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Yield Prediction Modeling Using Data Envelopment Analysis Methodology for Direct Seeding, Wetland Paddy Cultivation

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Abstract

A yield prediction model was developed using measured energy inputs data from 40 wetland paddy farms in Malaysia. Energy inputs from six sources were optimized using benchmarking and data envelopment analysis. The model developed based on Cobb-Douglas production function has coefficient of determination (R^2) of 91%. Analysis on the model revealed direct relationship of yield with machinery, fuel, fertilizer and pesticides energy expenditures and an inverse relationship of yield with seeding rate. Hence, suggesting the need to reduce farmers’ present seeding rate of 149 kg/ha to the optimum seeding rate of 128 kg/ha for higher yield and cost reduction.

Keywords: Wetland paddy cultivation; field energy expenditure; yield modeling; energy analysis; data envelopment analysis; Cobb-Douglas production function; optimization

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1. Introduction

Paddy cultivation has been an employment source to 150,000 people in Malaysia. Those who were involved depended exclusively on paddy cultivation for their source of income. At the government level, paddy is treated as a security crop and the staple food in the country. Typically the country produces about three quarter of its annual requirements for rice (Nawi et al., 2012) amounting to 2.75 million tons cultivated from 692,340 ha of farmlands (FAOSTAT, 2014). The shortfall in rice supply is met through imports from neighbouring countries such as Thailand, Vietnam and Pakistan. There are eight irrigation schemes located across the country that practices double

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cropping per year and they produced about 72% of the total wetland paddy in the country (Najim et al., 2007). Although over the years Malaysian Agricultural Research and Development Institute (MARDI) has successfully developed several good varieties having potential of more than 10 tons/ha, wide productivity gap still exists within and between schemes (DOA, 2010) which is a strong barrier for its quest to achieve the desired 100% level of self-sufficiency in paddy production with the given limited paddy cultivation area. Furthermore, it is worth mentioning here that paddy production in Malaysia is still expensive compared to what obtains in some neighbouring countries. As a matter of fact, the country lacks a competitive advantage (Murad et al., 2008), suggesting that the paddy production in the country be neither viable nor sustainable (Man and Sami, 2009). One possible way of raising farm productivity at reduced cost is through optimum use of resources to which on-farm energy analysis plays a central role by addressing the issues of excess energy utilization.

Traditional energy research in crop production revolve mainly around input and output analysis targeted at determining various measures of energy utilizations including energy use efficiency, energy intensity and energy productivity as reported in (Dahzong and Pimentel, 1984; Huge and Huge, 1990; Gajaseni, 1995; Ozkan et al., 2004; Bockari-Gevao et al., 2005; Chamsing, 2006). Other energy researches particularly those relating to the cultivation of rice offered a comparative analysis of energy requirements covering different cultivation systems (Freedman, 1980; Mendoza, 2002; Bautista and Minowa, 2010). Najim et al. (2010) reported irrigation energy requirement for lowland rice cultivation in farms equipped with pumping facilities in Malaysia as 12383.5 MJ/ha and 9341.2 MJ/ha for offseason and main season, respectively. In recognition of the rising cost of farm inputs, there is now a shift in emphasis on energy analysis in crop production towards finding values of energy inputs to culminate in optimum yield. Several optimization techniques have been tried to varying degrees by previous researchers. Singh et al. (2004) used linear programming model to optimize the energy input for wheat production in Punjab, India. The result of the study revealed that farmers in zone one could save about 22.26% of the energy inputs without affecting the current wheat productivity. Chauhan et al. (2006) used data envelopment analysis (DEA) methodology in their study to segregate the energy use levels between efficient and inefficient farmers. The study revealed that farmers could save about 11.6% of the total energy inputs used in the production without lowering yield. Other studies in energy analysis in crop production that employed DEA to quantify the level of excess energy use by farmers are reported in Nassiri and Singh (2009), Eyitayo et al. (2011), Banaeian et al. (2011) and Mohammadi et al. (2011).

Efficient management of resources in any production system relates with producing outputs with maximum economic returns. A mathematical model that relate inputs with output is used by researchers to gain insight on the responses of output due to changes in inputs, so that the most influencing input variables are managed for maximum yield. In crop production, yield is globally acknowledged as having a positive correlation with energy input (Singh, 1999). Knowledge about this relationship stirs the interests of researchers towards performing energy analysis with a view to improve performance of the production system through modelling. Several energy studies in crop production, linking energy flows with crop yield are available in the literature (Singh et al., 1994; Baruah and Dutta, 2007; Mohammadi and Omid, 2010). However, current available models do not predict optimum yield a farmer should expect from a given level of energy inputs, since they generally resulted from regressing crop yield on basic energy input data which have not been optimized. Thus, it is desirable for a farmer to have a user friendly model that can predict optimum yield for a given level of primary energy inputs. The model could readily serve as a useful tool for performance appraisal of previous paddy cultivations and quantified the level of underperformance for appropriate remedial to be taken to improve future paddy productivity. Until to date, there are no energy studies in Malaysia that investigated optimum energy input in direct seeding paddy cultivation system and relate it with the crop yield. Therefore, this study was undertaken to develop a yield predictive model by employing Cobb-Douglas production function on the measured paddy cultivation data (energy input and output) that be subjected to DEA and benchmarking methodology.

2. Materials and methods

The study was conducted at Block E5 Parit Lima Timur, Sungai Besar District of Selangor, Malaysia during the March to July, 2013 of the rice cropping season. The block is located at 3°41'51.60" to 3°41'19.01" latitude and 101°01'21.09" to 101°01'59.51" longitude. It has a net land area of 27.005 ha and is divided into 40 farm lots with area ranging from 0.255 – 1.125 ha and the average area of 0.675 ha. Data were collected on six farm inputs (human labour, machinery, fuel, seeds, fertilizer and pesticides) involving six field operations (tillage, seeding, fertilizing, spraying, harvesting and slashing operations) from the 40 farm lots. No, any data collection was made in respect of pumping operation for irrigation because all the farmers follow the scheduled water distribution under the scheme throughout the cultivation period. The source-wise energy budget in MJ/ha, total input energy, total output energy, energy use efficiency and energy intensity in each farm were then computed using classical equations as given in Eq. (1) to (10).

$$ME = \frac{Cf * W}{Fc * L} \tag{1}$$

Where ME is machinery energy (MJ/ha), Cf is energy conversion factor for machinery used (MJ/kg), W is weight of machinery (kg), Fc is the effective field capacity (ha/h) and L is economic life of machinery (h). The economic life of farm machineries used by the farmers was obtained from farm machinery management standard produced by ASABE (2006) as follows: 2 wheel drive tractor 12000 h, self-propelled combine harvester 3000 h, rotary tiller 1500 h, sprayer 1500 and spreader 1200 h. The energy conversion factors used for the machineries were assumed to be 96.61, 87.63 and 62.70 MJ/kg respectively for tractor, self-propelled combine harvester and others (Canakci et al., 2005).

$$FE = \frac{fcon * fc}{A} \tag{2}$$

Where FE is fuel energy (MJ/ha), $fcon$ is fuel consumed (l), fc is fuel energy conversion factor (47.80 and 46.30 MJ/l for diesel and petrol respectively. Gajaseni, 1995) and A is size of the farm (ha).

$$HE = \frac{H * lc}{A} \tag{3}$$

Where HE is human energy (MJ/ha), H is duration of operation (MJ/kg) and lc is energy conversion factor for human labour (1.96 MJ/h, Gajaseni, 1995).

$$SE = \frac{Sq * sc}{A} \tag{4}$$

Where SE is seed energy (MJ/ha), Sq is weight of seeds used (kg) and sc seed energy conversion factor (16.74 MJ/kg, Gajaseni, 1995). The total output energy due to paddy yield was also computed using Eq. (4).

$$\mathrm{PE} = \frac{Pq * Pc}{A} \tag{5}$$

Where PE is pesticides energy (MJ/ha), Pq is weight of pesticides used (kg) and Pc pesticides energy conversion factor (120 MJ/kg as in Mohammadi and Omid, 2010).

$$FTE = \frac{FTq * \sum_{i=1}^{n} FTi * FTci}{A} \tag{6}$$

Where FTE is fertilizer energy (MJ/ha), FTq is weight of fertilizer used (kg), FTi percent composition of i^{th} element (decimal) and $FTci$ is the energy conversion factor for the i^{th} fertilizer element (61.53, 12.56 and 6.70 MJ/kg respectively for nitrogen, phosphorus and potassium as in Pimentel and Pimentel, 1979 and 1 MJ/kg for organic fertilizer as in Khosruzzaman, 2010). The total energy budget in MJ/ha associated with wetland paddy cultivation in each farm lot is then determined using the following expression:

$$TEI = ME + FE + HE + SE + PE + FTE \tag{7}$$

Where TEI = Total energy input (MJ/ha) and ME, FE, HE, SE, PE, FTE are as defined previously.
Finally, the total energy output, energy use efficiency and energy intensity were calculated from Eq. (8) to (10).

$$TEO = Y * sc \tag{8}$$

Where $TOE =$ Total energy output (MJ/ha), Y = crop yield obtained (kg/ha) and sc is as defined previously.

$$EE = \frac{TEO}{TEI} \tag{9}$$

Where EE = energy use efficiency (decimal), TEO and TEI are as defined previously.

$$EI = \frac{TEI}{Y} \tag{10}$$

Where EI = energy intensity (MJ/kg), TEI and Y are as defined previously.

In order to quantify the level of inefficiency regarding each of the farm inputs used by the farmers in the block, the input and output data from the 40 farm lots were subjected to data envelopment analysis (DEA). The DEA as a performance analysis methodology helps in the effective segregation between farmers who are efficient in resource utilization and those that are not. Using the methodology facilitates in computing the technical efficiency which is expressed as the ratio of the sum of the weighted output to the sum of weighted input and it ranges between zero and one. If the calculated value for a farm is one, it is regarded as efficient and if less than one it is inefficient in resource use. The input oriented CCR model was considered in this study which in a form of linear program (Charmes et al. 1978) for computing the technical efficiencies is given in Eq. (11).

Maximize $\theta = \sum_{i=1}^{n} u_i y_{ij}$ (11)

Subject to:

(i) $\sum_{i=1}^{n} u_i y_{ij} - \sum_{s=1}^{m} v_s x_{sj} \leq 0$

(ii) $\sum_{s=1}^{m} v_s x_{sj} = 1\, for\ all\ j = 1, 2, \ldots, k$

(iii) $u_i \geq 0, for\ all\ i = 1, 2, \ldots, n$

(iv) $v_s \geq 0, for\ all\ s = 1, 2, \ldots, m$

Where θ = technical efficiency, y = output, x = input, u and v = weights assigned to output and input respectively, i and s = number of outputs ($i = 1, 2, \ldots, n$) and inputs ($s = 1, 2, \ldots, m$) respectively and $j = jth$ DMU under evaluation ($j = 1, 2, \ldots, k$).

Our objective of using DEA is to determine the optimum energy inputs in direct seeding wetland paddy cultivation among the selected farm lots in Malaysia and use the results to develop an optimum yield predictive model for assessment appraisal of farmers engaged in direct seeding paddy cultivation. The DEA model was run using energy input data from five operations namely tillage, seeding, fertilizing, spraying and harvesting operations and one output data the paddy yield. The model was developed using Cobb-Douglas production function given in Eq. (12) to (13) and its variables tested for autocorrelation using Durbin-Watson statistics (Mohammadi and Omid, 2010; Ozkan et al., 2011). The return to scale as a measure of the quantitative response in output due to a proportionate change in input was determined using Eq. (14).The marginal physical productivity (MPP) expressed in Eq. (15) was used for sensitivity analysis on the model's variables to determine their individual impact on yield.

$$Y = f(X).\exp(u) \tag{12}$$

This in linear form is rewritten as follows:

$$\ln(Y_I) = a + \sum_{j=1}^{k} \beta_j \ln(X_{ji}) + u_i \quad i = 1, 2, 3, \ldots, n \tag{13}$$

Where Y_i = paddy yield of ith farmer, a = intercept, β_j = coefficient of inputs and u_i = error term.

$$RTS = \sum_{j=1}^{k} \beta_j \tag{14}$$

Where RST = return to scale and β_j is as defined previously.

$$MPP_{ij} = \frac{GM(Y)}{GM(X_j)} \times \alpha_j \tag{15}$$

Where MPP_{ij} = marginal physical productivity of input j, GM(Y) = geometric mean of yield, $GM(X_j)$ = geometric mean of input j and α_j = regression coefficient of input j.

3. Results and discussion

3.1. Energy ratio analysis

The outcome of the DEA analysis on the energy input and output data of the 40 farm lots studied, showed that 15 farms were efficient, and the remaining 25 farms were inefficient in terms of farm inputs utilization in performing the paddy cultivation operations. About 44% of the inefficient farms had technical efficiency greater than 90%, with 56% of the inefficient farms having efficiency score of less than 90%. The mean technical efficiency for all the farm was 91.44% which is higher than that reported for paddy farms in India of 77.20 (Chauhan et al., 2006). Implying that paddy farmers in Malaysia on the average are technically more efficient in using available farm inputs compared to their counterparts in India. There is higher used of manual labour (2291.30 MJ/ha) and less machinery involvement (360.80 MJ/ha) in paddy farms in India compared to the used of human and machinery energy expenditure of 40.25 and 452.87 MJ/ha respectively on paddy farms in Malaysia. The result in this study, revealed that majority of the farms are technically inefficient, hence greater opportunity exist for them to improve on their performance by adopting practices of the efficient farms. As shown in Table 1, the inefficient farms used about 16.14% (2770.495 MJ/ha) higher mean energy input and obtained about 10% less yield compared to that of the efficient farms. Paddy yield was 8.076 and 7.355 tons/ha for efficient and inefficient farms respectively, with a mean value for all the farms of 7.625 tons/ha.

Table 1. Comparison of energy ratios for efficient and inefficient farms.

Details	Efficient farms	Inefficient farms
Energy input, MJ/ha	14397.670	17168.165
Energy output, MJ/ha	135192.030	123120.861
Energy gain, MJ/ha	120794.360	105952.696
Energy efficiency, %	948.600	738.500
Energy intensity, kg/MJ	0.567	0.441
Energy productivity, MJ/kg	1.807	2.349
Labour productivity, h/ton	2.387	2.897
Fuel productivity, l/ton	6.014	7.815
Technical efficiency	1.000	0.863

In terms of energy intensity, the efficient farms outperformed the inefficient farms by about 126g/MJ representing about 22.22% more paddies per unit energy expended. Comparison of labour productivity revealed a man-hour labour difference of 0.51 h/ton being less in efficient farms. Similarly, efficient farms had higher fuel use productivity compared to the inefficient farms with less fuel usage of about 1.801 l/ton (23.05%).

3.2. Determination of excess energy usage through benchmarking technique

As shown in Table 2 the mean observed energy input used by the farmers in cultivating one hectare of wetland paddy involving the five operations considered in the study and six energy sources was 16,129.230 MJ/ha which is about 18.07% greater than the mean optimum energy expenditure of 13,214.311 MJ/ha obtained through benchmarking methodology. The same level of paddy productivity of 7.625 tons/ha could be achieved with less mean energy input of 2,914.92 MJ/ha. In India, Chauhan et al. (2006) found excess usage of energy inputs of about 11.60% among paddy farmers. In terms of the individual energy inputs, the required reduction ranges from 12.11% for machinery to 20.30% for fertilizer. The result revealed that the farmers wasted about one-fifth of the fertilizer they used. Reduction in the used of fertilizer could be achieved by adopting practices such as a split application at proper interval and use of leaf test for detecting paddy plant nitrogen requirement (Yan et al., 2008).

Table 2. Observed versus optimum mean energy input based sources, MJ/ha.

Source	Observed	Optimum	Reduction	% Reduction
Human energy	40.249	34.207	6.042	15.01
Fuel energy	2545.087	2161.914	383.173	15.06
Machinery energy	452.874	398.020	54.854	12.11
Fertilizer energy	9931.306	7914.839	2016.466	20.30
Chemical energy	666.854	564.701	102.153	15.32
Seeds energy	2492.860	2140.631	352.229	14.09
Total	16129.230	13214.311	2914.919	18.07

3.2.1. Comparison of observed versus optimum human energy expenditures

As shown in Table 3, farmers in the study area could save about 15.01% (6.042 MJ/ha) or 3.083 h/ha of human labour expended, perhaps through proper work planning and management. The highest possible reduction is in fertilizing operation where about 2.576 MJ/ha representing 1.314 h/ha of human labour was in excess of the optimum requirements. The least reduction for human labour is in the harvesting operation with computed excess usage of 0.298 MJ/ha (about 9 min/ha). Although the desired reduction in human labour engagement, in the harvesting operation is insignificant, the need for the reduction may be a highlight on the fragmented nature of the farmlands that hinders combines' field capacity, hence requiring more machineries field time.

Table 3. Observed versus optimum mean human energy expenditure based operations, MJ/ha.

Operations	Observed	Optimum	Reduction	% Reduction
Tillage	5.634	4.632	1.001	17.77
Planting	3.054	2.491	0.563	18.43
Fertilizing	11.396	8.820	2.576	22.60
Spraying	17.153	15.548	1.604	9.35
Harvesting	3.013	2.716	0.298	9.89
Total	40.249	34.207	6.042	15.01

3.2.2. Comparison of observed versus optimum fuel energy expenditures

The mean observed energy embodied in the fuel was 2545.087 MJ/ha and is higher than the computed optimum fuel energy requirement by 15.06% as indicated in Table 4. About 15.06% of the current fuel used in the cultivation is wasted through suboptimal use of machinery. The highest fuel energy reduction suggested by benchmarking approach is in tillage operation with required reduction of 135.735 MJ/ha or about 2.84 l/ha of diesel used. The desired reduction in fuel consumption is achievable if the tractor operators adhere to driving practices capable of enhancing tractor field capacity. For example, by avoiding excessive overlaps, multiple passes over an already ploughed area, unnecessary circular turns at headland section of the fields and in stopping the habit of leaving the rotavator to remain engaged with soil throughout the period of operation, regardless of whether the tractor is turning at headland, reversing or moving forward. The least fuel reduction required to achieve optimum utilization is in the planting operation. Interestingly planting operation is done using knapsack power blowers same as those used in fertilizer application. However to achieve optimum fuel use efficiency farmers must reduce their fuel energy expenditure for fertilizing operation by about 2.39 times compared to the required reduction for fuel energy expenditure in the planting operation. The result showed the cumulative effect of higher application frequency in fertilizing operation (4.45 times) compared to planting operation performed only once.

Table 4. Observed versus optimum mean fuel energy based operations, MJ/ha.

Operations	Observed	Optimum	Reduction	% Reduction
Tillage	1022.455	886.720	135.735	13.28
Planting	51.041	35.747	15.295	29.97
Fertilizing	138.181	101.631	36.550	26.45
Spraying	384.448	284.277	100.171	26.06
Harvesting	948.961	853.539	95.422	10.06
Total	2545.087	2161.914	383.173	15.06

3.2.3. Comparison of observed versus optimum machinery energy expenditures

Table 5 shows that on the average farmers used 452.87 MJ/ha machinery energy in performing the five operations included in the study. However, about 12% of the machinery energy was used in excess of the optimum as suggested by benchmarking technique. The result suggests that farmers could achieve the same level of yield with less machinery energy expenditure of about 54.854 MJ/ha 60.67% (33.28 MJ/ha) comes from harvesting operation.

Table 5. Observed versus optimum mean machinery energy based operations, MJ/ha.

Operations	Observed	Optimum	Reduction	% Reduction
Tillage	108.729	88.282	20.447	18.81
Planting	0.945	0.783	0.162	17.14
Fertilizing	2.413	1.951	0.461	19.10
Spraying	3.972	3.470	0.502	12.64
Harvesting	336.814	303.533	33.281	9.88
Total	452.874	398.020	54.854	12.11

Tillage is the next operation requiring considerable machinery energy reduction where about 18.81% of the current machinery energy for the operation was in excess of the optimum, thus constituting about 37.28% of the total excess machinery energy used in wetland paddy cultivation. As for planting, fertilizing and spraying operations their collective required reduction for machinery energy is barely about 2% (1.126 MJ/ha) of the total excess machinery energy expenditure. The result clearly portrays the huge manual labour inclusion in performing the three operations. The required reductions could be achieved perhaps either by reducing machinery field time, increasing farmland area so as to boost machinery field capacity or reducing the frequency of some of the operations such as tillage.

3.2.4. Comparison of observed versus optimum fertilizer use rate

Table 6 reveals an excess usage of up to 19.91 kg/ha or about 15.28% of the current mean nitrogen use rate. Less pronounced excessive usage for phosphorus, potassium and magnesium oxide were also recorded as being 3.62, 3.21 and 0.26 kg/ha respectively. The observed nitrogen use rate of 130.311 kg/ha is about 11% higher than the reported average nitrogen use rate of 116.9 kg/ha in eight major Asian rice producing countries (Dobermann et al., 2002). Although the use of mineral fertilizer is an essential key to achieving bumper harvest (Uhlin, 1999), its overuse could lead to contamination of groundwater supply, the accumulation of nitrate on vegetative plants parts and elevated emission of nitrous oxide in the air (Yan et al., 2008) all of which contributes negatively to sustainable paddy cultivation.

Table 6. Comparison of observed versus optimum mean fertilizer use rate, kg/ha.

Details	Nitrogen	Phosphorus	Potassium	Magnesium Oxide
Observed	130.311	49.303	76.065	4.033
Optimum	110.405	45.681	72.852	3.773
Reduction	19.906	3.622	3.213	0.260
% Reduction	15.280	7.350	4.220	6.450

3.2.5. Comparison of observed versus optimum chemical pesticides use rate

An observed mean pesticides application rate of 5.557 comprising of insecticides, herbicides and fungicides were recorded in the study block as presented in Table 7. The result reveals that about 15.31% of the total pesticides was used in excess of the optimum. The highest reduction required to achieve optimum utilization for the chemicals was in herbicides, with demand reductions of up to 23.24% of the current mean application rate. Insecticides use rate has the least demand reduction of 4.58% even though it has the highest share contribution in terms of the total amount of pesticides used by the farmers. Key to realizing optimum benefits in the use of pesticides includes adherence to manufacturer’s recommendations both in terms of mixing formulation and dosage applied per hectare.

Table 7. Comparison of observed versus optimum pesticides used rate, kg/ha.

Pesticides	Insecticides	Herbicides	Fungicides	Total
Observed	1.813	2.935	0.809	5.557
Optimum	1.730	2.253	0.722	4.706
Reduction	0.083	0.682	0.087	0.851
% Reduction	4.580	23.240	10.75	15.31

3.2.6. Comparison of observed versus optimum seed use rate

A mean seeding rate of about 149 kg/ha was used by the farmers in the study area which was found to be 14.09% (21 kg/ha) in excess requirements. Although all the farmers in the study area used direct seeding method of paddy establishment which requires high seed rate for effective weed control, over-seeding leads to intra-plant competition with attendant yield decline due to a reduction in the size and number of panicles produced and filled grains. Study conducted by Upasani et al. (2012) showed that seeded wetland paddy sown with seeding rate of 80 kg/ha gives higher yield than those sown using seeding rates of 60, 100, and 120 kg/ha.

3.3. Optimum paddy yield predictive model

An optimum yield predictive model was developed by employing linear production function of Cobb-Douglas equation to the optimized energy input data from the 40 farms studied. In developing, the model paddy yield was assumed to be a function of six energy inputs used in the cultivation. The energy inputs considered in the model are human, fuel, machinery, fertilizer, chemicals and paddy seeds. The model is of the form:

$$lnY = A + C_1 lnX_1 + C_2 lnX_2 + C_3 lnX_3 + C_4 lnX_4 + C_5 lnX_5 + C_6 lnX_6 \tag{16}$$

Where Y = predicted optimum paddy yield (kg/ha), A = intercept (constant), X1, X2, X3, X4, X5 and X6 are respectively the human, fuel, machinery, fertilizer, chemical and seed energy (MJ/ha) and Cs are the model's estimated coefficients as given in Table 8.

Analysis of the model's independent variables revealed direct relationship of yield with all the variables except with seeding rate. The model supports the notion that intra-plant competition for soil nutrients increases with an increase in seeding rate, hence, low filled grains which hamper paddy yield. Farmers practicing direct seeding method of cultivation and targeting for high yield should adopt a mean seeding rate of 128 kg/ha. This will lead to about 14% reduction in the cost of seeds. Sensitivity analysis on the model's variables using the Marginal Physical Productivity function (MPP indicates that machinery energy had the highest positive impact on yield with an MPP value of 0.730 while seed energy had a negative impact on yield with MPP value of -0.131. Increasing machinery energy expenditure in direct seeding wetland paddy cultivation will facilitate in the timely completion of operations involved in the cultivation and even distribution of vital farm inputs such as pesticides and fertilizers, both of which leads to improvements in yield. Durbin – Watson test result of 1.9634 shows no auto-correlation at 5% significance level among the six variables used in the model but all contributed differently to paddy yield. The model has R^2 value of 0.9116, therefore, adequate to predict optimum paddy yield for given levels of energy inputs. The summation of the model's coefficients denoting its return to scale is less than one (0.9218) implying that a 1% additional total energy input will only result into 0.92% increase in the paddy yield.

Table 8. Estimated optimum yield predictive model parameters and t-statistics.

Variable	Coefficient (C)	Standard Error	t Value	MPP
Intercept (A)	3.0382	0.4364	6.96	-
Human energy (X1)	0.0918	0.0269	3.41*	0.237
Fuel energy (X2)	0.1970	0.0864	2.28*	0.230
Machinery energy (X3)	0.4885	0.1133	4.31*	0.730
Fertilizer energy (X4)	0.1488	0.0634	2.35*	0.148
Chemical energy (X5)	0.1076	0.0143	7.52*	0.156
Seed energy (X6)	-0.1119	0.0672	-1.66	-0.131
R – Square	0.9116	-	-	-
Durbin-Watson	1.9634	-	-	-
RTS	0.9218	-	-	

* Significant at 5% level.

4. Conclusions

In this study, the energy input and output data from 40 paddy farms covering five standard wetland paddy cultivation operations (tillage, seeding, fertilizing, spraying and harvesting) were subjected to DEA and benchmarking methodology to determine energy use efficiency of farmers and in developing optimum paddy yield predictive model. About 37.50% of the farms were efficient in terms of using the available energy inputs having a technical efficiency score of one compared to the technical efficiency score of 0.863 for the inefficient farms. The efficient farms had an output/input energy ratio of 9.486 which is about 22.15% higher than the output/input energy ratio of the inefficient farms. Benchmarking result showed that about 18.70% (2914.919 MJ/ha) of the total energy input used in the cultivation, was in excess of the optimum energy required to achieve the same level of paddy productivity of 7.625 tons/ha. In terms of the individual energy inputs, the required reduction ranges from 12.11% for machinery to 20.3% for fertilizer. Significant differences exist between observed and optimum energy expenditures due to fertilizer applications made by the farmers. The result revealed that the farmers wasted about one-fifth of the fertilizer they used. Reduction in the used of fertilizer could be achieved by adopting practices that promotes fertilizer use efficiency such as a split application at proper interval, alternate wetting and drying of fields, and use of leaf test for detecting nitrogen requirements of growing plants.

An optimum yield predictive model was developed by employing linear production function of Cobb-Douglas equation to the optimized energy input data generated through DEA and benchmarking methodology. The model was assumed to be a function of six energy inputs, namely human labour, fuel, machinery, fertilizer, chemicals and paddy seeds. The model has coefficient of determination (R^2) of 0.91, therefore, it could serve as a useful tool for performance appraisal to the paddy farmers in their use of farm inputs. By enabling them to make comparison between actual yield they obtained and the yield they should have by using the inputs optimally.

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