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Measurement of Technical, Allocative, Economic, and Scale Efficiency of Rice Production in Arkansas Using Data Envelopment Analysis

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Data envelopment analysis is used to calculate technical, allocative, economic, and scale efficiencies for fields enrolled in the University of Arkansas Rice Research Verification Program. The results reveal most fields have high technical and scale efficiencies, implying inputs are used in minimum levels necessary to achieve given output levels and fields are close to optimal in size. However, most fields exhibit allocative and economic inefficiencies and do not use inputs in the right combinations necessary to achieve cost minimization. Tobit analysis indicated allocative and economic efficiencies could be improved with better variety selection and better irrigation management.

Key Words: costs, data envelopment analysis, efficiency, inputs, production, rice

JEL Classifications: C61, D24, Q12

Arkansas is the leading rice-producing state in the United States, accounting for nearly one half of total U.S. rice production in 2012 (U.S. Department of Agriculture, Economic Research Service, 2013). Rice is a high-cost crop relative to other field crops grown in the United States such as cotton, corn, soybean, and wheat (Childs and Livezey, 2006). Variable production expenses for rice in Arkansas are higher than any other field crop grown in the state and range from $660/acre for conventional rice (rice using nonhybrid, non-Clearfield varieties) to $751/acre for Clearfield-hybrid rice (Flanders et al., 2012). Fertilizer and fuel expenses are the primary reason for the high cost of rice production, accounting for 38–42% of total rice variable expenses. Rice fertilizer expenses range from $137 to $156/acre depending on the variety. Rice fuel expenses average approximately $144/acre and are larger than any other crop grown in Arkansas as a result of the amount of irrigation water applied (30 acre inches applied on average to rice versus 12–15 acre inches on average applied to cotton and corn). Other expenses of note include seed and pesticide costs, which are largely dependent on the variety planted. Seed expenses range from $22/acre for conventional varieties to $167/acre for Clearfield-hybrid varieties. Pesticide expenses (herbicide,

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insecticide, and fungicide) range from $64/acre for fields planted with Clearfield-hybrids to $111/acre for fields planted with conventional varieties. Hybrid varieties have a better disease package than conventional varieties and therefore have lower fungicide expenses.

Because of the large expenses associated with rice production and the large dependence on energy-related inputs like fuel, fertilizer, and irrigation water in particular, rice producers in Arkansas and the United States seek production systems that use inputs efficiently and in least cost combinations to achieve profitability. Information explaining differences in rice production efficiency across fields or farms is therefore of major interest to rice producers. Rice production efficiency has not been examined in a U.S. setting. Studies evaluating rice production efficiency (Coelli, Rahman, and Thirtle, 2002; Dhungana, Nuthall, and Nartea, 2004; Kiatpathomchai, 2008; Nhut, 2007; Wadud and White, 2000; Xu and Jeffrey, 1998; Zahidul Islam, Bäckman, and Sumelius, 2011) come exclusively from developing countries with many focusing on rice production in subsistence farming settings. How these production efficiencies compare with rice production efficiency in a U.S. setting is currently unknown.

This study uses data envelopment analysis (DEA) to obtain technical, allocative, economic, and scale efficiency scores for rice production in Arkansas at the field level. Data envelopment analysis is a nonparametric, linear programming (LP) approach for measuring relative efficiency among a set of decision-making units (rice fields in this case). Data for the study are obtained from 158 fields enrolled in the University of Arkansas, Rice Research Verification Program (RRVP) for the period 2005 through 2012. Efficiency scores for RRVP fields are compared with those obtained from other rice-producing countries, and impacts of field characteristics on efficiency scores are evaluated using Tobit analysis.

Measurement of Production Efficiency

The methodology behind efficiency measurement begins with the work of Farrell (1957). Farrell introduced the notion of relative efficiency in which the efficiency of a particular decision-making unit (DMU) may be compared with another DMU within a given group. Farrell identified three types of efficiency, technical efficiency, allocative efficiency (referred to by Farrell as "price efficiency"), and economic efficiency (referred to by Farrell as "overall efficiency"). Technical efficiency (TE) measures the ability of a DMU to produce the maximum feasible output from a given bundle of inputs or produce a given level of output using the minimum feasible amounts of inputs. The former definition is referred to as output-oriented TE, whereas the latter definition is referred to as input-oriented TE. Allocative efficiency (AE) measures the ability of a technically efficient DMU to use inputs in proportions that minimize production costs given input prices. Allocative efficiency is calculated as the ratio of the minimum costs required by the DMU to produce a given level of outputs and the actual costs of the DMU adjusted for TE. Economic efficiency (EE), also known as cost efficiency, is the product of both TE and AE (Farrell, 1957). Thus, a DMU is economically efficient if it is both technically and allocatively efficient. Economic efficiency is calculated as the ratio of the minimum feasible costs and the actual observed costs for a DMU.

The efficiency measures proposed by Farrell assume a known production function for the fully efficient DMU. The production function of a DMU is generally unknown in practice, and relative efficiencies must be measured from the sample data available. Two approaches are used to estimate relative efficiency indices: the parametric or stochastic frontier production approach (SFA) and the nonparametric or DEA approach (Coelli, 1995). The SFA assumes a functional relationship between outputs and inputs and uses statistical techniques to estimate parameters for the function. It incorporates an error composed of two additive components: a symmetric component that accounts for statistical noise associated with data measurement errors and a nonnegative component that measures inefficiency in production (Coelli, 1995). The stochastic model specification of SFA also allows for hypothesis testing. The disadvantage of SFA is that it imposes specific assumptions on both the functional form of the frontier and the distribution of the error term. In contrast, DEA uses linear programming methods to construct a piecewise frontier of the data. Because it is nonparametric, DEA does not require any assumptions to be made about functional form or distribution type. It is thus less sensitive to misspecification relative to SFA. However, the deterministic nature of DEA means all deviations from the frontier are attributed to inefficiency. It is therefore subject to statistical noises resulting from data measurement errors (Coelli, 1995).

The choice of which method to use is unclear (Olesen, Petersen, and Lovell, 1996). A small number of studies make side-by-side comparisons of the two methods (Sharma, Leung, and Zaleski, 1997, 1999; Theodoridis and Anwar, 2011; Theodoridis and Psychoudakis, 2008; Wadud, 2003; Wadud and White, 2000), but none of these studies make any conclusions about which method is superior. These studies typically find quantitative differences in efficiency scores between the two methods, but the ordinal efficiency rankings among DMUs tend to be very similar for both methods. Therefore, the choice of which method to use appears to be arbitrary, as is pointed out by Dhungana, Nuthall, and Nartea (2004). We chose the DEA approach, because it imposes no a priori parametric restriction on the underlying technology (Chavas and Aliber, 1993; Fletschner and Zepeda, 2002; Lansink, Pietola, and Bäckman, 2002; Wu and Prato, 2006).

Empirical Studies of Rice Production Efficiency

Several studies evaluate rice production efficiency. A summary of the literature is presented in Table 1. Twenty studies are listed in Table 1, ranging in time from 1991–2011. Ten studies use SFA analysis, eight use DEA analysis, and two (Wadud, 2003; Wadud and White, 2000) use both approaches. Most studies deal exclusively with input-oriented TE measurement. Seven studies measure TE, AE, and EE, whereas one study (Huang, Huang, and Fu, 2002) measures EE only and another study (Abdulai and Huffman, 2000) measures profit efficiency (PE). Most rice production efficiency studies come from countries in southeast Asia, whereas two studies come from African countries. All 20 studies focus on developing countries with many evaluating rice production efficiency in subsistence farming settings. None evaluate data from more industrialized countries like the United States.

Mean TE scores across the 19 studies reporting such scores range from 0.63 to 0.95, implying on average that technical inefficiency for these 18 studies ranges from 5 to 37%. In other words, these studies reveal that rice producers could potentially reduce their input levels on average from 5 to 37% to achieve the same output levels. Mean AE scores across the seven studies estimating such scores range from 0.62 to 0.88, implying rice producers in these studies generally apply the “wrong” input mix given input prices and that on average costs are 12–38% higher than the cost-minimizing level. Finally, mean EE scores across the eight studies measuring such scores range from 0.39 to 0.83, implying the overall cost of rice production in these studies can be reduced on average by 17–61% to achieve the same level of output.

Seven of the 20 studies report scale efficiencies and returns to scale data. These studies are presented in Table 2. All but one of the studies report mean scale efficiencies of 0.90 or greater, indicating mean scale inefficiencies are small (10% or less) for all but one of the studies. Although mean scale efficiencies are similar across studies, the main source of scale inefficiency varies. Four of the studies report the majority of scale inefficiency resulting from decreasing returns to scale (DRS) (Brázdik, 2006, for rice production in Indonesia; Coelli, Rahman, and Thirtle, 2002, for Boro rice plots in Bangladesh; Wadud, 2003, for rice production if Bangladesh; Wadud and White, 2000, for rice production in Bangladesh) and one study reports scale inefficiency occurring nearly equally from both DRS and increasing returns to scale (IRS) (Dhungana, Nuthall, and Nartea, 2004). The remaining studies report the majority of scale inefficiency resulting from IRS (suboptimal scale efficiency).

The results from the rice production efficiency literature reveal the existence of inefficiency in rice production among developing countries.

Table 1. Empirical Studies on Efficiency Measurement of Rice Production

Author(s)	Country	Efficiency Approach[a]	Data Set	Mean Efficiency Results[b]
Bäckman, Zahidul Islam, and Sumelius (2011)	Bangladesh	SFA	Cross-section in 2009, 360 farms	TE = 0.83
Zahidul Islam, Bäckman, and Sumelius (2011)	Bangladesh	DEA	Cross-section in 2008–2009, 355 farms	TE (CRS) = 0.63, TE (VRS) = 0.72, AE (CRS) = 0.62, AE (VRS) = 0.66, EE (CRS) = 0.39, EE (VRS) = 0.47
Khan, Huda, and Alam (2010)	Bangladesh	SFA	Cross-section in 2007, 150 farms	Aman rice farmers TE = 0.91 Boro rice farmers TE = 0.95
Rahman et al. (2009)	Thailand	SFA	Cross-section in 1999–2000, 348 farms	TE = 0.63
Kiatpathomchai (2008)	Thailand	DEA	Cross-section in 2004–2005, 247 farming households	TE (VRS) = 0.87 AE (VRS) = 0.78 EE (VRS) = 0.68
Nhut (2007)	Vietnam	DEA	Cross-section in 2005, 198 farms	TE (VRS) = 0.92 AE (VRS) = 0.81 EE (VRS) = 0.75
Brázdik (2006)	Indonesia	DEA	Cross-section in 1999, 76 farming households	TE (CRS) = 0.59, TE (VRS) = 0.65 (pooled frontier)
Chauhan, Mohapatra, and Pandey (2006)	India	DEA	Cross-section in 2000–2001 (97 farms)	TE (CRS) = 0.77, TE (VRS) = 0.92
Dhungana, Nuthall, and Nartea (2004)	Nepal	DEA	Cross-section in 1999, 76 farming households	TE (CRS) = 0.76, TE (VRS) = 0.82, AE (CRS) = 0.87, EE (CRS) = 0.66
Krasachat (2004)	Thailand	DEA	Cross-section in 1999, 74 farming households	TE (CRS) = 0.71, TE (VRS) = 0.74

Table 1. Continued

Author(s)	Country	Efficiency Approach[a]	Data Set	Mean Efficiency Results[b]
Wadud (2003)	Bangladesh	SFA, DEA	Cross-section in 1997, 150 farms	SFA TE = 0.80, AE = 0.77, EE = 0.61 DEA (CRS) TE = 0.86, AE = 0.91, EE = 0.78 DEA (VRS) TE = 0.91, AE = 0.87, EE = 0.79
Coelli, Rahman, and Thirtle (2002)	Bangladesh	DEA	Cross-section in 1997, 406 farms (351 Aman plots; 422 Boro plots)	Aman plots: TE (VRS) = 0.66, AE (VRS) = 0.78, EE (VRS) = 0.52 Boro plots: TE (VRS) = 0.69, AE (VRS) = 0.81, EE (VRS) = 0.56
Huang, Huang, and Fu (2002)	Taiwan	SFA	Cross-section in 1998, 348 farms	EE = 0.81
Abdulai and Huffman (2000)	Ghana	SFA	Cross-section in 1992, 256 farms	PE = 0.73
Wadud and White (2000)	Bangladesh	SFA, DEA	Cross-section in 1997, 150 farms	TE (SFA) = 0.79 TE (CRS) = 0.79 TE (VRS) = 0.86
Xu and Jeffrey (1998)	China	SFA	Cross-section in 1985 and 1986, 180 farming households	Hybrid rice: TE = 0.85, AE = 0.72, EE = 0.61 Conventional rice: TE = 0.94, AE = 0.88, EE = 0.83

Table 1. Continued

Author(s)	Country	Efficiency Approach[a]	Data Set	Mean Efficiency Results[b]
Audibert (1997)	West Africa	SFA	Cross-section in 1989 and 1990, 1671 farming households	TE = 0.68
Tadesse and Krishnamoorthy (1997)	India	SFA	Cross-section in 1992–1993, 129 farms	TE = 0.83
Battese and Coelli (1992)	India	SFA	Panel data of 38 farms, 1975–1985	Mean TE range from 0.81 (1975–1976) to 0.94 (1984–1985)
Dawson, Lingard, and Woodford (1991)	Philippines	SFA	Subsample of 22 farms, (1970, 1974, 1979, 1982, 1984)	TE = 0.89

[a] SFA, stochastic frontier production approach; DEA, data envelopment analysis.
[b] TE, technical efficiency; AE, allocative efficiency; EE, economic efficiency; CRS, constant returns to scale; VRS, variable returns to scale. PE (Abdulai and Huffman, 2000), profit efficiency.

Our study estimates TE, AE, EE, and scale efficiency (SE) scores for rice production in Arkansas, thus allowing for comparison of rice production efficiency in a developed country setting to that observed in developing countries.

Technical, Economic, and Allocative Efficiency Data Envelopment Analysis Model Specifications

Using the DEA model specification, the TE score for a given field n is obtained by solving the following LP problem:

$$(1) \qquad TE_n = \min_{\lambda_i \theta_n} \theta_n$$

subject to:

$$\sum_{i=1}^{I} \lambda_i x_{ij} - \theta_n x_{nj} \leq 0$$

$$\sum_{i=1}^{I} \lambda_i y_{ik} - y_{nk} \geq 0$$

$$\sum_{i=1}^{I} \lambda_i = 1$$

$$\lambda_i \geq 0$$

where i = one to I fields; j = one to J inputs; k = one to K outputs; λ_i = the nonnegative weights for I fields; x_{ij} = the amount of input j used on field i; x_{nj} = the amount of input j used on field n; y_{ik} = the amount of output k produced on field i; y_{nk} = the amount of output k produced on field n; and θ_n = a scalar $\leq$ one that defines the TE of field n, with a value of one indicating a technically efficient field and a value less than one indicating a technically inefficient field with the level of technical inefficiency equal to one – TE_n (Coelli, 1995). The constraint $\sum_{i=1}^{I} \lambda_i = 1$ in equation (1) ensures the TE_n in equation (1) is calculated under the variable returns to scale (VRS) assumption (Coelli, 1995). Equation (1) is therefore the TE formulation proposed by Banker, Charnes, and Cooper (1984). When the $\sum_{i=1}^{I} \lambda_i = 1$ constraint is omitted, constant returns to scale (CRS) are assumed, and equation (1) becomes the TE formulation proposed by Charnes, Cooper, and

Table 2. Comparison of Mean Scale Efficiencies and Returns to Scale Percents Across Empirical Rice Production Efficiency Studies

Author(s)	Country	Observations	Mean SE	CRS[a]	IRS	DRS
Zahidul Islam, Bäckman, and Sumelius (2011)	Bangladesh	355	0.88	11%	73%	16%
Brázdik (2006)	Indonesia	960	0.90	5%	18%	77%
Dhungana, Nuthall, and Nartea (2004)	Nepal	76	0.93	11%	47%	42%
Krasachat (2004)	Thailand	74	0.96	32%	49%	19%
Wadud (2003)	Bangladesh	150	0.95	17%	20%	63%
Coelli, Rahman, and Thirtle (2002)	Bangladesh (Aman plots)	351	0.93	8%	54%	38%
Coelli, Rahman, and Thirtle (2002)	Bangladesh (Boro plots)	422	0.95	11%	31%	58%
Wadud and White (2000)	Bangladesh	150	0.92	15%	14%	71%

[a] SE, scale efficiency; CRS, constant returns to scale; IRS, increasing returns to scale; DRS, decreasing returns to scale.

Rhodes (1978). The TE score obtained from equation (1) is a radial measure and is restrictive in that it assumes the inefficient field can be brought to the frontier only by shrinking all inputs equiproportionately. In other words, this framework assumes the technically inefficient field will have the same degree of input overuse for all inputs (Fernandez-Cornejo, 1994). We use the more common radial framework in our analysis to better facilitate comparison of results with those from other rice production efficiency studies using radial efficiency measures.

The EE score for a given field n is obtained by first solving the following cost-minimizing LP model:

$$(2) \qquad MC_n = \min_{\lambda_i x^*_{nj}} \sum_{j=1}^{J} p_{nj} x^*_{nj}$$

subject to:

$$\sum_{i=1}^{j} \lambda_i x_{ij} - x^*_{nj} \leq 0$$

$$\sum_{i=1}^{I} \lambda_i y_{ik} - y_{nk} \geq 0$$

$$\sum_{i=1}^{I} \lambda_i = 1$$

$$\lambda_i \geq 0$$

where MC_n = the minimum total cost for field n; p_{nj} = the price for input j on field n; and x^*_{nj} = the cost-minimizing level of input j on field n given its input price and output levels. All other variables in equation (2) are as previously defined. The constraint $\sum_{i=1}^{I} \lambda_i = 1$ in equation (2) again ensures that the minimum total costs for the field are calculated under the VRS assumption (Fletscher and Zepeda, 2002; Wu and Prato, 2006). Economic efficiency (EE_n) for each field is then calculated using the following equation:

$$(3) \qquad EE_n = \frac{\sum_{j=1}^{J} p_{nj} x^*_{nj}}{\sum_{j=1}^{J} p_{nj} x_{nj}}$$

where the numerator $\sum_{j=1}^{J} p_{nj} x^*_{nj}$ = the minimum total cost obtained for field n using equation (2) and the denominator $\sum_{j=1}^{J} p_{nj} x_{nj}$ = the actual total cost observed for field n. The EE_n for a given field takes on a value ≤ one with an EE_n = one indicating the field is economically efficient and an EE_n < one indicating the field is economically inefficient with the level of economic efficiency equal to one – EE_n.

The EE for a DMU can also be represented as the product of both the TE and the AE for the DMU, or $EE_n = TE_n \times AE_n$ (Farrell, 1957). Thus, the AE score for field n can be determined given both the EE and TE for the field using the following relationship:

$$(4) \qquad AE_n = \frac{EE_n}{TE_n}$$

where EE_n = the economic efficiency calculated for field n using equation (3) and TE_n = the technical efficiency calculated for field n using equation (1). Like with TE_n and EE_n, the value for AE_n will be ≤ one with an AE_n = one meaning the field is allocatively efficient and an AE_n < one meaning the field is allocatively inefficient with the level of allocative inefficiency equal to one – AE_n.

Scale Efficiency and Determination of Returns to Scale Using Data Envelopment Analysis

The DEA models discussed thus far assume VRS. As indicated, CRS may be imposed by omitting the constraint $\sum_{i=1}^{I} \lambda_i = 1$ in both equations (1) and (2). Imposing both CRS and VRS on TE in equation (1) allows for calculation of scale efficiency. Scale efficiency is determined for each field as follows:

$$(5) \qquad SE_n = \frac{TE_{CRSn}}{TE_{VRSn}}$$

where TE_{CRSn} = technical efficiency of field n under constant returns to scale and TE_{VRSn} = technical efficiency of field n under variable returns to scale.

The value for SE_n will be ≤ one with SE_n = one meaning the field is operating at an optimal scale and SE_n < one meaning the field is scale-inefficient with the level of scale inefficiency equal to one – SE_n. Scale inefficiency arises as a result of the presence of either IRS or DRS. The value derived from equation (5) can indicate if a field is scale-inefficient but provides no indication as to whether this inefficiency arises as a result of IRS or DRS. Increasing or decreasing returns to scale may be determined for each field by running the TE model in equation (1) and replacing $\sum_{i=1}^{I} \lambda_i = 1$ with $\sum_{i=1}^{I} \lambda_i \leq 1$. The result is TE calculated under nonincreasing returns to scale (TE_{NIRSn}). If $TE_{NIRSn} = TE_{VRSn}$, the field exhibits DRS (larger than optimal scale); if $TE_{NIRSn} \neq TE_{VRSn}$, the field exhibits IRS (suboptimal scale) (Coelli, Rahman, and Thirtle, 2002).

Data

Production efficiency scores are calculated for Arkansas rice production using data from fields enrolled in the University of Arkansas, RRVP. The RRVP was originally established in 1983 as a means of public demonstration of research-based University of Arkansas extension recommendations in actual fields with less than optimal yields or returns (Mazzanti et al., 2012). The goals of the RRVP are to 1) educate producers on the benefits of using University of Arkansas extension recommendations; 2) verify University of Arkansas extension recommendations on farm-field settings; 3) identify research areas needing additional study; 4) improve or refine existing University of Arkansas extension recommendations; 5) incorporate RRVP data into state and local education programs; and 6) provide in-field training for county agents. From 1983 to 2012, the RRVP has been conducted on 358 commercial rice fields in 33 rice-producing counties in Arkansas (Mazzanti et al., 2012). Different fields are enrolled into the program each year with few fields occurring in consecutive years of the program.

Input quantities, inputs costs, prices, and output data for the DEA analysis are obtained from 158 rice fields enrolled in the RRVP for the period 2005–2012 (Table 3). The period 2005–2012 was chosen because rice management practices and varieties have remained fairly steady over this timeframe. Inputs for the DEA analysis include field size (acres); irrigation water (acre inches); diesel fuel (gallons); nitrogen, phosphorus, and potassium (lbs); seed (lbs); costs of other soil amendments ($); herbicide, insecticide, and fungicide costs ($); and custom charges ($). Output for the DEA analysis is measured as the value of rice production (rice yield × milling yield adjusted rice price × field size). Input prices for irrigation water, nitrogen, phosphorus, potassium, and seed are also obtained from the RRVP for the EE and AE analyses. A land charge of 25% of rice value was assumed for the value of land in the EE and AE analyses. A 25% share of the crop is a typical rental payment for rented cropland in eastern Arkansas. All economic data (prices and costs) are converted to 2012 dollars using the Producer Price Index.

Table 3. Output, Inputs, and Input Prices Summary Statistics Used in the DEA Analysis

Variable	Mean[a]	SD	CV	Minimum	Median	Maximum
Output[b]						
Rice production value ($)[c]	64,036	40,579	63	7,622	53,004	228,122
Inputs						
Field size (acres)	61	32	53	9	51	183
Irrigation water (acre inches)	1,847	1,058	57	270	1,604	7,360
Diesel fuel (gallons)	543	332	61	54	452	1,988
Nitrogen (lbs)[d]	10,139	5,457	54	1,183	8,903	33,672
Phosphorus (lbs)[d]	1,975	1,995	101	0	1,656	8,100
Potassium (lbs)[d]	2,655	3,334	126	0	1,515	15,012
Seed (lbs)	4,372	3,466	79	216	3,282	19,980
Other soil amendments ($)[e]	710	1,440	203	0	242	9,420
Herbicides ($)	4,012	2,489	62	397	3,388	13,332
Insecticides ($)	190	352	185	0	0	2,384
Fungicides ($)	559	882	158	0	0	4,060
Custom charges ($)	3,013	1,998	66	140	2,522	11,570
Input prices						
Land charge ($/acre)[f]	261.63	76.00	29	118.76	254.17	473.40
Irrigation price ($/acre inch	2.47	1.03	42	0.31	2.31	4.53
Diesel price ($/gallon)	2.97	0.72	24	2.31	2.74	4.53
Nitrogen price ($/lb)	0.53	0.12	22	0.32	0.52	0.75
Phosphorus price ($/lb)	0.55	0.21	37	0.26	0.53	1.02
Potassium price ($/lb)	0.45	0.19	41	0.10	0.47	0.82
Seed price ($/lb)	2.07	2.26	109	0.10	0.61	7.01

[a] Summary statistics calculated from 158 fields enrolled in the University of Arkansas Rice Research Verification Program for the period 2005–2011.
[b] Rice values, input costs, and input prices are adjusted to 2011 dollars using the Producer Price Index.
[c] Rice production value = field yield (bu/acre) * rice price adjusted for milling quality ($/bu) * field size (acres).
[d] Input levels for nitrogen, phosphorus, and potassium are in elemental levels.
[e] Other soil amendments include chicken litter, zinc, and/or Agrotain, a urease inhibitor.
[f] Land charge = 25% rice production value.
DEA, data envelopment analysis; SD, standard deviation; CV, coefficient of variation.

Tobit Analysis

Regression analysis was conducted to determine impacts of different field characteristics on production efficiency scores. A two-limit Tobit model was used in this analysis (Maddala, 1983), because efficiency scores are bounded between zero and one (unity). The Tobit model is expressed as follows:

$$(6) \qquad y_i{*} = \beta_0 + \sum_{m=1}^{M} \beta_m x_{im} + \varepsilon_i,\ \varepsilon_i \sim IN\left(0, \sigma^2\right)$$

where $y_i{*}$ = a latent variable representing the efficiency score for field i; β_0 and β_m are unknown parameters to estimate; x_{im} = 1 to M explanatory field characteristic variables associated with field i; and ε_i = an error term that is independently and normally distributed with zero mean and constant variance σ^2. The latent variable $y_i{*}$ is expressed in terms of the observed variable y_i (the efficiency score calculated using DEA analysis) as follows:

$$y_i = \text{one if } y_i{*} \geq 1$$

$$y_i = y_i{*} \text{ if zero} \leq y_i{*} \leq 1$$

$$y_i = \text{zero if } y_i{*} \leq 0$$

The explanatory variables used in the Tobit regression analysis are listed in Table 4. Explanatory variables include field size, the year the field was in the program (2005, 2006, . . . , 2012), the field location (Northeast region, central East region, Southeast region, other locations), the rice variety type used on the field

Table 4. Field Characteristic Variables Used in the Tobit Analysis

Field Characteristic	Description	No.[a]	Mean
Field Size	Size of field (acres)	150	62
2012	Field in Rice Research Verification Program in 2012	19	0.127
2011	Field in Rice Research Verification Program in 2011	16	0.107
2010	Field in Rice Research Verification Program in 2010	22	0.147
2009	Field in Rice Research Verification Program in 2009	21	0.140
2008	Field in Rice Research Verification Program in 2008	22	0.147
2007	Field in Rice Research Verification Program in 2007	10	0.067
2006	Field in Rice Research Verification Program in 2006	18	0.120
2005	Field in Rice Research Verification Program in 2005	22	0.147
Northeast region	Field in Northeast Arkansas (Statistical District 3)	54	0.360
Central East region	Field in Central East Arkansas (Statistical District 6)	58	0.387
Southeast region	Field in Southeast Arkansas (Statistical District 9)	25	0.167
Other locations	Field located outside of Eastern Arkansas	13	0.087
Conventional	Conventional long grain rice varieties	66	0.440
Medium grain	Conventional medium grain rice varieties	14	0.093
Clearfield	Clearfield rice varieties	17	0.113
Hybrid rice	Hybrid rice varieties	13	0.087
Clearfield-hybrid	Clearfield-hybrid rice varieties	40	0.267
Silt loam	Soils with silt loam texture	93	0.620
Clay	Soil with clay texture	57	0.380
Soybean	Soybean planted on field previous year	99	0.660
Other crop	Rice, grain sorghum, corn, fallow	51	0.380
Contour levees	Field contains contour levees	64	0.427
Straight levees	Field contains straight levees	67	0.447
Zero-grade	Field has been graded to a zero slope	19	0.127
Multiple inlet	Field using poly pipe to irrigate paddies	46	0.307
No multiple inlet	Field without poly pipe	104	0.693

[a] No., number of fields. The Tobit analysis included 150 of the 158 fields enrolled in the Rice Research Verification Program (RRVP) for the period 2005–2012. Eight fields (four fields with sand texture and four fields with furrow irrigation) were excluded from the Tobit analysis.

(conventional, medium grain, Clearfield, hybrid, Clearfield-hybrid), the soil texture of field (silt loam, clay), the crop grown in the previous year (soybean, other crop), the field topography chosen for water movement across the field (contour levees, straight levees, zero grade), and whether the field used multiple inlet irrigation (multiple inlet, no multiple inlet). Field size is measured in acres. All other explanatory variables are zero-one dummy variables (one if field was enrolled in 2012, zero otherwise; one if the field was planted to a "conventional" rice variety, zero otherwise, etc.).

Field size is included to determine if larger fields lead to increased efficiency scores. Year dummies are included to account for the effect of weather on efficiency scores. Rice fields are distributed fairly uniformly across the 2005–2012 period with the exception of 2007, which had only 10 fields enrolled that year. Rice is primarily grown in eastern Arkansas in National Agricultural Statistics Service Statistical Reporting Districts 3, 6, and 9. Thus, the majority of fields enrolled from 2005 to 2012 are in eastern Arkansas (137 fields; Table 4) with only 13 fields located in counties outside this region. Rice is grown mostly on silt loam or clay texture fields (Wilson, Runsick, and Mazzanti, 2009). The majority of fields enrolled in the RRVP have a silt loam texture (93 fields; Table 4). Four RRVP fields had a sandy texture and were excluded from the Tobit analysis as a result of lack of observations. Soybean is the typical crop rotated with rice (Wilson, Runsick, and Mazzanti, 2009), and most fields enrolled in the RRVP have soybean as the previous crop in the rotation (93 fields; Table 4). The variable "other crop" in Table 4 includes RRVP rice fields planted in crops other than soybeans (rice, corn, grain sorghum, fallow) during the previous year.

Rice producers have the choice of planting a range of rice variety types, including conventional public varieties, Clearfield varieties, hybrid varieties, and Clearfield-hybrid combinations (Nalley et al., 2009). Conventional varieties include both long and medium grain variety types. These variety types differ in the size and shape of the kernel with long grain rice having a longer, more slender kernel than medium grain rice. Clearfield varieties are resistant to imidazoline herbicides and allow for greater control of red rice without killing rice growing in the field. Hybrids provide greater disease resistance and higher yields and use less nitrogen relative to conventional varieties. Clearfield-hybrids combine the red rice control of Clearfield lines with the higher-yielding and disease-resistant traits of hybrids.

Rice field typography varies across Arkansas depending on the amount of precision leveling conducted on each field. Contour levee fields account for over 55% of rice acres in Arkansas (Wilson, Runsick, and Mazzanti, 2009) and have minimal land improvements. Contour levees are constructed annually to manage water across uneven terrain. An estimated 45% of Arkansas rice acres are precision-leveled to some degree (Wilson, Runsick, and Mazzanti, 2009) with most fields graded to a 0.05–0.2% slope. Most precision-leveled fields have straight levees. Some rice fields in Arkansas are leveled to a zero slope and are referred to as zero-grade rice fields. Zero-grade rice production accounts for approximately 10% of planted rice acres in Arkansas (Wilson, Runsick, and Mazzanti, 2009). Zero-grade rice production eliminates the need to build levees each year and results in significantly less irrigation and fuel when compared with contour-levee rice production. A small number of rice acres in Arkansas (approximately 3%) is managed using furrow irrigation (Wilson, Runsick, and Mazzanti, 2009). Furrow-irrigated rice or row rice management refers to planting rice in furrows on raised beds. Water is applied in the furrows to maintain adequate soil moisture. Four RRVP fields were furrow-irrigated. These fields were excluded from the Tobit analysis as a result of lack of observations.

Multiple inlet (MI) irrigation uses poly pipe to distribute irrigation water to all paddies simultaneously. This differs from conventional flood irrigation in which water is applied to the first paddy at the top of the field and then flows over spills to lower paddies until the entire field is flooded (Vories, Tacker, and Hogan, 2005). Multiple inlet irrigation allows the field to be flooded much faster than conventional flood irrigation. Water savings may be achieved using MI over conventional flood irrigation because the field is flooded quicker and irrigation efficiency is increased through reduced pumping time during the season. Other possible benefits of MI include reduced irrigation labor and possible higher grain yields (Vories, Tacker, and Hogan, 2005).

Results

Technical, Allocative, Economic, and Scale Efficiency Scores

Technical, allocative, economic, and scale efficiency score summary statistics are presented in Table 5. The LINDO What's Best! spreadsheet solver was used to conduct the DEA linear programming analysis for each field in the study (Lindo Systems, 2007). Technical efficiency score summary statistics are presented under both CRS and VRS. The mean TE score under CRS is 0.803 and ranges from 0.380 to 1.000, whereas the mean TE score under VRS is 0.875 and ranges from 0.440 to 1.000. The median TE scores under CRS and VRS are 0.837 and 1.000, respectively, and indicate that over half the fields in the RRVP have TE scores of 0.837 or higher under CRS and achieve full technical efficiency (TE = 1) under VRS. Thus, most fields enrolled in the RRVP achieve high technically efficiency. This result is likely the result of the general objective of the RRVP to apply production inputs to each field based on University of Arkansas extension recommendations to achieve specified yield goals. Although mean TE scores are high across RRVP fields, high TE scores are not

Table 5. Efficiency Score Summary Statistics of 158 University of Arkansas Rice Research Verification Program Fields

Efficiency[a]	Mean	SD	CV	Minimum	Median	Maximum
TE_{CRS}	0.803	0.186	23	0.380	0.837	1.000
TE_{VRS}	0.875	0.171	20	0.440	1.000	1.000
AE	0.711	0.165	23	0.332	0.731	1.000
EE	0.622	0.199	32	0.291	0.625	1.000
SE	0.920	0.113	12	0.428	0.964	1.000

[a] TE, technical efficiency; AE, allocative efficiency; EE, economic efficiency ; SE. scale efficiency; CRS, constant returns to scale; VRS, variable returns to scale.
SD, standard deviation; CV, coefficient of variation.

unprecedented in the literature. Other studies report mean TE scores above the TE_{VRS} mean of 0.875 reported in this study (Khan, Huda, and Alam, 2010, for rice producers in Bangladesh; Nhut, 2007, for rice producers in Vietnam; Chauhan et al., 2006, for rice producers in India under the VRS assumption; Wadud, 2003, for rice producers in Bangladesh under the VRS assumption; Xu and Jeffrey, 1998, for conventional rice producers in China; Battese and Coelli, 1992, for India rice producers; and Dawson, Lingard, and Woodford, 1991, for rice producers in the Philippines).

The mean AE score across RRVP fields is 0.711 with a range of 0.332–1.000. The median AE score across RRVP fields is nearly identical to the mean score (0.731 in Table 5). Both scores imply that on average, rice fields enrolled in the RRVP are not using inputs in cost-minimizing levels given the input prices they face and that on average costs may be reduced by approximately 29% to achieve the same output levels. The mean and median AE scores for the RRVP fields fall within the range of mean AE scores observed across rice production efficiency studies cited in Table 1 (from 0.62 to 0.88).

The mean EE score across RRVP fields is 0.622 and ranges from a minimum of 0.291 to a maximum of 1.000 (Table 5). The median EE score is close to the mean score (0.625 in Table 4). These results indicate rice fields enrolled in the RRVP are economically inefficient on average and that the total cost of rice production for each field could be reduced on average by approximately 38% to achieve the same level of output. The mean and median EE scores for the RRVP fields fall within the range of mean EE scores observed across rice production efficiency studies cited in Table 1 (from 0.39 to 0.83).

Scale efficiency summary statistics in Table 6 average 0.920 and range from 0.428 to 1.000. The median SE across RRVP fields is 0.964. The mean and median SE statistics are similar to mean SE values reported in other studies (Table 2) and indicate that most RRVP fields operate at close to optimal scale (operate at close to optimal field size). Although small, scale inefficiency on average is approximately 8% for the 158 fields enrolled in the RRVP. Most of the scale inefficiency arises from fields exhibiting IRS (fields at suboptimal field size) (Table 5). Nearly half of the fields enrolled in the RRVP exhibit IRS, whereas one-fourth of the fields exhibit DRS (operate at larger than optimal field size). Slightly over one-fourth of the fields enrolled in the RRVP exhibit CRS (operate at optimal field size). The average size of fields exhibiting CRS is 55 acres, whereas the average size of fields exhibiting IRS and DRS is 46 and 97 acres, respectively.

Table 6. Returns To Scale Summary Statistics of 158 University of Arkansas Rice Research Verification Fields

Scale Classification[a]	Number	Percent
CRS	42	26.6%
IRS	77	48.7%
DRS	39	24.7%
Total	158	100%

[a] CRS, constant returns to scale; IRS, increasing returns to scale; DRS, decreasing returns to scale.

The distribution of technical, allocative, economic, and scale efficiency scores are reported by efficiency range for the 158 RRVP fields in Table 7. Sixty-four of the 158 fields (41%) have TE_{CRS} scores exceeding 0.90, whereas 95 of the 158 fields (61%) have TE_{VRS} scores exceeding 0.90. Forty-two of the 158 fields (27%) and 83 of the 158 fields (53%) achieve full technical efficiency under CRS and VRS, respectively. Seventy-three percent of the fields enrolled in the RRVP (114 of 158) have scale efficiencies at or exceeding 0.90. Thus, a large portion of fields enrolled in the RRVP achieve both high technical and scale efficiency. However, only five of the 158 fields (3% of all fields) achieve AE and EE scores of 1.0. Eighty-nine percent of the 158 fields have AE scores less than 0.90, whereas 90% of the 158 fields have EE scores less than 0.90. Thus, despite the high technically and scale efficiency of most fields enrolled in the RRVP, the majority of fields do not use inputs in the right combinations to achieve cost minimization and are therefore allocatively and economically inefficient.

Impact of Field Characteristics on Efficiency Scores

Tobit analysis results of field characteristic impacts on efficiency scores are presented in Table 8. Tobit efficiency score models were estimated using the SAS QLIM procedure (SAS Institute, 2004). Field characteristic variables omitted from each model include 2012, central East region, conventional, clay, other crop, contour levees, and no multiple inlet. The effects of these variables are captured in the intercept of each model.

Coefficients for field size produced mixed results across efficiency measures. The coefficient for field size is negative and significant at the 1% level for the TE_{VRS} model. This result occurs because the majority of fields in the RRVP during 2005–2012 exhibited full technical efficiency under VRS (Table 7), and these fields were smaller on average (55 acres) than fields exhibiting technical inefficiency under VRS (68 acres). Alternatively, the field size coefficient for the AE and SE models is

Table 7. Distribution of Efficiency Scores by Efficiency Range Across 158 University of Arkansas Rice Research Verification Program Fields

	TE_{CRS}[a]		TE_{VRS}		AE		EE		SE	
Efficiency Range	Number	Percent	Number	Percent	Number	Percent	Number	Percent	Number	Percent
= 1.0	42	27%	83	53%	5	3%	5	3%	42	27%
> 0.9 < 1.0	22	14%	12	8%	13	8%	11	7%	72	46%
> 0.8 < 0.9	28	18%	18	11%	31	20%	19	12%	24	15%
> 0.7 < 0.8	20	13%	16	10%	44	28%	21	13%	9	6%
> 0.6 < 0.7	16	10%	11	7%	31	20%	28	18%	5	3%
> 0.5 < 0.6	15	9%	11	7%	16	10%	23	15%	4	3%
> 0.4 < 0.5	15	9%	7	4%	6	4%	24	15%	2	1%
> 0.3 < 0.4	—	—	—	—	12	8%	25	16%	—	—
< 0.3	—	—	—	—	—	—	2	1%	—	—
Sum	158	100%	158	100%	158	100%	158	100%	158	100%
Mean efficiency	0.803		0.875		0.711		0.622		0.920	
Median efficiency	0.837		1.000		0.731		0.625		0.964	

[a] TE, technical efficiency; AE, allocative efficiency; EE, economic efficiency; SE, scale efficiency; CRS, constant returns to scale; VRS, variable returns to scale.

Table 8. Tobit Analysis of Rice Technical, Allocative, Economic, and Scale Efficiency as a Function of Field Characteristics

Independent Variables	TE_{CRS}[a]		TE_{VRS}		AE		EE		SE	
Intercept	0.7301	***[b]	1.0560	***	0.6140	***	0.5444	***	0.8090	***
	(0.0702)[c]		(0.1173)		(0.0485)		(0.0445)		(0.0527)	
Field size	–0.0002		–0.0024	***	0.0010	***	0.0001		0.0011	***
	(0.0004)		(0.0007)		(0.0003)		(0.0003)		(0.0003)	
2011	–0.1058	*	–0.2118	**	–0.0107		–0.1120	***	0.0421	
	(0.0587)		(0.0936)		(0.0402)		(0.0370)		(0.0449)	
2010	–0.2816	***	–0.2300	***	–0.1569	***	–0.2436	***	–0.1501	***
	(0.0511)		(0.0808)		(0.0352)		(0.0324)		(0.0384)	
2009	0.0238		0.1031		–0.0387		–0.0140		–0.0089	
	(0.0552)		(0.0947)		(0.0366)		(0.0337)		(0.0415)	
2008	0.1097	**	0.2814	***	0.0416		0.1127	***	0.0050	
	(0.0543)		(0.1014)		(0.0355)		(0.0327)		(0.0405)	
2007	0.0174		0.0321		–0.0484		–0.0479		0.0240	
	(0.0651)		(0.1092)		(0.0445)		(0.0409)		(0.0500)	
2006	–0.0825		–0.0151		–0.1201	***	–0.1278	***	–0.0565	
	(0.0565)		(0.0932)		(0.0390)		(0.0358)		(0.0424)	
2005	–0.1366	**	–0.0617		–0.1936	***	–0.2202	***	–0.0846	**
	(0.0544)		(0.0868)		(0.0380)		(0.0349)		(0.0408)	
Northeast region	0.0635	**	0.0351		0.0281		0.0403	**	0.0548	**
	(0.0312)		(0.0529)		(0.0217)		(0.0199)		(0.0235)	
Southeast region	0.0804	*	–0.0170		0.0308		0.0250		0.0851	**
	(0.0477)		(0.0796)		(0.0324)		(0.0298)		(0.0355)	
Other locations	–0.0156		–0.0818		–0.0484		–0.0526		–0.0015	
	(0.0521)		(0.0835)		(0.0362)		(0.0333)		(0.0397)	
Medium grain	0.2082	***	0.2318	**	0.1414	***	0.2396	***	0.0705	*
	(0.0565)		(0.0955)		(0.0384)		(0.0354)		(0.0424)	
Clearfield	–0.0098		–0.0054		0.0267		0.0193		–0.0033	
	(0.0501)		(0.0809)		(0.0358)		(0.0329)		(0.0372)	
Hybrid	0.2132	***	0.2169	**	0.1950	***	0.2591	***	0.1319	***
	(0.0559)		(0.1005)		(0.0369)		(0.0338)		(0.0438)	
Clearfield-hybrid	0.1721	***	0.1906	***	0.1183	***	0.1845	***	0.0797	***
	(0.0395)		(0.0710)		(0.0268)		(0.0246)		(0.0295)	
Silt loam	0.0161		–0.0211		0.0471	**	0.0301		0.0334	
	(0.0318)		(0.0553)		(0.0221)		(0.0203)		(0.0238)	
Soybean	0.0108		–0.0182		0.0000		0.0125		0.0006	
	(0.0322)		(0.0539)		(0.0226)		(0.0208)		(0.0242)	
Straight levee	0.0124		0.0254		–0.0196		0.0031		–0.0255	
	(0.0315)		(0.0537)		(0.0221)		(0.0203)		(0.0237)	
Zero grade	0.1000	*	0.0284		0.0601		0.0727	**	0.0787	*
	(0.0552)		(0.0954)		(0.0370)		(0.0340)		(0.0415)	
Multiple inlet	0.0694	**	0.0516		0.0229		0.0417	**	0.0362	
	(0.0318)		(0.0548)		(0.0219)		(0.0201)		(0.0237)	
σ	0.1489	***	0.2233	***	0.1077	***	0.0990	***	0.1104	***
	(0.0103)		(0.0203)		(0.0064)		(0.0059)		(0.0077)	
Observations	150		150		150		150		150	
Log likelihood	27.3		–35.6		111.6		123.8		59.9	

[a] TE, technical efficiency; AE, allocative efficiency; EE, economic efficiency; SE, scale efficiency; CRS, constant returns to scale; VRS, variable returns to scale.
[b] Asterisks ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.
[c] Numbers in parentheses are standard errors.

positive and significant at the 1% level, implying these efficiency measures are improved by increasing field size. These results are likely the result of the high proportion of RRVP fields exhibiting IRS (Table 6). Such fields are suboptimal in field size and stand to gain in scale efficiency by increasing acres.

The year each field was enrolled into the RRVP program significantly impacts efficiencies scores, particularly if the year was hot and dry (2005, 2010) or had a cool or wet spring delaying rice planting (2006, 2011). In each of these instances, year has a negative and often significant impact on efficiency scores. Fields located in the Northeast and Southeast counties of Arkansas have positive and significant impacts on TE_{CRS} and SE scores. Fields located in Northeast counties of Arkansas also have a positive and significant impact on EE scores. These results signify a higher proportion of fields closer to optimal scale in the Northeast and Southeast regions relative to other regions in Arkansas where rice is grown. Soil type has little impact on efficiency scores. The one exception is the AE model, in which the coefficient for silt loam is positive and significant at the 5% level. The soybean coefficient is not significant in any efficiency score model, implying the previous crop grown in the rotation has little if any impact on efficiency scores.

The type of variety grown on the field significantly impacts efficiency scores. Coefficients for medium grain, hybrid, and Clearfield-hybrid are positive and significant across all efficiency measures, implying these variety types increase efficiency scores relative to conventional varieties. Alternatively, coefficients for Clearfield are not significant across efficiency models, implying Clearfield varieties have essentially the same effect as conventional varieties on efficiency scores. These results are largely the result of higher yields for medium grain, hybrid, and Clearfield-hybrid varieties relative to conventional and Clearfield (nonhybrid) varieties. Hybrids, Clearfield-hybrids and medium grain varieties averaged higher yields in the RRVP than Clearfield or conventional varieties during the 2005–2012 period.

The zero grade coefficient is positive across all models, implying that leveling fields to a zero grade positively impacts all five efficiency scores. However, the zero grade coefficient is significant at the 5% level for only the EE model, indicating that zero-grade fields have a strong positive impact on economic efficiency. This result is likely the result of the fuel and water savings associated with zero-grade fields relative to fields with straight or contour levees. Coefficients for MI are also positive across all efficiency measures and significant at the 5% level for both TE_{CRS} and EE models. These results imply fields using MI irrigation have higher efficiencies relative to fields without MI irrigation, particularly with regard to economic efficiency and technical efficiency under CRS. The efficiency advantage appears to be the result of higher yields for fields using MI irrigation compared with fields not using MI irrigation. Comparisons of the two types of fields in the RRVP revealed little difference in input use or input costs between MI and non-MI fields. However, yields were significantly larger on average for fields using MI irrigation.

Summary and Conclusions

This study uses DEA to estimate technical, allocative, economic, and scale efficiency scores for 158 fields enrolled in the University of Arkansas, RRVP during 2005–2012. Efficiency scores are summarized and compared with those obtained from rice production studies in developing countries, and Tobit analysis is used to evaluate the effects of field characteristics on efficiency scores. This study is the first to evaluate rice production efficiency in the United States.

Fields enrolled in the RRVP exhibit high technical and scale efficiency. Over half the fields in the RRVP achieve full technical efficiency (TE = 1) under VRS, whereas 73% of the fields in the RRVP exhibit high scale efficiency (SE > 0.90). Thus, RRVP fields for the most part use the minimum level of inputs necessary to achieve a given level of output and are nearly optimal in scale (field size). The SE scores observed in this study are comparable to SE values reported in other rice efficiency studies. However, the mean TE scores observed in this study are larger than those observed in many rice efficiency studies. This could be an indication that rice production in Arkansas is more efficient at using production inputs than rice production in many other countries. However, the high TE results could also be a reflection of the success of the RRVP, which is aimed as applying University of Arkansas extension recommendations to achieve specific rice yield goals on fields enrolled in the program.

Although the results reflect high technical and scale efficiencies for Arkansas rice production, comparison of allocative and economic efficiency scores reveals the existence of inefficiencies with regard to input mix and cost minimization. Mean AE and EE scores for RRVP fields were 0.711 and 0.622, respectively, and fall within the range of mean AE and EE scores reported in other rice efficiency studies. Only 3% of the fields enrolled in the RRVP achieve full AE and EE (AE and EE scores equal to one). Thus, although the majority of RRVP fields exhibit high technical and scale efficiency, most fields do not use inputs in the right combinations necessary for achieving cost minimization and are both allocatively and economically inefficient. This may reflect dichotomy between the goal of profit maximization and the goal of agronomic yield maximization among both rice producers and the RRVP program itself.

Tobit analysis revealed that economic and allocative efficiency scores could be improved by better variety selection. Varieties exhibiting high yields (medium grain varieties, hybrids, and Clearfield-hybrids) had a positive and highly significant impact on AE and EE scores. The higher AE and EE efficiencies associated with these variety types may be the result of the types of fields enrolled into the RRVP. These fields tend to be marginal in nature and produce low yields. Hybrids and Clearfield-hybrids have good disease resistance and work better on marginal fields. These varieties would be expected to increase production efficiency on such fields.

Tobit analysis also indicated that EE scores could be improved by better irrigation management, either by shaping fields to a zero grade or by using multiple inlet irrigation. Zero-grade fields use significantly less irrigation water and fuel than fields with levees. However, zero-grade fields require a high initial capital investment for field shaping and are not very conducive to rotation of rice with other crops. Producers wishing to remain flexible at planting crops like corn or soybeans according to market signals may not wish to sink such investment into zero-grade fields. The Tobit analysis also revealed that MI irrigation has a positive and significant impact on EE scores. Multiple inlet irrigation uses poly pipe to distribute irrigation water to all paddies simultaneously. Input use appears to be the same for both MI and non-MI fields. However, average rice yields were significantly larger on MI fields in the RRVP. This could be the result of faster field flooding. Flooding up the field faster allows for greater nitrogen efficiency (less nitrogen volatilization) and greater herbicide efficiency from better timing of herbicide activation with water. This represents a good future research topic for agronomists.

Some shortcomings of the study need to be mentioned to avoid overgeneralization of efficiency results. One shortcoming is that the study uses radial measures of technical efficiency, which assumes technically inefficient fields have the same degree of input overuse for all inputs. Although this approach is appropriate for comparison with other radial efficiency studies, the approach may become more restrictive and problematic when quantifying overuse of specific inputs such as water or fertilizer. Thus, a future direction for this research would be to conduct efficiency analysis using nonradial efficiency measurement methods like those used by Fernandez-Cornejo (1994) and Piot-Lepetit, Vermersch, and Weaver (1997). A second shortcoming lies with the absence of rice producer characteristics in the Tobit analysis. Other rice efficiency studies use Tobit analysis to determine impacts of producer-specific variables such as age, education, tenancy, and experience on efficiency scores (Coelli, Rahman, and Thirtle, 2002; Dhungana, Nuthall, and Nartea, 2004; Kiatpathomchai, 2008; Zahidul Islam, Bäckman, and Sumelius, 2011). Such producer-specific information is not collected in the RRVP and is thus unavailable for analysis.

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