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Two–Stage DEA on Technical Efficiency and the Effect of Water Management on Rice Production of 122 Paddy Fields from a Large–Scale Farm in Japan

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In Japan, rice production is undergoing a transition from acreage reduction to an improvement in efficiency and competitiveness. Owing to the global warming, water management is increasingly important in maintaining soil temperature and fertility for rice productivity. This paper aimed to measure the production efficiency of rice yield, using a two–stage data envelopment analysis (DEA). The data comprised of 122 paddy fields of Koshihikari, one of the most popular Japanese rice varieties, which were sampled from a large–scale farm located in the Hokuriku Region of Japan in 2015. In the first stage of the analysis, the outputs included yields of raw paddies, paddies with 15% moisture, unsorted, sorted, perfectly shaped, and milled brown rice. The inputs included the field area, temperature, solar radiation, fertilizer nitrogen, soil capacity, and farming conditions. The results indicated that there was a large margin to increase the yields, and an enlarged scale could increase the efficiency of most paddy fields; the largest input slacks occurred in land capacity and field area. In the second stage, we determined the significant effects of water management on rice production efficiency at different growth stages in the 20 paddy fields of highest and lowest efficiency. Finally, we discussed the interactions between air temperature, water depth and water temperature.

Key words: Koshihikari, Slack analysis, Technical efficiency, Water depth, Water temperature

INTRODUCTION

Confronting decreases in gross production and high input costs of rice (*Oryza sativa L.*), the Japanese government is promoting the transition from acreage reduction to improvements in efficiency and competitiveness. In 2014, the production of sorted brown rice was 8.43×10^6 t, 40% lower than the 1985 production of 11.83×10^6 t (MAFF, 2016a). In 2015, the average production cost of sorted rice was 257 Japanese Yen (JPY) per kg (MAFF, 2016b). The cost typically decreased as farming scale increased. In the large farms over 15 ha, the average production cost of sorted rice was 193 JPY/kg. From our research consortium, we found that the cost per kg decreased further to 155 JPY and 150 JPY for farms with 30 ha and over 100 ha of land, respectively (Nanseki *et al.*, 2016). Nevertheless, it was difficult to reduce the production costs further by merely increasing the scale, thereby increasing production efficiency, without technological innovation. Thus, we analyzed rice production from the perspective of technical efficiency using field–level data from a large–scale farm. To isolate the bias arising from the differences in rice varieties, we concentrated the study on Koshihikari. As one of the most popular rice varieties in Japan, it accounts for approximately 35.6% of the total domestic planting area (Komenet, 2018).

Many studies, including Abdullah and Ali (2014), Barrett *et al.* (2010), and Kozak *et al.* (2007), focused on the determinants of rice yield using overseas field–level on–farm data. In addition to these studies, a study by Hirai *et al.* (2012) used experimental data sampled in Japan. In our prior study, we analyzed the determinants of Koshihikari yield, using 2014 data from a large–scale farm in the Kanto Region of Japan (Li *et al.*, 2016). However, we have not found similar studies sampling field–level on–farm data in Japan. Therefore, it is important to accumulate further empirical evidences on the research fields.

In this study, we applied the analytical flamework employed in our previous study (Li *et al.*, 2016) to another farm in the different prefecture and analyzed the determinants of the 2015 rice yield, using data envelopment analysis (DEA) in the first stage. The effect of water management on rice production efficiency was analyzed in the second stage. Water management is the control and movement of water resources to minimize damage to life and property and to maximize efficient beneficial use. Irrigation water management systems make the most efficient use of limited water supplies for agriculture (NRCS, 2017).

Based on the pioneering work of Farrell (1957), studies devoted to the estimation of efficiency mainly embrace two approaches: the parametric function symbolized by the stochastic frontier production (SFP, Aigner *et al.*, 1977) and the nonparametric approach of DEA (Charnes *et al.*, 1978). SFP requires the specification of the function between inputs and outputs. In contrast, DEA is advantageous in that it includes multiple inputs and outputs with different units, simultaneously. Moreover, it avoids the parametric specification of technology and the distributional assumption (Coelli *et al.*, 2005).

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A multi–input model is necessary to measure agricultural efficiency when parameters such as land, fertilizer, and water are considered. Furthermore, a variety of yield variables should be used to measure not only quantity, but also quality, which is linked to the market value. The input and output variables may be in different units without any relevant parameters that can be assumed accurately beforehand. Moreover, the farmers can control the quantity of inputs rather than the outputs relatively freely. Farms are difficult to operate at an optimal scale because of varying socio–economic factors, including natural and marketing risks, government regulations, and financial constraints (Nanseki *et al.*, 2016). Therefore, we adopted an input–oriented DEA model assuming variable returns to scale (VRS).

To interpret the differences in production efficiency and adjustable slacks measured by DEA, we adopted water management practices in the second stage. As an indispensable factor, water affects many aspects of rice productivity e.g., nutrition supplication and weed control (Goto *et al.*, 2000; Sellamuthua *et al.*, 2011). Rice is also a major water–consuming crop and in Asia, about 80% of the irrigated fresh water is consumed by rice (Bouman and Tuong, 2001; Wang *et al.*, 2016). Moreover, with global warming, it is increasingly important to stabilize soil temperature, control excessive decomposition of organic matter, and maintain soil capacity through proper water management practices (Goto *et al.*, 2000; Tsujimoto *et al.*, 2009). Many studies have measured the effects of water management from two perspectives. Roel *et al.* (2005) estimated the effects of water temperature on rice production in California, US, by calculating the total number of hours and days it was below a given threshold. Saga *et al.* (2010) included water temperature as a form of energy in estimating the high–yield rice plants of Japan. Tao *et al.* (2015), Choudhury and Singh (2016) estimated the impact of water management on rice yield in China and India, respectively. As the effects of water management may vary at different growth stages and conditions, its subsequent analysis rather than its inclusion in the first stage of the DEA model was preferable. Based on the analyzing model presented in Li *et al.* (2018), this study included both water temperature and water depth, and analyzed their effects on various paddy fields. To further amplify the effects, a comparison of 20 paddy fields of high and low efficiency was conducted.

We composed this manuscript based on an oral presentation conducted on the annual symposium of the Japan Farm Management Society (Li *et al*, 2017), to fulfill several objectives in this study. (1) We formulated a DEA model appropriate for analyzing the efficiency of rice production using the paddy fields as the decision making units (DMUs); (2) revealed the overall attributes of rice production efficiency; (3) determined the theoretical margins for increasing yields and saving inputs; (4) identified the effects of the depth and temperature of water on rice production and technical efficiency; and (5) summarized our major findings, and put forward recommendations to improve rice yield.

MATERIALS AND METHODS

Sample and data

The dataset used in this study was constructed in NoshoNavi1000 project (Nanseki *et al.*, 2016, Nanseki 2019). In the DEA model of this paper, the following six rice yield variables were measured: raw paddy, paddy with 15% moisture, unsorted, sorted, perfectly shaped, and milled brown rice (Table 1). The raw paddy weight and percentage of moisture content were monitored directly by the combines equipped with advanced information technologies (IT). Furthermore, the yield of the paddy with 15% moisture was calculated using the raw paddy yield and average moisture content measured by IT combines. Brown rice was then weighed after hulling, and for sorted brown rice we retained only grains thicker than 1.85 mm. Milled rice referred to the fluffy white–yellow rice with the bran and germ removed, while perfectly shaped rice excluded the deformed, crashed, immature, and dead grains. Quantity was the focus of our first four outputs, while the last two outputs were more focused on quality. In the domestic market of Japan, the first–class rice, composed of about 70% perfect grains, fetches the highest price.

Within the IT combine, a small matchbox sized sensor, set at the input slot of the grain tank, monitored yield. The sensor probed the grain flow rate, whereas conventionally a much larger load cell is set at the bottom to measure the total grain weight in the tank. This innovation enabled real–time, precise, and low–cost monitoring, expelling the bias out of the grain tank stuffing state—whether the tank is filled or not. The IT combines could detect the threshing or screening yield with loss sensors and minimize it by automatic operation. Finally, the field–specific data was conveyed, via the global navigation satellite system (GNSS), to the cloud server shared by the company, institutes, and farms. Thereafter, the yield, moisture content, and farming time were automatically mapped, using Google Maps. The maps were essential for farms to capture the yield variations among the paddy fields, and update their farming plans, accordingly (Nanseki *et al.*, 2016).

The inputs included the field area, average temperature, and solar radiation within 20 days after heading, the amount of fertilizer nitrogen, soil capacity, and farming conditions. The temperature and solar radiation were monitored through meteorological observation devices every 10 min, and average values of these parameters were calculated. Fertilizer nitrogen was estimated based on the amount of chicken manure, chemical fertilizer, ammonium sulfate, and urea fertilizers, as well as their corresponding nitrogen contents, used. The soil capacity was measured using the compound values of five principals of 21 soil analysis indicators. Farming condition scores consisted of the managers' appraisal of the farming conditions of the paddy fields, including height difference, water depth, water leakage, former crop, water inletting, fertility unevenness, illumination, and herbicide application (Table 1).

Table 1. The yield of six forms of rice constituting the outputs and six determinants as inputs in the DEA model of the sampled paddy fields

Variable	N	Min	Max	Mean	S.D	CV (%)
Output: yield of (kg ha^{-1})						
Raw paddy	122	5948.64	9983.33	8058.98	758.36	9.41
Paddy of 15% moisture	122	5423.76	9114.20	7358.73	666.46	9.06
Unsorted brown rice	122	4401.63	7360.44	5934.22	530.20	8.93
Sorted brown rice [1]	122	4172.75	6753.21	5438.19	493.49	9.07
Milled rice [2]	122	3613.42	5843.36	4797.12	436.53	9.10
Perfectly shaped rice	122	2934.91	5226.98	4111.93	408.09	9.92
Input variables						
Field area (m^2)	122	452.00	4458.00	1354.70	1028.80	75.94
Temperature (˚C) [3]	122	25.55	26.60	26.19	0.29	1.11
Solar radiation (MJ m^{-2}) [3]	122	18.07	21.82	20.37	1.17	5.73
Fertilizer nitrogen (kg ha^{-1}) [4]	122	92.01	136.01	112.49	7.71	92.01
Land capacity [5]	122	0.00	0.92	0.48	0.18	37.98
Farming condition score [6]	122	27.00	38.00	33.97	1.68	4.93

[1] Grains with the thickness over 1.85 mm. [2] Fluffy white–yellow grain with the bran and germ removed. [3] Average values within 20 days after the heading. [4] Calculated according to the amounts of chicken manure, chemical fertilizer, ammonium sulfate, and urea fertilizers and the corresponding nitrogen contents. [5] Compound value of 5 principals of 21 soil analysis indicators transformed using (xi–maxX)/(maxX–minX). [6] Managers' appraisal of the farming condition of paddy fields, including height difference, water depth, water leakage, former crop, water inletting, fertility unevenness, illumination, and herbicide application.
Data source: survey by the authors

Comparing the coefficient of variation (CV) we found that among the output variables, perfectly shaped rice had the largest CV (9.92%), while the CVs of other yield indicators were approximately 9%. Among the input variables, the largest CV was observed in the field area, followed by land capacity and amount of fertilizer nitrogen, respectively, both of which were measured as the most important yield determinants by Tsujimoto *et al.* (2009). At the same time, the temperature, solar radiation, and farming conditions score varied to a lesser degree, with CVs less than 6% (Table 1). Both the temperature and solar radiation varied negatively with a later date of transplantation (Fig. 1). The estimated regression equations indicated that delaying transplanting by 1 d resulted in an approximately 0.06˚C reduction in temperature and a 0.21 MJ reduction in solar radiation per m^2. Hence, to some extent, the average temperature and solar radiation within 20 days after heading were discretionary variables, when adjusting the date of transplantation.

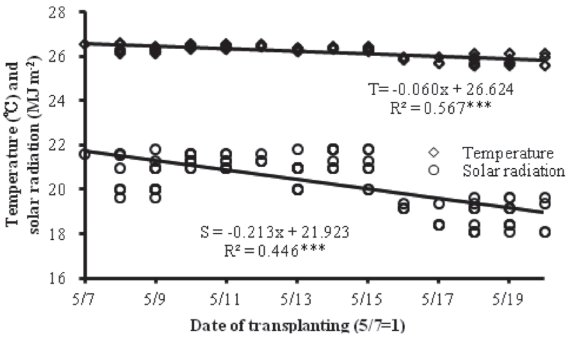

Fig. 1. Temperature and solar radiation at different dates of transplanting in the sampled paddy fields, where significant linear and negative relationships were identified.

Theory of the DEA model

DEA measures the efficiency of the DMUs relative to a frontier constructed through linear programming. This nonparametric method was proposed by Charnes *et al.* (1978), with the assumption of constant returns to scale (CRS), which holds when all firms are operating at an optimal scale (Coelli *et al.*, 2005). It was generalized by Banker *et al.* (1984), assuming VRS and that the weight of each DMU add up to unity. Thus get the input–oriented VRS model:

$$\begin{aligned} &\min \theta i \\ &\text{subject to } -\mathbf{y}_i + \mathbf{Y}\boldsymbol{\lambda} \geq 0 \\ &\qquad \theta_i \mathbf{x}_i + \mathbf{X}\boldsymbol{\lambda} \geq 0 \ (\, i = 1, 2, \dots, \mathrm{n}) \\ &\qquad \mathbf{I1}'\boldsymbol{\lambda} = 1 \\ &\qquad \boldsymbol{\lambda} \geq 0, 0 \leq \theta_i \leq 1 \end{aligned} \tag{1}$$

where **Y** and **X** are the output and input matrix, respectively; $\mathbf{y}_i$ and $\mathbf{x}_i$ are the output and input vector of the i–th DMU, respectively; $\boldsymbol{\lambda}$ is an $n \times 1$ vector, serving as a weight system to each DMU in forming an optimal combination of inputs and outputs, the frontier, for the i–th DMU; θ_i is a scalar for the i–th DMU, used to scale the $\mathbf{x}i$ to achieve the optimal combination of inputs, with a value of unity indicating a point on the frontier—a technically efficient DMU; and **I1** (**I1**' means its transpose) is an $n \times 1$ vector of unities, ensuring that the sum of all the weights assigned to the benchmarking DMUs equals 1. Thus, the fabricated benchmarks (the optimal combination of inputs and outputs) are similar in scale to the i–th DMU (Coelli *et al*., 2005), and so, the DEA model of Eq. (1) seeks to reduce the inputs as much as possible, relative to the empirically–constructed identical and optimal combination of inputs and outputs for each DMU.

Eq. (1) represents the VRS DEA model, and the θ_i showcases the pure technical inefficiency. Removed the constraint of $\mathbf{I1}'\boldsymbol{\lambda} = 1$, Eq. (1) becomes the CRS DEA model, and the corresponding θi indicates the total inefficiency (i.e., production or economic efficiency). If the θ_i obtained from the CRS DEA, differs from that calculated by the VRS DEA, there exists scale inefficiency (Coelli *et al*., 2005), which is the ratio of the total efficiency (i.e. CRS θ_i) to the pure technical inefficiency (i.e. VRS θ_i). Thus, the total efficiency is decomposed into two components arising from scale inefficiency and pure technical inefficiency (Li *et al*., 2018).

Effects of water management

In the second stage, the High–10 and Low–10 paddy fields (the ten fields with the highest and lowest technical efficiency, respectively) were analyzed based on the technical efficiency and slack measured in the DEA.

Based on Tsujimoto *et al*. (2009) and the model published by the Food and Agriculture Organization (Allen *et al*., 1998) and cited by Choudhury and Singh (2016), we divided the total growth duration into four stages. S1 included the 40 d from transplanting to fully tillering, S2 covered the duration from fully tillering to heading, S3 referred to the 25 d from heading to grain filling, i.e., the early–middle maturity stage, and S4 consisted of the remaining days until complete maturity (Fig. 2). Water management was measured in terms of water depth and temperature. The monitoring device consisted mainly of three parts: (1) the sensor head immersed in water to detect the depth and temperature, (2) the sensor box to process the data gathered and sent to the farming visualization system (FVS) via (3) the antenna. The FVS can report field–specific water depth and water temperature in form of maps, graphs, and tables. All are accessible by internet terminals or mobile apps, and thus, promote precise and efficient water management practices (Nanseki *et al*., 2016). Although being monitored every 10 min, the data used in this study was collected at 18:30 h, when the soil temperature was most easily affected by the performance of water management in the paddy fields (Matsue, 2016). Fig. 2 showed the varying water depths and temperatures at 18:30 h for all growth stages, in a paddy field of high production efficiency across the sample.

RESULTS

DEA analysis of production efficiency

The summary of efficiency in Table 2 showed that 19 paddy fields were fully efficient and served as benchmarks for the other paddy fields. For convenience of analysis, they were defined as Type I. The remaining 103 paddy fields had a total efficiency less than 1, within which 27 paddy fields had a technical efficiency score equal to 1 and were referred to as Type Ⅱ. This indicated that in these paddy fields, the production efficiency could only be improved through equi–proportional

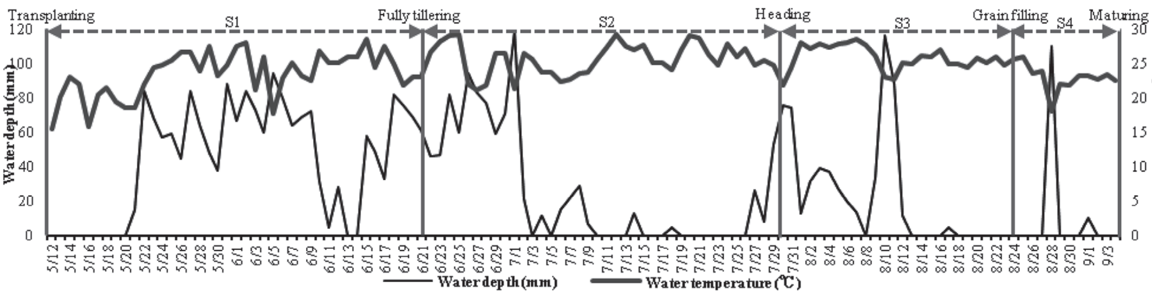

Fig. 2. Water management in a paddy field of high production efficiency, where the water depth and water temperature were monitored at 18:30 h, and divided into four growth stages from transplanting to maturation.

Table 2. Efficiency and status of returns to scale for the paddy fields in different types categorized in terms of their total, technical and scale efficiencies

Type	Number of DMUs	Mean of efficiency			Number of DMUs		
		Total	Technical	Scale	*crs*	*irs*	*drs*
I	19	1.000	1.000	1.000	19	0	0
Ⅱ	27	0.921	1.000	0.921	0	27	0
Ⅲ	76	0.884	0.987	0.895	0	76	0
Total	122	0.910	0.992	0.917	19	103	0

Note: *crs* = constant returns to scale; *irs* = increasing returns to scale; *drs* = decreasing returns to scale
Software: DEAP 2.1
Data source: Li *et al* (2017)

adjustments of all the inputs. Here, the scale should be increased according to the returns to scale information provided in the last columns of Table 2. An average scale efficiency of 0.921 indicated that the scale adjustment could increase the production efficiency by 7.9% (Coelli *et al*., 2005).

The 76 paddy fields left were referred to as Type Ⅲ, having a technical and scale efficiency less than 1. In these paddy fields, the production efficiency could be improved by reducing the inputs and increasing the scales, while keeping the outputs constant. The average technical efficiency of Type Ⅲ was 0.987, implying that 1.3% of the inputs could be reduced by eliminating technical inefficiency. Meanwhile, production efficiency could only be improved by 10.5% through increases in the scales of the paddy fields. For the entire sample, the total production efficiency could be improved by 9.0%, of which 0.8% could be fulfilled through technical improvement and, thus, input reduction, while about 8.3% could be realized by increasing the scales of 103 of the 122 paddy fields.

The slack of an output shows the margin for output improvement by a benchmarking DMU identified by DEA. Here, the output slacks occurred only in Type Ⅲ; the ratio of slack calculated in all paddy fields were less than that of Type Ⅲ (Table 3). For instance, considering the entire sample, the yields of the sorted brown rice and Type Ⅲ could be increased by 1.76% and 2.82%, respectively. Not much dispersion existed among the paddy fields, in terms of the different types of rice yields. Within the entire sample, the ratios of yield slack ranged from 1.7–3.0%, while in Type Ⅲ, they ranged from 2.8–5.0%. The largest and smallest slack ratios occurred in the raw paddy and sorted brown rice, respectively.

The DEAP 2.1 provided the input slack movement for each DMU. As mentioned above, for the paddy fields of Type I and Ⅱ, the pure technical efficiencies equaled 1, and hence, there was no margin needed to adjust the input, maintaining a constant output level. Therefore, radial and slack analysis was conducted only for Type Ⅲ.

In the DEA analysis, the slacks showed the inputs that were in excess supply or not completely used (Audibert *et al*., 2003). As shown in Table 3, land capacity had the largest slack of 13.81%, followed by field area with 5.94%, for all paddy fields, and the corresponding slacks increased to 21.64% and 10.86%, respectively, for Type Ⅲ. These ratios showed the relatively redundant or inefficient use of the two kinds of inputs. Meanwhile, the temperature, fertilizer nitrogen, and farming conditions demonstrated an efficient use by the much smaller slacks. The slack analysis of each variable, i.e., the constraining factor of each paddy field, could be beneficial in increasing the production efficiency through the appropriate adjustment of the inputs.

Effects of water management on production efficiency

In the second stage, we analyzed the effects of water management on the production efficiency measured by DEA. As mentioned above, we chose 20 paddy fields to represent paddy fields with high and low efficiency. The output and input variables were summarized in Table 4.

The paddy fields with high efficiency had higher yields than those with low efficiency for all the output variables. Moreover, the results of the t–test showed that the average yield per hectare of efficient paddy fields were significantly higher than that of the inefficient fields. For instance, according to the mostly used rice yield indicator in Japan, the average yield of sorted brown rice in High–10 paddy fields was 5715 kg per hectare, 795 kg (approximately 16%) higher than that of the Low–10 fields. Among the input variables, temperature,

Table 3. Output and input slacks of rice yield, of all the paddy fields and of Type Ⅲ. The slacks are shown in terms of both absolute values and percentages

Variable	All paddy fields				Type Ⅲ			
	Origin	Target	Slack	Slack (%)	Origin	Target	Slack	Slack (%)
Output: Yield (kg ha^{-1})								
Raw paddy	8058.98	8304.34	245.36	3.04	7926.96	8317.86	390.90	4.93
Paddy with 15% moisture	7358.73	7560.70	201.97	2.74	7257.63	7578.49	320.86	4.42
Unsorted brown rice	5934.22	6090.75	156.53	2.64	5855.25	6103.27	248.02	4.24
Sorted brown rice	5438.19	5533.67	95.48	1.76	5378.64	5530.29	151.66	2.82
Milled rice	4797.12	4902.08	104.96	2.19	4728.70	4890.35	161.65	3.42
Perfectly shaped rice	4111.93	4202.37	90.44	2.20	4083.58	4228.28	144.70	3.54
Input								
Field area (m^2)	1354.70	1274.25	80.44	5.94	1189.57	1060.43	129.14	10.86
Temperature (˚C)	26.19	25.98	0.21	0.80	26.26	25.93	0.33	1.27
Solar radiation (MJ m^{-2})	20.37	19.58	0.80	3.91	20.62	19.34	1.28	6.20
Fertilizer nitrogen (kg ha^{-1})	112.49	110.84	1.66	1.47	112.89	110.46	2.43	2.16
Land capacity	0.48	0.41	0.07	13.81	0.47	0.37	0.10	21.64
Farming condition score	33.97	33.41	0.55	1.63	34.35	33.47	0.88	2.56

Software: DEAP 2.1
Data source: Li *et al* (2017)

Table 4. Outputs and inputs of the High–10 and Low–10 paddy fields in terms of the technical efficiency measured using DEA. A t–test was conducted to calculate the significance of their differences

Paddy field	Output: Yield (kg ha^{-1})					
	Raw paddy	Paddy with 15% moisture	Unsorted brown rice	Sorted brown rice	Milled rice	Perfectly shaped rice
High–10	8521.72	7770.51	6251.73	5715.04	5086.84	4467.55
Low–10	7108.40	6518.14	5281.32	4919.50	4320.11	3809.73
Differ [1]	1413.32***	1252.37***	970.41***	795.53***	766.73***	657.82***
Paddy field	**Input variable**					
	Field area (m^2)	Temperature (°C)	Solar radiation (MJ m^{-2})	Fertilizer nitrogen (kg ha^{-1})	Land capacity	Farming condition score
High–10	1336	26.07	19.98	108.52	0.48	32.80
Low–10	1151	26.46	21.35	113.40	0.38	34.90
Differ [1]	185	–0.39***	–1.38**	–4.87	0.10	–2.10***

[1] the balance of high – low, **and ***indicate significance at 5% and 1% probability levels, respectively.

Table 5. Water depth and temperature of the High–10 and Low–10 paddy fields, in terms of the technical efficiency measured using DEA. A t–test was conducted to calculate the significance of their differences

Paddy field	Peer count [1]	Technical Efficiency	Water depth (Mean at 18:30 h, mm)				Water temperature (Mean of 18:30, °C)			
			S1	S2	S3	S4	S1	S2	S3	S4
High–10	24.9	1.000	36.72	22.18	16.43	5.58	23.26	26.23	26.16	23.00
Low–10	00.0	0.974	51.68	29.90	12.75	9.55	24.42	26.36	27.39	24.24
Differ [b]	24.9	0.026	–14.96**	–7.71	3.68	–3.97	–1.16**	–0.13	–1.23**	–1.24***

[1] the number of times it was a benchmark for other DMUs; b: the balance of high – low, **and ***indicate significance at 5% and 1% probability levels, respectively
Data source: Li *et al* (2017)

solar radiation, fertilizer nitrogen, and farming conditions of the efficient paddy fields were less than the corresponding variables of the inefficient fields. This indicated that higher yields and lower inputs were related to efficient production.

As shown in Table 5, the average water level was the deepest in S1. In this stage, a high water depth may have resulted in rotten roots or even plants thus, inhibiting yield and production efficiency. The average water depth of the Low–10 paddy fields was 51.68 mm, which was 40% higher than the average for the Top–10 fields. Thus, a lower average water depth benefitted the production efficiency. In these efficient fields, the average water depth for harvest preparation was the lowest in S4 followed by S3, where the lower water levels facilitated the top dressing and the decomposition of organic survival substances. On the other hand, higher water depths in S3 may have improved efficiency by resisting the strong evaporation and over–absorption of cadmium (Goto *et al*., 2000).

In contrast, the water temperature of the High–10 paddy fields was significantly lower than that of the Low–10 paddy fields, in S1, S3, and S4. In S3, the early–middle maturity stage included the 25 d from heading to grain filling, vital for starch accumulation. In this stage, especially after flowering occurs, lower temperature is necessary to facilitate the branching, extension, and vitality maintenance of the roots (Asaoka *et al*., 1985). In S4, a lower water depth and water temperature may have helped to resist lodging, constrain the activity of the plant, and facilitate harvesting conducted soon after the end of this stage. In the entire growth season, lower water temperature may limit over–evaporation thereby, preventing the withering of plants (Goto *et al*., 2000) thus, contributing to higher rice yields. Therefore, for the 20 paddy fields, technical efficiency was much more affected by water temperature than water depth. This finding was in accordance with Roel *et al*. (2005) and Saga *et al*. (2010), where water temperature was identified as the determining factor in rice production.

DISCUSSION

The DEA analysis conducted above mainly indicated two ways to increase rice production efficiency. The first was to eliminate the input slacks under the present scale and level of returns. This was adoptable in DMUs with a technical efficiency less than 1, i.e., the paddy fields of Type Ⅲ. According to the results summarized in Table 3, the largest average slack ratio occurred in land capacity. For each paddy field, land capacity was the compound value of five principals of 21 soil analysis indicators. Thus, in some paddy fields, land capacity was not completely cultivated because of the constraints of other resources. The field area was estimated to be positively related to rice yield in our previous studies (Li *et al*., 2016; Nanseki *et al*., 2016). The large average slack ratio indicated that an enlarged area of some paddy fields could increase efficiency. Although much smaller than the above two inputs, the average slack ratios of other input variables indicated additional ways and extents to which the inputs could be adjusted. Considering the significantly negative relationship as illustrated in Fig. 1, lower temperature and solar radiation were acceptable in some paddy fields, from dispersed farming plans and hence, postponed the dates of transplanting or sowing. Some paddy fields yielded less, relative to the improved farming conditions including a leveled height difference and fertility, irrigating system, illumination, and herbicide application. In addition, efficiency could be increased by reducing the amount of fertilizer, with a given content of nitrogen, used. In the second approach, the production efficiency could be increased by changing the scales. In other words, by increasing or decreasing the inputs with the same proportions, according to the status of returns to scale. As shown in Table 2, scale adjustments were applied to Type Ⅱ and Ⅲ, where scales of all the 103 paddy fields could be enlarged. Nevertheless, due to the law of diminishing returns to scale, there should be boundary values for the inputs. For instance, a significant quadratic relationship was detected between the average solar radiation during the 20 days after heading and rice yields, of which the optimal values ranged from 20.27 to 20.39°C. In addition, roughly 0.7 ha was measured as the optimal paddy area for the highest yields (Li *et al*., 2016). Thus, in establishing farming plans, it was necessary to conduct a general optimization considering interactions of the inputs and tradeoffs from costs and revenue, using professional technologies.

In the second stage, water temperature was measured as significantly affecting production efficiency. Thus, it was necessary to identify the determinants of water temperature from the perspectives of air temperature and water depth. Fig. 3 illustrated the average water depth (AWD), average air temperature (AAT), and average water temperature (AWT) at 18:30 h, of the 117 paddy fields in the growth stages of S1 through S4. It was obvious that the AWT varied closely with the AAT. In fact, a high correlation coefficient of 0.90, significant at 0.01, existed between the AWT and AAT. It indicated that the former was highly affected by the latter. Moreover, the AWT was higher than the AAT in each growth stage. In total, the AWT was 1.45°C higher than the AAT, across the four stages.

These relationships were illustrated in Fig. 4 (a), where a significantly linear regression was fitted between the AAT and AWT; the AWT was larger than the AAT in most cases, as represented by the diagonal line. However, the CVs of AWT and AAT were 11.94% and 15.49%, respectively. Thus, it showed that water temperature was more stabilized, and it helped to maintain the land temperature, which promoted plant growth. In addition, the average technical efficiency of the Low–10 paddy fields was 0.974, only 0.026 lower than that of the High–10 paddy fields (Table 5). This indicated that little inequality existed in the efficiency of the paddy fields sampled from the same farm. In total, the means of water temperature and air temperature were 25.02°C and 23.57°C, respectively, while the CVs were 11.94% and 15.49%, respectively. Hence, water functioned in maintaining the land temperature.

In contrast, no significant linearity was observed between water depth and water temperature, as shown in Fig. 3 and Fig. 4 (b). Nevertheless, a significant quadratic relationship was identified and fitted between the variables. Calculations based on the equation shown in Fig. 4 (b), showed that the AWT peaked when the AWD was roughly 36 mm, over the entire growth season. This implied that before reaching this threshold, the water temperature was preserved with increasing depths. On the other hand, heat from solar radiation and the air was separated when the water depth exceeded this threshold. Thus, to some extent, the water temperature could be adjusted by properly controlling the water depth.

CONCLUSIONS

The results of the DEA showed that among the 122 paddy fields, 19 paddy fields were fully efficient and acted as benchmarks for the other inefficient paddy fields. There were 27 paddy fields with technical efficiency scores of 1, indicating that an input adjustment did not change the output efficiency. Thus, in these paddy fields, increasing the scales was the only solution for improving production efficiency. There remained 76 paddy fields with technical efficiencies less than 1, where inputs could be reduced further. Altogether, in more than 84% of the paddy fields, the efficiency could be increased by increasing the scales. Slack analysis of the outputs showed that not much of a margin existed between the yields of the six types of rice. The largest slack ratios were observed in the raw paddy and sorted brown rice, respectively. From our analyses and the similar CVs of the yields shown in Table 1, we concluded that that the quantity and quality were balanced by large, among the paddy fields. On the other hand, slack analysis of the inputs indicated that land capacity had the largest slack, followed by field area, in terms of relatively redundant or inefficient usage. In contrast, the temperature, fertilizer nitrogen, and farming conditions showed efficient usage with the smallest slacks. Further comparisons indicated that the efficient paddy fields yielded significantly more than those with low efficiency. Among the input variables, temperature, solar radiation, fertilizer nitrogen, and farming conditions of the high–efficiency paddy fields had lower values than those of the inefficient fields. Thus, higher yields and lower inputs related to efficient production.

A comparison of water management practices indicated that in S1 alone, the water depth of the High–10 paddy fields was significantly lower than that of the Low–10 paddy fields. In contrast, the average water temperature of the High–10 paddy fields was significantly lower than that of the Low–10 paddy fields, in all stages, except for S3. In these 20 paddy fields, water temperature and depth in all the four growth stages except for S3 were identified as significant to the meas-

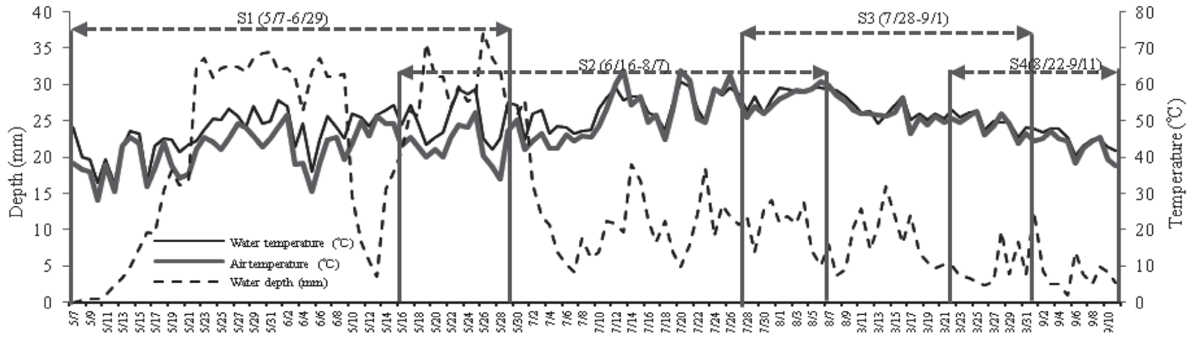

Fig. 3. Average water depth, air temperature, and water temperature, at 18:30 h, of the 117 paddy fields across the four growth stages.

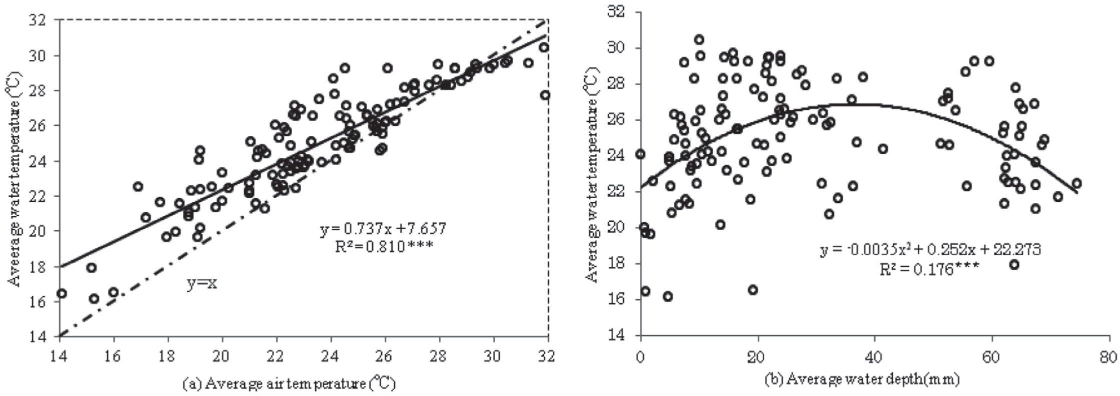

Fig. 4. Average air temperature (AAT), water temperature (AWT), and water depth (AWD) at 18:30 h across the four growth stages in the 20 paddy fields.

urement of technical efficiency, although the direction of the effect, positive or negative, varied in different stages. Taking the paddy fields as a whole, further discussion revealed that water temperature was linearly affected by air temperature. Moreover, a significant quadratic relationship showed that water temperature peaked at a water depth of approximately 36 mm, thus the water temperature could be adjusted by properly controlling the water temperature.

Therefore, water management, including depth and temperature, is an essential factor affecting rice production. In addition to real–time monitoring, an analysis of the interactions, effects, and determinants of water managerial indicators are necessary for increasing rice yield and technical efficiency. Thus, in future studies, the DEA models should be expanded to incorporate non–discretionary variables, e.g., the stage–specific average and the corresponding daily ranges of air temperature and solar radiation. Furthermore, other empirical models — e.g., covariance structure analysis and multivariate regression — could be adopted to identify the effects of the yield determinants, including water temperature, and the interactions between them.

AUTHOR CONTRIBUTIONS

All listed authors have contributed in this manuscript. Dongpo Li carried out the detail study design, statistical analysis and drafted the manuscript. Teruaki Nanseki built up the research flame and carried out the basic study design as well as advised the interpretation of statistical analysis and edited the manuscript. Yosuke Chomei assisted in the study design, advised the data interpretation and edited the manuscript. All authors have read and approved the final version that builds on the manuscript of **"Two–Stage DEA on Technical Efficiency and the Effect of Water Management on Rice Production of 122 Paddy Fields from a Large–Scale Farm in Japan"**.

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REFERENCES

Abdullah, D. and S. Ali 2014 Influence of subsurface drainage on the productivity of poorly drained paddy fields, *Eur. J. Agron.*, **56**: 1–8

Aigner, D., C. K. Lovell and P. Schmidt 1977 Formulation and estimation of stochastic frontier production function models, *J. Econometrics*, **6**: 21–37

Allen, R. G., L. S. Pereira, D. Raes and M. Smith 1998 *Crop Evapotranspiration: Guidelines for Computing Crop Water Requirements. United Nations Food and Agriculture Organization, Irrigation and Drainage Paper 56*, Rome, Italy: pp. 95–97, 103–109. Retrieved on Oct 14, 2018 from:

https://appgeodb.nancy.inra.fr/biljou/pdf/Allen_FAO1998.pdf

Asaoka, M., K. Okuno, T. Sugimoto and H. Fuwa 1985 Developmental changes in the structure of endosperm starch of rice (Oryza sativa L.), *Agr. Biol. Chem.*, **49**: 1973–1978

Audibert, M., J. Mathonnat and M. C. Henry 2003 Social and health determinants of the efficiency of cotton farmers in Northern Côte d'Ivoire, *Soc. Sci. Med.*, **56**: 1705–1717

Banker, R. D., A. Charnes and W. Cooper 1984 Some models for estimating technical and scale inefficiencies in data envelopment analysis, *Manage. Sci.*, **30**: 1078–1092

Barrett, C. B., M. F. Bellemare and J. Y. Hou 2010 Reconsidering conventional explanations of the inverse productivity–size relationship, *World Dev.*, **38**: 88–97

Bouman, B. A. M. and T. P. Tuong 2001 Field water management to save water and increase its productivity in irrigated lowland rice, *Agr. Water Manage.*, **49**: 11–30

Charnes, A., W. Cooper and E. Rhodes 1978 Measuring the efficiency of decision–making units, *Eur. J. Oper. Res.*, **2**: 429–444

Choudhury, B. U. and A. K. Singh 2016 Estimation of crop coefficient of irrigated transplanted puddled rice by field scale water balance in the semi–arid Indo–Gangetic Plains, India, *Agr. Water Manage.*, **176**: 142–150

Coelli, T. J., D. S. P. Rao, C. J. O'Donnell and G. E. Battese 2005 *An Introduction to Efficiency and Productivity Analysis* (2nd edition), Springer, New York, US: pp. 211–213, 261

Goto, Y., Y. Nitta and S. Nakamura 2000 *Crops I: Paddy Cultivation, Japan Agricultural Development and Extension Association (JADEA)*, Tokyo, Japan: pp. 137–142 (in Japanese)

Farrell M. J. 1957 The measurement of productive efficiency, *J. R. Stat. Soc.*, **120**: 253–290

Hirai, Y., K. Saruta and K. Hamagami 2012 Evaluation of an analytical method to identify determinants of rice yield component and protein content, *Comput. Electron. Agr.*, **83**: 77–84

Komenet 2018 *Planting areas of the major Japonica varieties in Japan*, Retrieved on Oct 15, 2018 from: http://www.komenet.jp/jukyuudb/826.html (in Japanese)

Kozak, M., P. K. Singh, M. R. Verma and D. K. Hore 2007 Causal mechanism for determination of grain yield and milling quality of lowland rice, *Field Crop Re.*, **102**: 178–184

Li, D., T. Nanseki, Y. Matsue, Y. Chomei and S. Yokota 2016 Determinants of paddy yield of individual fields measured by IT combine: empirical analysis from the perspective of large–scale farm management in Japan, *Agr. Inf. Res.*, **25**: 39–46

Li, D., T. Nanseki, Y. Chomei, T. Sasaki and T. Butta 2017 Technical Efficiency and the Effects of Water Management on Rice Production in Japan: Two–Stage DEA on 122 Paddy Fields of a Large–Scale Farm, *Annual Symposium of the Farm Management Society of Japan, Sep. 16, Kyushu University, Fukuoka City, Japan*, Retrieved on Oct 14, 2018 from: https://fmsj.jp/?action=common_download_main&upload_id=568&nc_session=cdd339debc6ab540062946d9893879c8

Li, D., T. Nanseki, Y. Chomei and S. Yokota 2018 Production efficiency and effect of water management on rice yield in japan: two–stage DEA analysis on 110 paddy fields of a large–scale farm, *Paddy Water Env.*, **16**: 643-654

MAFF 2016a *Statistics on the paddy yield of Japan in 2014*, Retrieved on Nov 21, 2017 from: http://www.maff.go.jp/j/tokei/kouhyou/sakumotu/sakkyou_kome/pdf/syukaku_suiriku_14.pdf (in Japanese)

MAFF 2016b *Statistics on agricultural production costs of Japan*, Retrieved on Nov 21, 2017 from: http://www.maff.go.jp/j/tokei/sihyo/data/12–2.html (in Japanese)

Matsue, Y. 2016 Rice production technology for yield and quality improvement of high temperature during the ripening period. In: *Proceeding of the Annual Symposium of the Japanese Agricultural Systems Society*, Fukuoka, Japan: pp. 9–10 (in Japanese)

Nanseki, T., Y. Chomei and Y. Matsue [Ed] 2016 *Rice Farm Management Innovation and Smart Agriculture in TPP Era: Farming Technology Package and ICT Applications*, Yokendo, Tokyo, Japan: pp. 2–22, 128–135, 168–178, 198–237 (in Japanese)

Nanseki, T. [Ed] 2019 *Smart Agriculture Practice in Rice–farming and Perspective of farm in next–generation*, Yokendo, Tokyo, Japan, 363 (in Japanese)

NRCS (National Resources Conservation Services, USDA) 2017 *Water Management– NRCS National Ag Water Management (AGWAM) Team*, Retrieved on Nov 20, 2017 from: https://www.nrcs.usda.gov/wps/portal/nrcs/main/national/water/manage/

Roel, A,, R. G. Mutters, J. W. Eckert and R. E. Plant 2005 Effect of low water temperature on rice yield in California, *Agrono. J.*, **97**: 943–948

Saga, K., K. Imou, S. Yokoyama and T. Minowa 2010 Net energy analysis of bioethanol production system from high–yield rice plant in Japan, *Appl. Energ.*, **87**: 2164–2168

Sellamuthua, R., G. Liu, C. Ranganathan and R. Serraj 2011 Genetic analysis and validation of quantitative trait loci associated with reproductive-growth traits and grain yield under drought stress in a doubled haploid line population of rice (Oryza sativa L.), *Field Crop Re.*, **124**: 46–58

Tao, Y., Y. Zhang, X. Jin, G. Saiz, R. Jing, L. Guo, M. Liu, J. Shi, Q. Zuo, H. Tao, K. Butterbach–Bahl, K. Dittert and S. Lin 2015 More rice with less water: evaluation of yield and resource use efficiency in ground cover rice production system with transplanting, *Eur. J. Agron.*, **68**: 13–21

Tsujimoto, Y., T. Horie, H. Randriamihary, T. Shiraiwa and K. Homma 2009 Soil management: the key factors for higher productivity in the fields utilizing the system of rice intensification (SRI) in the central highland of Madagascar, *Agr. Syst.*, **100**: 61–71

Wang, Z., W. Zhang, S. Beebout, H. Zhang, L. Liu and J. Zhang 2016 Grain yield, water and nitrogen use efficiencies of rice as influenced by irrigation regimes and their interaction with nitrogen rates, *Field Crop Re.*, **193**: 54–69