



Investigation of energy consumption for rice production using artificial neural networks in Guilan province, Iran

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ARTICLE INFO

Article history:

Received: 1 April 2014;

Received in revised form:

25 April 2014;

Accepted: 6 May 2014;

Keywords

Artificial neural networks,
Energy,
Modeling,
Sensitivity analysis,
Rice.

ABSTRACT

The main aim of this study was to determine modeling and sensitivity analysis of rice production based on energy inputs and farm sizes using artificial neural networks in Guilan province of Iran. For this purpose the initial data were collected from 120 rice farmers by a face-to-face questionnaire in Astaneh Ashrafiyeh city of Guilan province of Iran. Total energy consumption and output energy was 51430 and 66387 MJ ha⁻¹, respectively. Diesel fuel with 44.61% had the highest energy use among all of the inputs. Medium farms had the best condition in three group sizes from average of total energy consumption point of view. The Levenberg-Marquardt Learning Algorithm was trained for calculation of prediction models for rice yield based energy inputs and area. The results of the ANN model revealed the 12-13-1 structure belonged to the best topology with highest R² and lowest RMSE and MAPE. The rate of R², RMSE and MAPE was computed as 0.972, 0.153 and 0.007, respectively. With respect to sensitivity analysis human labor had the highest sensitivity with 0.311. It indicates that using an additional of 1 MJ either for human labor or seed energy would result in increasing the yield by 0.311 and 0.286 kg, respectively.

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Introduction

Energy consumption of agricultural activity has developed in response to increasing populations, limited supply of arable land and desire for an increasing standard of living. In all societies, these factors have encouraged an increase in energy inputs to maximize yields, minimize labor-intensive practices, or both (Esengun et al., 2007). Effective energy use in agriculture is one of the conditions for sustainable agricultural production, since it provides financial savings, fossil resource preservation and air pollution reduction (Pahlavan et al., 2012). In Iran, rice has a special place in people's daily feed. Accordingly, mainly many agricultural activities belong to the rice crop. The total production of rice in 2012 was about 2,746,500 tons in Iran and the cultivated land area was about 575,000 ha. Also, Guilan province is one of major rice producers in Iran with 664721 ton year⁻¹ in 2012 (FAO, 2011). Since the middle of 1980s, artificial neural networks (ANNs) have been used in economic, energy and environmental modeling as well as to extend the field of statistical methods. In recent years, several researchers have investigated energy analysis in agricultural production; Pahlavan et al. (2012) studied the energy use pattern for basil production and predicted the basil yield using ANN. In another study, Khoshnevisan et al. (2013) applied ANN to modeling and sensitivity analysis of wheat production. In another study, Nabavi-Pelesaraei et al. (2013) investigated the energy modeling of eggplant production by ANN.

The main objective of this study was prediction of rice yield based on ANN modelling with energy inputs in Guilan province of Iran. Also, sensitivity analysis by ANN (SAANN) was the other aim of this research.

Materials and methods

Astaneh Ashrafiyeh city of Guilan province located in the north of Iran; within 37° 15' and 38° 27' north latitude and 49° 56' (Anon, 2013). The initial data were collected from 120 rice farmers of the Astaneh Ashrafiyeh city by face-to-face questionnaire in March 2013. For determination of sample size, the random sampling method was used (Kizilaslan, 2009). After determination of input consumption and rice yield, the inputs and output energy was calculated by multiplying the amount of them with standard coefficient (Table 1). Also, the farms were classified based on three groups of farm sizes. The small farms (<1 hectare), medium farms (between 1 and 3 hectares) and large farms (>3 hectare). The ANOVA test and Duncan compare mean test were used for comparison of means and find out whether the calculated values for three groups of farm sizes are significantly different or not.

The basis of ANN modeling methods is biological neuron activities. Neurons in the brain learn to respond to a situation from a collection of examples represented by inputs and outputs. (Taki et al., 2013). In this study, the Levenberg-Marquardt Learning Algorithm was used for modeling the rice yield based on energy inputs. The three sections were necessary for the creation of ANN modeling. These sections included: input layer, hidden layers, and output layer. Human labor, machinery, diesel fuel, nitrogen, phosphate, potassium, herbicide, insecticide, fungicide, electricity, seed and the area was considered as inputs and rice yield was only outputting of the ANN model in this research. All links between input layers and hidden layers composed the input weight matrix and all links between hidden layers and output layers composed the output weight matrix. Weight (*w*) which controls the propagation value (*x*) and the

output value (O) from each node is modified using the value from the preceding layer according to Eq. (1) (Zhao et al., 2009):

$$O = f\left(T + \sum w_i x_i\right) \quad (1)$$

where ' T ' is a specific threshold (bias) value for each node. ' f ' is a non-linear sigmoid function, which increased monotonically.

Three statistical parameters were used for performance analysis. Root mean square error (RMSE), mean absolute percentage error (MAPE), and coefficient of determination (R^2) were computed to estimate the overall model performance.

These parameters can be written as (Khoshnevisan et al., 2013):

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (t_i - z_i)^2} \quad (2)$$

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{t_i - z_i}{t_i} \right| \quad (3)$$

$$R^2 = 1 - \left(\frac{\sum_{i=1}^n (t_i - z_i)^2}{\sum_{i=1}^n t_i^2} \right) \quad (4)$$

where ' n ' is the number of the points in the data set, and ' t ' and ' z ' are actual output and predicted output sets, respectively.

Sensitivity Analysis via ANN (SAANN) can rank and select the major and input variables through its analysis. So, the sensitivity of each input on rice yield was determined by SAANN.

Basic information on energy inputs in rice production was entered into Excel 2013 spreadsheets and Matlab 7.2 (R2012a) software package.

Results and Discussion

Analysis of input–output energy use in rice production

The energy inputs and output of rice production are given in Table 2 based three group sizes farms. Total energy consumption was calculated as 51429.95 MJ ha⁻¹. Also, the highest percentage of energy use belonged to diesel fuel by 44.61%. The small and medium farms had the highest and lowest total energy use among all of group farms. Accordingly, it's suggested that the energy use pattern of farms should be closed to medium farms. For this purpose, the diesel fuel consumption should be reduced by applying appropriate pumps for water extraction, utilizing standard machinery and timely maintenance in the studied area. Moreover, the compare means by Duncan test indicated the difference between groups wasn't significant for total energy use in rice production.

In similar results, Pishgar-Komleh et al. (2011) reported the total energy use of rice production was 39333 MJ ha⁻¹ and diesel fuel (with 46%) had the highest share of energy consumption followed by chemical fertilizer (with 36%).

Evaluation and analysis of model

The results of ANN model are illustrated in Table 3. Based on the Levenberg-Marquardt learning algorithm, the best topology was found in input layer with 12 neurons, one hidden layer with 13 neurons and output layer with 1 neuron (12-13-1 structure). The statistical parameters of the ANN model, including R^2 , RMSE and MAPE were computed as 0.972, 0.153 and 0.007, respectively. It should be noted the R^2 had the highest value; while the RMSE and MAPE had the lowest value for ANN model. So, the performance of the ANN model for

prediction rice yield based on energy inputs and sizes was acceptable.

Safa and Samarasinghe (2011) developed an ANN model based on a modular neural network with two hidden layers that could predict energy consumption based on farm conditions (size of crop area), social factors (farmers' education level), and energy inputs (N and P use, and irrigation frequency).

Sensitivity analysis (SAANN)

In order to assess the predictive ability and validity of the developed models, a sensitivity analysis was performed using the best network selected (Fig 1). The robustness of the model was determined by examining and comparing the output produced during the validation stage with the calculated values (Pahlavan et al., 2012). In this study, SAANN was done by withdrawing each input item one at a time while not changing any of the other items for every pattern using Levenberg-Marquardt learning Algorithm. The results revealed human labor (with 0.311) has the most sensitive inputs on rice yield; followed by seed (with 0.286) and area (with 0.247).

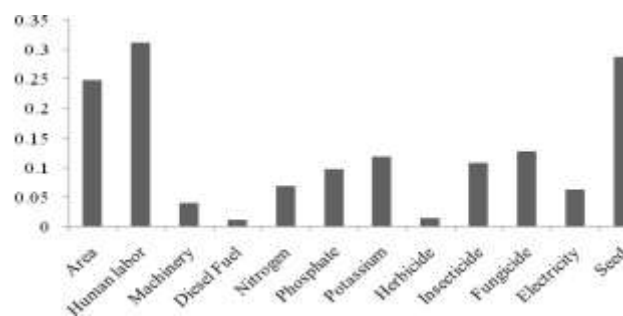


Fig 1. Sensitivity analysis of various input energies on rice yield output.

Khoshnevisan et al. (2013) reported the farmyard manure had the highest sensitivity on wheat yield energy.

Conclusion

Summary of conclusions can be stated as follows:

- The total energy inputs and output of rice production was calculated about 51430 and 66387 MJ ha⁻¹, respectively. Diesel fuel with 44.61% was the most widely used input in rice production. So, It is suggested that the diesel fuel use should be reduced by the recommendations cited in the paper. The highest and lowest total energy consumption belonged to small and medium farms, respectively. So, all farms should be closed to medium farms from the energy consumption point of view (especially in diesel fuel and nitrogen fertilizer).
- With respect to the ANN model, the best topology was evaluated with 12-13-1 structure for prediction of rice yield based on energy inputs in Guilan province of Iran. Also, the R^2 , RMSE and MAPE were found to be 0.972, 0.153 and 0.007, respectively.
- The results of SAANN showed the human labor had the highest rate of sensitivity with 0.311; followed by seed (with 0.286) and area (with 0.247).

Acknowledgment

The financial support provided for this research under grant number 7314485/1/11 by the University of Tabriz, Iran, is duly acknowledged. Also, I want to express my deep appreciation of all Mr. Kamran Taromi's efforts to help me revise the study.

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Items	Unit	Energy equivalent (MJ unit ⁻¹)	Reference
<i>A. Inputs</i>			
1. Human labor	h	1.96	(Taki et al., 2013)
2. Machinery	kg yr ^a		
(a) Tractor and self-propelled		9-10	(Hatirli et al., 2005)
(b) Implement and machinery		6-8	(Hatirli et al., 2005)
3. Diesel fuel	L	56.31	(Nabavi-Pelesaraei et al., 2014)
4. Chemical fertilizers	kg		
(a) Nitrogen		66.14	(Mousavi-Avval et al., 2011)
(b) Phosphate(P ₂ O ₅)		12.44	(Rafiee et al., 2010)
(c) Potassium (K ₂ O)		11.15	(Nabavi-Pelesaraei et al., 2014)
5. Pesticides	kg		
(a) Herbicide		85	
(b) Insecticide		199	
(c) Fungicide		92	
6. Electricity	kWh	11.93	(Khoshnevisan et al., 2013)
7. Seed	kg	14.7	(Pishgar-Komleh et al., 2011)
<i>B. Output</i>			
Rice	kg	17	(Pishgar-Komleh et al., 2011)

^a The economic life of machine (year).

Items	Farm size groups (ha)			Average (MJ ha ⁻¹)	Percentages (%)
	Small (<1)	Medium (1-3)	Large (>3)		
<i>A. Inputs</i>					
1. Human labor	1535.30 ^a	1361.31 ^b	1440.88 ^b	1451.71	2.82
2. Machinery	1015.95 ^a	891.07 ^b	920.60 ^c	949.75	1.85
3. Diesel fuel	25342.75 ^a	21023.49 ^b	21548.72 ^b	22941.36	44.61
4. Chemical fertilizers					
(a) Nitrogen	7705.63 ^a	7237.38 ^a	7689.09 ^a	7534.12	14.65
(b) Phosphate (P ₂ O ₅)	5124.94 ^a	4810.69 ^b	5110.95 ^c	5007.94	9.74
(c) Potassium (K ₂ O)	2405.01 ^a	2258.86 ^b	2399.85 ^b	2351.48	4.57
5. Pesticides					
(a) Herbicide	822.98 ^a	999.86 ^a	977.89 ^a	921.22	1.79
(b) Insecticide	1742.00 ^a	1363.00 ^b	1547.08 ^c	1562.33	3.04
(c) Fungicide	276.65 ^a	229.50 ^a	235.24 ^a	250.44	0.49
6. Electricity	5541.65 ^a	4985.53 ^b	4965.68 ^c	5212.78	10.14
7. Seed	3241.10 ^a	3238.40 ^{ab}	3270.85 ^b	3246.83	6.31
The total energy input	54750.97 ^a	48399.09 ^a	50106.82 ^a	51429.95	100
<i>B. Output</i>					
Rice	67445.71 ^a	64667.35 ^b	67166.14 ^c	66387.22	

Item	R ²	RMSE	MAPE
Rice yield	0.972	0.153	0.007

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