilson 2002, Badunenko and Mozharovskyi 2016) is used to identify the most and least participated activities (Table 4). The Chi-Square value is 132.36, with a p value of <0.001**, indicating a significant difference among the mean ranks regarding farmers' participation in WUAs. The highest mean ranks are obtained for fixation of water charges (8.40) and distribution of irrigation water, sharing, and distribution (7.04), marking them as the most important items. Conversely, the least important items are labour contribution towards tank repair and maintenance (3.80) and monetary contributions for WUA functioning (3.42).

While water charge fixation and equity aspects are the key highlights that attracted participants to engage in WUAs, understanding the constraints faced by the farmers to participate in the WUA also helps in addressing their issues. For this, Garrett Ranks was estimated and the most prominent constraint, identified by 73.47% of respondents, is the need for more unity, cooperation and interest among the water users. This is followed by inadequate water allocation or inequity in water distribution, affecting 51.14% of respondents. Additionally, 48.17% of the farmers reported a lack of communication among the water users, while 47.58% noted that water availability and rotation need to align with crop requirements. Other constraints include rigid, rule-bound producers for adapting to changing conditions (30.47%) and insufficient funds for repairing field channels (29.14%).

In conclusion, this study comprehensively examines rice farming efficiency in the NSP command area of Andhra Pradesh, highlighting key aspects such as input costs, technical efficiency, determinants of efficiency and dynamics of farmer participation in WUAs. The analysis emphasises the significance of robust methodologies, particularly the double bootstrap approach, which reveals the scope for substantial potential input savings and identifies farm-size as a crucial factor in enhancing technical efficiency. Active WUA participation is essential for successful water management, with specific activities like fixing water charges deemed vital. However, challenges such as a lack of unity among water users and inadequate resources hinder participation. The study suggests that policy promoting, improving access to formal credit, and fostering farmer engagement in WUAs could significantly enhance efficiency and sustainability in rice farming within the NSP command area.

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