Technical- and Environmental-Efficiency Analysis of Irrigated Cotton-Cropping Systems in Punjab, Pakistan Using Data Envelopment Analysis

Asmat Ullah & Sylvain R. Perret

Environmental Management

ISSN 0364-152X
Volume 54
Number 2

Environmental Management (2014)
54:288-300
DOI 10.1007/s00267-014-0300-4

Springer

Environmental Management (2014) 54:288–300
DOI 10.1007/s00267-014-0300-4

Technical- and Environmental-Efficiency Analysis of Irrigated Cotton-Cropping Systems in Punjab, Pakistan Using Data Envelopment Analysis

Asmat Ullah · Sylvain R. Perret

Received: 28 April 2013 / Accepted: 21 May 2014 / Published online: 15 June 2014

Abstract Cotton cropping in Pakistan uses substantial quantities of resources and adversely affects the environment with pollutants from the inputs, particularly pesticides. A question remains regarding to what extent the reduction of such environmental impact is possible without compromising the farmers' income. This paper investigates the environmental, technical, and economic performances of selected irrigated cotton-cropping systems in Punjab to quantify the sustainability of cotton farming and reveal options for improvement. Using mostly primary data, our study quantifies the technical, cost, and environmental efficiencies of different farm sizes. A set of indicators has been computed to reflect these three domains of efficiency using the data envelopment analysis technique. The results indicate that farmers are broadly environmentally inefficient; which primarily results from poor technical inefficiency. Based on an improved input mix, the average potential environmental impact reduction for small, medium, and large farms is 9, 13, and 11 %, respectively, without compromising the economic return. Moreover, the differences in technical, cost, and environmental efficiencies between small and medium and small and large farm sizes were statistically significant. The second-stage regression analysis identifies that the entire farm size significantly affects the efficiencies, whereas exposure to extension and training has positive effects, and the sowing methods significantly affect the technical and environmental efficiencies. Paradoxically, the formal education level is determined to affect the efficiencies negatively. This paper discusses policy interventions that can improve the technical efficiency to ultimately increase the environmental efficiency and reduce the farmers' operating costs.

Keywords Cotton farming · Data envelopment analysis · Technical efficiency · Environmental efficiency · Production costs

Introduction

Cotton Production in Pakistan

Cotton is economically the most important clothing fiber of the world (Proto et al. 2000). Pakistan is the fourth largest cotton-producing country in the world. Cotton makes a significant contribution to the national economy, is a major cash crop for farmers and provides employment for the rural poor. The domestic and export textile industries heavily depend on cotton. Cotton contributes 7.8 % of the total agricultural output value and 1.6 % of the Gross Domestic Product (GDP) of Pakistan (Economic Survey of Pakistan. 2011–2012).

As of 2010–11, the total area of cultivated cotton in Pakistan was 2,689,000 hectares. Cotton is mainly cultivated in the Punjab and Sindh provinces under arid conditions with low soil fertility and can be at risk from pests because certain insects are particularly harmful to the yield and fiber quality. As a result, since the Green Revolution, cropping practices usually include a high use of chemical fertilizers, pesticides, irrigation water, and energy per unit

A. Ullah (✉)
School of Environment, Resources and Development, Asian Institute of Technology, Pathumthani, Bangkok 12120, Thailand
e-mail: asmat.ait@gmail.com

S. R. Perret
Centre de Coopération Internationale en Recherche Agronomique pour le Développement, UMR G-Eau, 34398 Montpellier, France

area of land, which results in high land productivity. The quantity of farm inputs that are used in cotton-cropping systems depends on the farmer's production target, environmental conditions (e.g., soil quality, pest hazard) and socioeconomic conditions for the farmer.

Overall, cotton cropping usually has a high use of agrochemicals, irrigation, and mechanization, which leads to a high potential for environmental impacts. The excessive use of fertilizers contributes to greenhouse gas emissions and water pollution (IPCC 2006). Azizullah et al. (2011) reported that runoff or leaching of nitrates from agricultural lands is significant in Pakistan and contaminates surface and ground water in many places, which is sometimes beyond the safety limits for human health. Tariq et al. (2007) established that freshwater resources are constantly contaminated because of the overuse and misuse of pesticides in the cotton-growing area of Pakistan. The use of non-renewable energy has also increased because of technological advancement. The magnitude of these environmental impacts and energy use in different forms varies depending upon the farm management practices, soil properties, and agro-ecosystem conditions (Choudhury and Kennedy 2005).

There is a cotton-poverty-environment-economy nexus in Pakistan: the country depends on cotton production for the domestic economy and export revenue, poverty alleviation, and rural development; however, the production systems have significant environmental issues.

This cotton-poverty-environment-economy nexus is related to the possibility of reducing the environmental impacts and resource use of cotton-cropping systems, while sustaining the yields and income of farmers and the country position of producing and exporting of cotton. A workable approach to the sustainability at the farm level consists of evaluating whether the producers are efficiently using resources and minimizing the environmental impacts while achieving their economic objectives. Thus, the economic-environmental efficiency may be a useful operational approach.

Toward Environmental and Economic Efficiency

The global demand for environmentally friendly food and fiber production is increasing. To produce eco-friendly products, considering the environmental impact of products over a broader range is necessary (Keating et al. 2010). The present environmental hazards that are related to cotton production are considerable challenges to sustainable cotton production. In the absence of incentives or regulations, farmers tend to maximize their short-term personal utility without considering the longer-term environmental consequences (Picazo-Tadeo et al. 2011). Thus, there is an urgent need for joint approaches to assess the technical, economic, and environmental performances of cotton-cropping systems to link the resource productivity and environment with the help of economic logic.

The objective of our study was to address the efficiency of cotton-cropping systems (i.e., their combined and relative technical, economic, and environmental performances). Our study jointly assesses the technical, economic, and environmental efficiencies of cotton-cropping systems in the Punjab province of Pakistan using data envelopment analysis (DEA). We aim to identify the relationships among multiple inputs and outputs. Our study also attempts to assess the differences of technical, cost, and environmental efficiencies across all small, medium, and large farms.

Materials and Methods

Approaching Efficiency with DEA

Efficiency has emerged as a practical concept to approach and measure the sustainability of industrial (Callens and Tyteca 1999) and agricultural (De Koeijer et al. 2002) production systems because efficiency analyses may combine the environmental and economic components of sustainable development and provide quantitative metrics.

DEA is a non-parametric approach that was initially developed by Charnes et al. (1978) to calculate the relative efficiency of a set of production and/or management units (hereafter called decision-making units or DMUs). The overall idea is to comparatively measure how these units generate outputs while mobilizing the inputs. Because the inputs and outputs were originally technical in nature, the early authors referred to this concept as technical efficiency (TE).

The basic idea of calculating the relative efficiency of a set of DMUs is to construct a piecewise frontier; all efficient DMUs lie on the frontier, and the DMUs below the frontier are considered inefficient. The DMU efficiency score ranges between 1 (full efficiency) and 0 (full inefficiency).

The production frontier symbolizes the minimum input requirement to produce a certain amount of output. A cost efficiency (CE) frontier describes the minimum incurred cost to produce a certain amount of output (Nguyen et al. 2012), and the environmental efficiency (EE) frontier represents the minimum production environmental impacts or undesirable outputs without compromising the given level of desirable output.

Cropping systems are typical DMUs because they mobilize a set of production factors (e.g., land, labor, agrochemicals, mechanization, and water) and result in a set of outputs (e.g., yield, environmental impacts, income). DEA has only recently been used in agricultural case studies with the pioneering works by De Koeijer et al. (2002) and Reig-Martínez and Picazo-Tadeo (2004).

There are three approaches to study the efficiency using DEA. The first approach seeks to reduce the amount of input to produce a constant output (input-oriented DEA); the second approach seeks to increase the output while maintaining the input level (output-oriented DEA); the third approach is a mixed approach of reducing the input while increasing the output. Regarding agricultural production, the farmers only control the amount of inputs that they use; therefore, the input-oriented efficiency model was selected for the TE and CE analysis.

All DEA-based efficiency analyses in our study have been analyzed using MaxDEA Pro as data envelopment analysis software, which was developed by Gang and Zhenhua (2013).

Input-Oriented Technical Efficiency

The input-oriented TE was developed by Charnes et al. (1978) and is called the CCR model after the initials of the authors. In the CCR model, a farm or a DMUj produces a vector of y desirable outputs, which are denoted by $y = (1,2,\ldots,S) \in R_{+}^{S}$ using the input vector $x = (1,2, \ldots, M), \in \boldsymbol{R}_{+}^{M}$. As proposed by Cooper et al. (2007), the TE was calculated using the following DEA model:

$$\text{Minimize}\,\theta$$

$$\text{Subject to}$$

$$\theta x_j - X\lambda \geq 0 \tag{1}$$

$$Y\lambda \geq y_j$$

$$\lambda \geq 0$$

where θ is a scalar, and its value is the TE value of the jth farm, and λ is the intensity vector of the weights of the efficient DMUs, which helps to project the inefficient DMUs to an efficient frontier. The data for all n farms or DMUs in the sample are represented by an m $\times$ n input matrix X and an s $\times$ n output matrix Y, where x_j represents the input vector of the jth farm, and y_j represents the desirable output vector of the jth farm.

When all three usual assumptions (convexity, scalability, and free disposability) of a DEA are satisfied, the production possibility set refers to a constant return to scale (CRS); if the second assumption of scalability is not satisfied, then the production possibility set refers to the variable return to scale (VRS). Equation 2 assumes the CRS because all three mentioned assumptions are satisfied. However, farming is considered a typical variable-return-to-scale activity because of the potential economies of scale. Adding an additional constraint of $\sum \lambda_j = 1$ into Eq. 1 leads to a VRS frontier, which is called the pure technical efficiency (TE_{BCC}) and the BCC model after the initials of the authors (Banker et al. 1984), which can separate technical and scale efficiencies (SE).

A VRS model does not indicate whether an inefficient DMU is operating in the region of increasing or decreasing return to scale. This problem can be solved by applying an additional model, which is called non-increasing return to scale (NIRS) and modeled by adding a constraint $\sum \lambda \leq 1$ into equation 1 (Cooper et al. 2007). Comparing the TE_{CRS} and TE_{NIRS} help to determine whether the production is characterized by the decreasing or increasing return to scale. If $TE_{CRS} < 1$ and $TE_{CRS} = TE_{NIRS}$, the inefficiency results from the increasing return to scale, i.e., the farmer produces at an inefficiently small output level. If $TE_{CRS} < 1$ and $TE_{NIRS} > TE_{CRS}$, the inefficiency is caused by operating at an inefficiently large output level (Wossink and Denaux 2006).

Cost Efficiency

The CE can be calculated using a cost-minimizing model, where the cost of each input per hectare (ha) is used instead of the physical units for those inputs. The cost-minimizing approach leads to the CE of cotton-cropping systems using a strictly positive vector of input price $w = (w_1, w_2, \ldots, w_M) \in R_{+}^{M}$. In the cost-minimization model (equation 1), the m $\times$ n input matrix x is transformed into $w'x$, where w' is the transpose of the input price vector. The CE is the ratio of the smallest total cost of the input vector to the observed total cost of the input vector. The cost-efficient frontier provides the minimum required expenditure to produce a given output.

The CE can be used to derive the cost allocative efficiency (AE) from the TE. This derivation can help to reveal the sources of improvement, which are a proportional decrease in the input vectors and a cheaper input mix. The AE is the ratio of the CE to the TE.

$$\text{CAE} = \frac{\text{CE}}{\text{TE}} \tag{2}$$

The decomposition of the CE into TE and AE indicates the sources of inefficiencies. The TE refers to the proportional decrease of the input vectors; however, the AE relates to the least cost combination of inputs.

Figure. 1 is a simple illustration of the relationship between two inputs (x_1 and x_2) and one output y. The cc line indicates the iso-cost line, and ss indicates the isoquant curve. As explained by Coelli et al. (1998), if a production process, which is represented by point p, generates a quantity of output using the inputs x_1 and x_2, then the technical inefficiency of that firm under the CRS assumption is the distance qp, which indicates that both inputs can be proportionally reduced without reducing the amount of output. In percentage terms, the technical inefficiency of a production process is the ratio of qp/op; hence, the TE can be calculated by subtracting the amount of computed inefficiency from 1, which is equal to the amount of oq/op.

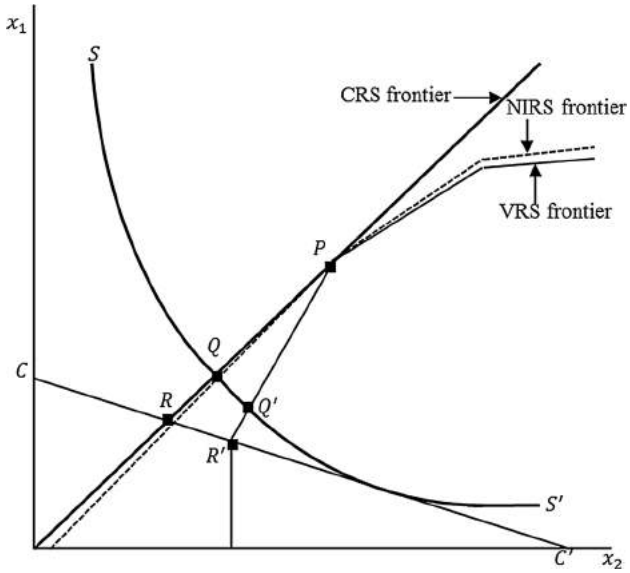

Fig. 1 Input-oriented efficiency frontiers and representation of the overall, technical and allocative efficiencies

The CE can be computed using the iso-cost line, and CE is the ratio of *or/op*, where *rp* is the distance that represents the amount of proportional cost reduction. The AE can be computed from the ratio of cost and TE, which is defined as *or/oq*. Under the assumption of VRS or NIRS, the efficiency can be similarly explained.

Environmental Efficiency

The model supposes that a farm or a DMU uses a vector of inputs $x = (1,2, \ldots, \mathrm{M}) \in \boldsymbol{R}_{+}^{\mathrm{M}}$ in the production process and produces the desirable output $y = (1,2, \ldots, \mathrm{S}) \in \boldsymbol{R}_{+}^{\mathrm{S}}$ and undesirable outputs or environmental impacts $b = (1,2, \ldots, \mathrm{P}) \in \boldsymbol{R}_{+}^{\mathrm{P}}$. Then, the production technology is given by:

$T = [(x, y, b)\text{: } x \text{ produce } (y, b)]$.

To reasonably model the EE of the DMU, we want to produce a certain amount of desirable output using as few inputs as possible and as few environmental impacts as possible. The reference technology can provide all feasible relationships among multiple inputs and multiple outputs, and it can be modeled using either the output set or the input set (Picazo-Tadeo et al. 2005). There are different approaches to analyze the EE of a firm. Those approaches may include reducing the environmental impacts while maintaining constant inputs and outputs, reducing the environmental impacts and increasing the desirable output while maintaining the constant input, or simultaneously reducing the inputs and environmental impacts while maintaining the constant output (Kuosmanen and Kortelainen 2004). However, the disposability assumption of the environmental impact or undesirable output gained considerable attention in the literature (Kuosmanen 2005). In the crop production processes, the farmers do not have any direct control on the intended output increase because many external factors affect the output. Following Kuosmanen and Kortelainen (2004), the EE has been modeled by reducing the inputs and the environmental impacts while maintaining the constant output. The efficiency measure can be computed using the following equation:

Minimize ϑ

Subject to

$$\begin{aligned} &\vartheta x_j - X\lambda \geq 0 \\ &Y\lambda \geq y_j \\ &B\lambda = \vartheta b_j \\ &\sum \lambda_j = \vartheta \\ &\lambda \geq 0 \text{ and } 0 \leq \vartheta \leq 1 \end{aligned} \tag{3}$$

where ϑ is a scalar, whose value is the EE value of the *j*th farm, and λ is the intensity vector of the weights of efficient DMUs, which helps to project the inefficient DMUs to an efficient frontier. *X*, *Y*, and *B* represent the input, desirable output, and undesirable output matrices of N number of farms, respectively, x_j represents the input vector of the *j*th farm, y_j represents the desirable output vector of the *j*th farm, and b_j represents the undesirable output vector of the *j*th farm.

The environmental impact variables were selected to calculate the EE of each cotton-cropping system. All but one of the variables were adopted from Picazo-Tadeo et al. (2011), (2012) and Gómez-Limón et al. (2012). One additional variable, which is the water use, was selected because water use is a notably important environmental indicator because of water scarcity in arid Pakistan. To make cumulative environmental impacts on each cropping system, each environmental pressure must be assigned a proper weight (Picazo-Tadeo et al. 2011). In this case, the DEA weights were applied to assess the relative EE of each cropping system. As per area unit, the environmental impacts that are incurred by cotton crops are related to the inputs/practices that are used by the farmers, and farming is considered a typical variable returns to scale activity. Therefore, the VRS model was used.

The EE model can assess the radial efficiency of each farm and helps to assess the potential equi-proportional reduction of the amount of input variables. Following the methodology developed by Torgersen et al. (1996), the impact-specific EE of each cotton-cropping system was assessed using equation 4 for each environmental pressure.

$$\text{Impact} - \text{specific EE} = \frac{\vartheta P_{nj} - S_{nj}^{p}}{P_{nj}} \tag{4}$$

where P_{nj} denotes the impact *n* of *j* farms, and ϑ denotes the EE. In this frictional equation, the numerator indicates the total amount of potential impact reduction, which consists of the radial reduction and the slack-based reduction of the impact, and the denominator indicates the observed or the actual amount of impact that is generated by farm j.

The Bootstrap Truncated Regression Approach

A regression analysis was performed to investigate the factors that influence the TE, CE, and EE of the DMUs. Thus, a set of socio-economic and technical variables was selected. In many cases, a Tobit model was used at the second stage of the efficiency analysis and recently by Mohapatra and Sen (2013), Gómez-Limón et al. (2012) and Wossink and Denaux (2006). Nevertheless, considering the recent criticism of the potential bias in the efficiency scores, we used the bootstrapped efficiency scores following the method that was developed by Simar and Wilson (2000) and (2007). They emphasized that the DEA-generated efficiency scores strongly depended on one another, which might violate the basic assumption of the regression model in the second stage. Instead, Simar and Wilson (2007) proposed a truncated regression and bootstrapping procedure, which enables consistent inferences in the second-stage regression. After calculating the bias-corrected efficiency score, the following regression model was used to regress the bias-corrected efficiency score with the contextual variables.

$$\hat{y} = z_i\beta + \varepsilon_i \tag{5}$$

where $\hat{y}$ represents the efficiency score of each DMU, β represents the vectors of unknown parameters, z_i is the vector of factors that represent the explanatory variables i ($i = 1, 2,\ldots,$m), and ε_i is the error term $N(0,\sigma_\varepsilon^2)$ with left truncation 1- $z_i\beta$. The step-by-step bootstrapping truncated regression is described by Simar and Wilson (2007), Barros and Assaf (2009) and Barros and Garcia-del-Barrio (2011).

Table 1 explains the variables that are used in the second-stage truncated regression analysis. The educational levels of the farmers, age of the farm operators, size of farm, access to leased land and owned land, sowing method, and exposure to extension education and trainings are the variables that were regressed against the TE, CE, and EE scores of the DMUs to see if these socio-economic and technical variables affect the farm efficiency.

Sampling and Data Collection Strategy

The previously described efficiency analyses were performed on sampled cotton-cropping systems in selected farms in Punjab, Pakistan. The data were collected using a structured questionnaire at the farm level and a field survey of Lodhran and Vehari districts, which are in the southern part of the Punjab province. Two hundred farms that comprised cotton-cropping systems were surveyed. Cotton is normally rotated with wheat on an annual basis. Data were collected from different farm categories that were randomly selected, which included small (less than 5 hectares), medium (5–20 ha), and large (greater than 20 ha) farms. Such classification refers to the land-holding classification of the State Bank of Pakistan. Some questionnaires were discarded because of missing data, and 169 cropping systems (as DMUs) remained and were used for the efficiency analyses. The questionnaires mainly consisted of recording the consumption of all production factors (inputs per ha) that were used during the cropping season of 2010, which included labor, seed, machinery, energy consumption, fertilizers, and pesticides. In addition, the yields in seed cotton (i.e., unginned picked cotton) and the market value of all inputs and the cotton seed were recorded.

Table 1 Description of the variables that are used in the second stage truncated regression

Variables	Description
Field charactristics	
Medium farm	1 for medium-sized farm and 0 otherwise
Large farm	1 for large-sized farm and 0 otherwise
Sowing method	1 for raised-bed sowing and 0 for flatbed sowing method
Access to land	1 for renter operator and 0 for owner operator
Education and age	
High school	1 for high school and 0 otherwise
Beyond high school	1 for beyond high school and 0 otherwise
Age (years)	Age in years of the farm's operator
Exposure to extension and training	1 for interaction with an extension agent and 0 for no interaction with an extension agent

Data Sources and the Development of Indicators

To calculate all efficiencies, the net income per hectare was used as an output instead of the physical product (seed cotton) or the total revenue, which includes the production costs. To calculate the TE, we used the physical quantities of water (volume), seed (mass), labor (time), fossil fuel (volume), nitrogen, phosphorus, and pesticides (mass). To calculate the CE, we used the prices of the aforementioned inputs. Table 2 recaps different variables that were used, their units, and methodologies or sources that were used for the calculations.

The following variables were used to assess the EE of each cropping system as suggested by Picazo-Tadeo et al. (2011), (2012) and Gómez-Limón et al. (2012).

Table 2 Cotton-cropping inputs, units, and methods or sources that are used for the calculations

Input	Units	Method or source for calculation
Water	cubic meter (m^3)	CropWat (FAO)
Seed	kilogram (kg)	Primary data (field survey)
Labor	man-hours	"
Fossil fuel	liter	Primary data and conversion standards
Nitrogen	kilogram (kg)	Primary data (field survey)
Phosphorus	kilogram (kg)	"
Pesticides	gram (g) of active ingredients	"

Water Use

This indicator is the amount of used water in cubic meter (m^3) per hectare by each cropping system throughout the cropping season. Because there is no measuring device for individual farm water consumption in Punjab, the cotton crop irrigation water requirement (IWR) was used as a proxy for the actual water use. The IWR was calculated using the CropWat software (FAO 1992) assuming a field application efficiency Ea of 75 %, a canal conveyance efficiency Eb of 75 %, and a water-course conveyance efficiency of 70 % according to Hussain et al. (2011).

Energy Ratio

The energy ratio is the ratio of the energy input to the output (Equation 6). The energy input is the amount of energy used per hectare, which is mostly in the form of fossil-fuel consumption by machinery and agrochemicals, including the energy-equivalent content; the energy output is the amount of energy equivalent for cotton seed (11.8 MJ/kg), which was given by Dagistan et al. (2009), and cotton stalk (17.88 MJ/kg), which was proposed by Kumar and Kandpal (2007). The energy input and output were calculated in mega joules (MJ/ha) (Pimentel 1980). A higher energy ratio corresponds to a lower energy efficiency of a given cropping system.

$$\text{Energy ratio} = \frac{\text{Energy input (MJ/ha)}}{\text{Energy output (MJ/ha)}} \qquad (6)$$

Nitrogen Balance

The nitrogen balance was calculated based on the difference between the total amount of nitrogen that was applied per hectare (as fertilizers) and the total amount of exported nitrogen by cotton seeds at the time of harvest (see Eq. 7). Both nitrogen input and output were calculated in kilograms per hectare (N kg/ha). The nitrogen balance provides a metric that quantifies the amount of nitrogen that was released into the environment. A higher nitrogen balance corresponds to a higher potential environmental impact of nitrogen for a given cropping system.

$$\text{Nitrogen Balance} = \text{Nitrogen}_{\text{input}} - \text{Nitrogen}_{\text{Output}} \qquad (7)$$

Phosphorus Balance

A similar approach was applied to measure the phosphorus balance for each cropping system (see Eq. 8). The phosphorus balance is expressed in kilograms per hectare (P_2O_5 kg/ha). This indicator helps to quantify the contribution of cotton farming to eutrophication by phosphorus pollution. A higher phosphorus balance corresponds to a higher potential environmental impact.

$$\text{Phosphorus Balance} = \text{Phosphorus}_{\text{input}} - \text{Phosphorus}_{\text{output}} \qquad (8)$$

Pesticide Risk

The data for the pesticides that are used by each farmer are available, but quantifying the environmental impacts of the chemical used per hectare is difficult because of its characteristic non-point source. Therefore, a pesticide risk indicator that determines the overall toxicity of the pesticides that were released into the environment was used to measure the potential environmental risk of each category of pesticides [i.e., insecticides, weedicides, and fungicides used on each farm (as performed by Picazo-Tadeo et al. 2011, 2012, and Gómez-Limón et al. 2012)].

$$\text{Pesticide risk} = \sum_{m=1}^{M} 1000 \, \frac{\text{Amount of pesticide active ingredients}_m^k \text{ (g/ha)}}{\text{Lethal dose 50 m (g/kg rat)}} \qquad (9)$$

The pesticide risk was calculated by dividing the quantity of active ingredients in the pesticide m (g/ha) that was applied to the cotton crop in farm k and the so-called "lethal dose 50", which is the sufficient amount of pesticide product m to kill 50 % of a rat population (milligrams of pesticide product per kilogram of rat body mass) (see Eq. 9). If the value of this indicator increases, the environmental impact of that farm also increases, which indicates that more toxic pesticide products were used on that farm.

Results and Discussion

This section presents the efficiency analysis for all surveyed cotton-cropping systems. In addition, cotton-

Table 3 Variables of the efficiency assessment. Sample descriptions for different farm size categories (mean and standard deviation)

Variables	Farm categories					
	Small farms		Medium farms		Large farms	
	Mean	SD	Mean	SD	Mean	SD
Inputs						
Water use (m^3/ha)	9220.77	2461.19	9345.11	1902.84	8674.16	1969.89
Seed (kg/ha)	22.73	4.90	23.80	5.87	25.57	5.03
Labor (man-hours/ha)	738.85	403.42	790.14	284.65	709.85	368.49
Fuel (liter/ha)	107.33	31.78	128.73	43.07	138.90	48.03
Nitrogen (kg/ha)	259.07	109.92	284.01	113.98	271.95	95.99
Phosphorus (kg/ha)	52.55	37.97	42.72	27.31	43.67	31.22
Pesticides (g/ha)	5679.89	3138.67	7651.36	2992.59	7454.56	2755.12
Cost of inputs (US$/ha)						
Water	173.25	99.29	169.18	67.54	148.12	53.90
Seed	45.41	15.63	43.31	22.79	48.92	38.79
Labor	199.23	102.68	216.22	86.29	180.30	111.21
Fuel	115.63	37.30	124.29	38.37	128.04	44.00
Nitrogen	101.77	45.04	111.71	49.15	103.21	45.20
Phosphorus	150.12	119.25	186.21	97.35	183.07	102.63
Pesticides	108.41	57.83	118.30	56.61	113.51	40.53
Environmental detrimental effects						
Water use (m^3/ha)	9220.77	2461.19	9345.11	1902.84	8674.16	1969.89
Energy ratio	0.30	0.09	0.30	0.14	0.31	0.12
Nitrogen balance (kg/ha)	213.29	87.52	235.27	102.57	226.42	79.34
Phosphorus balance (kg/ha)	37.45	34.09	26.84	22.24	29.15	25.22
Pesticide risk (kg rats per hectare)	43869.15	51619.27	62898.43	53489.02	60717.95	51167.99
Yield (kg/ha)	1998.19	1450.50	2186.90	1013.02	1996.51	1197.93
Net income (US$/ha)	1125.95	1171.83	1252.57	869.29	1127.91	1034.19
No. of observations	40		68		61	
$N = 169$						

cropping systems were clustered per farm size to assess the effect of the farm size on the performances and efficiencies.

Computing Variables for the Efficiency Analysis

Table 3 presents the descriptive statistics for the variables that were used in the analysis. The input-oriented radial efficiencies for each farm were computed using DEA, which calculated the proportional reduction of each input while maintaining the output level. This radial reduction helps to analyze the potential profitability of the farmers and the potential reduction in environmental impacts that can be generated without compromising the output level.

Agronomic management practices and resource use always synergistically affect the cotton crop yield and the environment. Resource use intensification depends on the availability of the resources and the farmer's financial status. Generally, small-scale farmers have fewer available resources particularly because of weak financial position and less access to credit, which makes them unable to purchase inputs and leads to less land productivity (Fan and Chan-Kang 2005). The frequency distribution of yield per farm size (Fig. 2) and the active ingredients in the pesticides (Fig. 3) show the diversity of farm inputs and outputs in Punjab, Pakistan. The empirical results from the efficiency analysis can help to investigate the potential improvement in input savings. The observed diversities follow a normal distribution. Figure 3 highlights the overall lower use of pesticides by smaller farms.

Efficiency Analysis

Table 4 summarizes the results of the efficiency analysis using DEA. The analysis showed that the small farms had the highest TE_{BCC}, which indicates that the small farms made better use of the inputs and resources than medium and large farms. Similarly, the small farms had the highest mean CE, followed by large farms, and the medium-sized

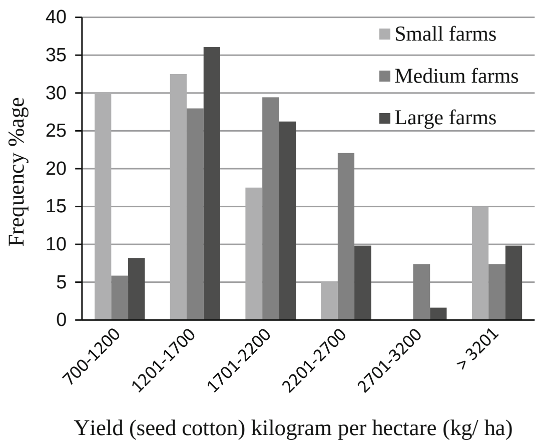

Fig. 2 Frequency distribution of the yield/ha of different farm categories

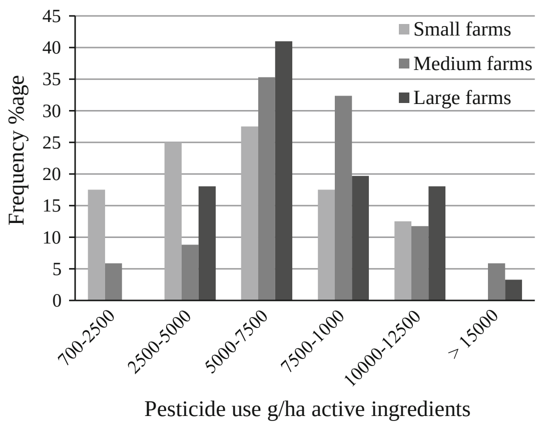

Fig. 3 Frequency distribution of the active ingredients in the used pesticides (g/ha)

Table 4 Technical and cost efficiency analysis per farm size

Efficiency	Small farms		Medium farms		Large farms	
	Mean	SD	Mean	SD	Mean	SD
TE^{a}_{BCC}	0.958	0.065	0.917	0.082	0.911	0.097
TE^{b}_{CCR}	0.539	0.236	0.586	0.234	0.539	0.206
CE[c]	0.842	0.174	0.767	0.165	0.799	0.180
AE[d]	0.878	0.169	0.833	0.141	0.872	0.158
SE[e]	0.564	0.245	0.631	0.223	0.590	0.207

[a] Total technical efficiency
[b] Pure technical efficiency
[c] Cost efficiency
[d] Cost allocative efficiency
[e] Scale efficiency

farms had the lowest CE. The Mann–Whitney U-test (two-sided) was used to test whether the differences in efficiencies of different farm sizes were significant. Assuming a CRS, the TE of different farm sizes was not significantly different. Assuming variable return to scale, the TE between small and medium farms and between small and large farms were significantly different at the 5 % confidence level. The CE differences between small and medium farms were also significant at the 5 % confidence level. Significant differences were also found between small and medium farmers in the AE and SE analyses at the 10 % confidence level. However, no significant difference was found between medium and large farms. A statistically significant difference among the efficiencies of farm sizes was observed using a VRS, which indicates that these farmers are technically operating at an efficient level, but their small output levels with the given inputs are significantly different. This result was confirmed by comparing the TE coefficients using the CRS and NIRS for the inefficient DMUs. All inefficient farmers exhibited increasing returns to scale, which indicates that they can reduce their inputs without compromising the given income level or produce more seed cotton, which increases their income level within the given input mix.

An increasing trend in using fuel and other agrochemicals was observed from the small- to medium-sized farms and from the medium to large farms, which indicated that the small farms tended to have lower costs than medium and large farms. The Spearman's rho correlation coefficients (r) between CE and TE_{BCC} was 0.684, and the Spearman's rho correlation coefficient (r) between CE and AE was 0.935 (see Appendix A), which indicates that there is a direct linear relationship between CE and TE_{BCC} and between CE and AE.

The frequency distribution of TE in Table 5 indicates that most DMUs were inefficient. The percentage of efficient DMUs using a CRS model was 5, 8.82, and 6.56 % for small, medium, and large farms, respectively. Nevertheless, the number of efficient DMUs increased when the VRS model was used. The highest percentage of DMUs at the BCC-efficient frontier was observed among the small farms (45 %), followed by large (28 %), and medium (21 %) farms. The greatest increase of the efficient DMUs at the BCC-efficient frontier indicated the highest scale inefficiency, which implied that these DMUs were not using the inputs with an optimal mix, and the level of scale inefficiencies could help to adjust the scale size. Inadequate timing of using different inputs in crop production can also cause scale inefficiencies. From the scale inefficiency, the extent to which resources can be saved and the adjustment of the scale size for optimal production may be inferred. The BCC-inefficient farms had technological and allocative inefficiencies, which indicated that they used an inappropriate amount of different input and deviated from the most productive scale size (MPSS) (Banker 1984). From the mean SE analysis,

Table 5 Frequency distribution for technical, pure technical, and cost efficiency per farm category

	Small farms	%	Medium farms	%	Large farms	%
CCR Model						
<60 %	27	67.50	40	58.82	38	62.30
60–70 %	3	7.50	9	13.24	8	13.11
70–80 %	3	7.50	7	10.29	10	16.39
80–90 %	1	2.50	1	1.47	0	0.00
>90 %	4	10.00	5	7.35	1	1.64
Efficient	2	5.00	6	8.82	4	6.56
Number of farmers	40		68		61	
Mean efficiency score	0.539		0.585		0.539	
BCC Model						
<60 %	0	0.00	0	0.00	0	0.00
60–70 %	0	0.00	0	0.00	1	1.64
70–80 %	2	5.00	8	11.76	7	11.48
80–90 %	4	10.00	19	27.94	14	22.95
>90 %	14	35.00	21	30.88	18	29.51
Efficient	20	50.00	20	29.41	21	34.43
Number of farmers	40		68		61	
Mean efficiency score	0.957		0.916		0.911	
Cost efficiency						
<60 %	6	15.00	12	17.65	9	14.75
60–70 %	2	5.00	12	17.65	12	19.67
70–80 %	7	17.50	19	27.94	10	16.39
80–90 %	5	12.50	8	11.76	7	11.48
>90 %	5	12.50	1	1.47	2	3.28
Efficient	15	37.50	16	23.53	21	34.43
Number of farmers	40		68		61	
Mean efficiency score	0.841		0.767		0.798	

the highest SE was observed in medium farms, followed by large farms and small farms.

Environmental Efficiency

The EE scores for all farm categories were estimated. We used all growers as a reference to calculate the EE assuming a CRS, VRS, and NIRS. Using the CCR, only 9 DMUs were operating at an efficient level (i.e., only 5.32 % had an EE coefficient of 1.0, which implied that no other cotton grower was more efficient in producing a given level of income with the same environmental impact). Using the VRS, the number of efficient DMUs increased to 50, which showed that 41 more farmers were technically operating at an environmentally efficient level, but they are producing inefficiently small output levels with the given environmental impacts. This result is confirmed by comparing the EE coefficients using the CRS and NIRS for the inefficient DMUs; all inefficient farmers exhibited increasing returns to scale, which indicates that they can reduce their inputs and ultimately their environmental impacts without compromising the given income level or produce more seed cotton, which increases their income level for the given input mix.

Table 6 shows the mean value of the overall EE score and pressure-specific EE score for the sampled DMUs, which were calculated using the DEA model that was described in Eq. 5. The mean radial EE values suggest that the small, medium, and large farms can equi-proportionally reduce their environmental pressure by 9, 13, and 11 %, respectively. However, after incorporating the impact-specific slack for each environmental impact, the impact-specific EE was calculated, and further reduction of the environmental pressure was possible without compromising the income level. For small farms, the highest pressure-specific EE was observed in the phosphorus balance, where the maximum attainable reduction was 20 %, followed by the nitrogen balance, where the maximum attainable reduction was 17 %. For medium and large farms, these groups of farmers were responsible for contributing a high pesticide impact to the environment and creating a more toxic effect possibly because these farmers were using high doses of pesticides or pesticides with high lethality. The Mann–Whitney U-test was again applied to the efficiency indices (i.e., the radial- and impact-specific EE) to determine whether the efficiencies of different farm categories were significantly different. The radial EE and impact-specific EE of the pesticide risk were significantly different at the 5 % confidence level between small and medium farms and between small and large farms. The impact-specific EE of water use, nitrogen balance, and phosphorus balance between small and medium farms was also significantly different at the 5 % confidence level. The energy ratio between small and medium farms and the nitrogen balance between small and large farms were also significant at the 10 % confidence level. In contrast, no significant difference was found between medium and large farms.

Table 7 indicates the potential reduction in actual and percentage form of the environmental impacts for each farm category. To illustrate the sources of environmental inefficiency in small farms, the potential saving was 862.34 m^3 ha^{-1} for irrigation water, 34.91 kg ha^{-1} for nitrogen fertilizers, and 7.24 kg ha^{-1} for P_2O_5, and the energy-input-to-energy-output ratio reduced by 13.5 %. Similarly, 22.77 % of the toxic effect of the pesticide use can be saved if the farmers reduced the quantity of

Table 6 Radial- and pressure-specific environmental efficiencies

	Small farms		Medium farms		Large farms	
	Mean	SD	Mean	SD	Mean	SD
Radial efficiency	0.931	0.108	0.874	0.106	0.896	0.108
Pressure-specific environmental efficiency						
Water use	0.907	0.136	0.850	0.121	0.880	0.119
Energy ratio	0.865	0.166	0.804	0.189	0.804	0.172
Nitrogen balance	0.837	0.211	0.735	0.194	0.764	0.198
Phosphorus balance	0.804	0.254	0.709	0.259	0.751	0.241
Pesticide risk	0.894	0.162	0.662	0.292	0.746	0.281

pesticides used to an optimal level or substituted them with a less lethal product.

The environmental inefficiency can be explained using the technical inefficiency as discussed by Picazo-Tadeo et al. (2011) and (2012). The TE was measured to understand the extent of environmental inefficiency that may be caused by inefficient management of cotton-farming systems. The Spearman's rho correlation coefficients among the TE_{CCR} and TE_{BCC}, CE, AE, radial EE, and impact-specific EE were analyzed. The Spearman's rho correlation coefficient was used to see the relationship among different efficiency measures in the sustainability perspective. The Spearman's rho correlation usually suggested an abnormally distributed efficiency score; to avoid such a misleading correlation, Spearman's rho was selected. The Spearman's rho correlation coefficient (r) (see Appendix A) between TE_{BCC} and EE was 0.800. In addition, the Spearman's rho (r) between TE_{BCC} and the pressure-specific EE were 0.698, 0.590, 0.661, 0.667, and 0.641 for the water use, energy ratio, nitrogen balance, phosphorus balance, and pesticide risk, respectively, and were significant at a 0.01 confidence level. From a technical perspective, the farmers did not efficiently manage farm inputs, which enhanced the environmental pressures and negatively affected the environment. Improving the TE can help reduce costs and enhance the EE in cotton farming. From the farmers' social and behavioral perspectives, there are two other important sets of considerations for environmental inefficiency as established by Picazo-Tadeo et al. (2011) and Picazo-Tadeo et al.(2012). First, the farmers generally consider the environmental pressure an externality; second, the farmers do not always consider the direct economic benefit or profit maximization but often consider a complex set of objectives to enhance the utility (e.g., risk minimization, production steadiness, and drudgery avoidance; Ellis 1998).

Analyzing Determinants of Efficiencies

Table 8 shows the bootstrapped left-truncated regression results of the TE, CE, and EE at variable return to scale of the selected DMUs. The number of bootstrap replications was set to be 2000 following Afonso and Auby (2006) and Barros and Assaf (2009). The estimated coefficients of the factors that affect different efficiencies of the DMUs are provided in Table 8. In some cases, different selected factors significantly affect the TE, CE, and EE of the DMUs such as the farm size, raised-bed sowing, education level and exposure to extension trainings. Farmers prefer to grow cotton on the raised seedbed to avoid damages if rainfall occurs in the early stages of crop growth and saves irrigation water, which ultimately requires extra management activities. It was observed that the raised-bed sowing had a statistically significant effect on the TE and EE of the DMUs, which suggests that the increased use of mechanical and other management practices causes the

Table 7 Target quantities and potential reduction of the environmental impacts

	Water use (m^3/ha)	Energy ratio	Nitrogen (Kg/ha)	Phosphorus (Kg/ha)	Pesticide risk (Kg rat/ha)
Small farms					
Observed quantity	9272.44	0.30	214.14	36.95	40615.10
Target quantity	8410.10	0.26	179.23	29.71	36309.90
Difference (%)	−9.30	−13.50	−16.30	−19.60	−10.60
Medium farms					
Observed quantity	9311.06	0.30	234.12	27.45	64252.89
Target quantity	7914.40	0.24	172.08	19.46	42535.41
Difference (%)	−15.00	−19.60	−26.50	−29.10	−33.80
Large farms					
Observed quantity	8674.16	0.32	226.42	29.15	60717.95
Target quantity	7633.26	0.26	172.98	21.89	45295.59
Difference (%)	−12.00	−19.60	−23.60	−24.90	−25.40

Table 8 Truncated bootstrap regression estimates

Explanatory variables	Explained variable		
	Technical efficiency	Cost efficiency	Environmental efficiency
	Coeff.	Coeff.	Coeff.
Medium farms	−0.0290*	−0.0516*	−0.0443**
Large farms	−0.0222	−0.0162	−0.0070
Sowing method	−0.0267**	−0.0386**	−0.0255*
Access to land	0.0028	0.0192	−0.0011
High school	−0.0116	−0.0480*	−0.0108
Beyond High School	−0.0263*	0.0453*	−0.0379**
Age	−0.0008	0.0004	0.0002
Exposure to extension trainings	0.0326**	0.0322	0.0380**
Constant	0.9153***	0.8801***	0.8843***
Sigma	0.0807***	0.1210***	0.0856***
Wald chi2 (*p* value)	30.51***	15.39*	28.24***

* = Significance level $p \leq 0.10$

** = Significance level $p \leq 0.05$

*** = Significance level $p \leq 0.01$

environmental inefficiencies of the farms. Paradoxically, higher education level is significantly related to technical, cost, and environmental inefficiencies of the farms, which deviates from the usual assumption that higher education leads to higher efficiency. It is plausible that the higher awareness and knowledge of the importance of agro-chemicals of the educated farmers are a negative factor because they tend to over-apply agrochemicals, which is also enabled by their relatively better-off financial status. In other words, they tend to extensify (use more inputs) instead of intensifying production (be more efficient). Finally, high exposure to extension services and trainings significantly relates to high TE and EE.

Conclusions

Our study estimates and analyzes the technical, cost, and environmental efficiencies of irrigated cotton-cropping systems in Punjab, Pakistan. The farms were grouped into small, medium, and large sizes as decision-making units (DMUs), and the efficiencies of the sampled farms were determined using data envelopment analysis (DEA). Measuring the efficiencies of irrigated cotton-farming systems allows us to determine the heterogeneity in efficiency and the level of reduction in the inputs and environmental impacts, while sustaining the economic return. The analysis also identifies areas of intervention to improve the efficiencies. Improvement in the technical efficiency (TE) was found to help reduce the cost and improve the environmental performance of the studied farming systems.

The results also indicate that there is a substantial opportunity to properly manage the inputs to obtain a better economic return with less environmental impact and lower cost. In addition, the medium farms operate at the highest scale efficiency level compared to the small and large farms, which indicates that medium farms operate at a near-efficient scale size. Here, the scale refers to the use of variable inputs in cotton production instead of the optimal farm size. In terms of environmental efficiency, the farms are also environmentally inefficient, and heterogeneity in environmental efficiency was found between small and medium farms and between small and large farms. Besides the radial environmental efficiency, the pesticide risk efficiency was also significantly different between small and medium farms and between small and large farms. Additionally, nitrogen use, phosphorus use, and water use are statistically significantly different between small- and medium-sized farms. In terms of pesticide toxic effect, the small farms tended to use less lethal products than the medium and large farms. The results of the second-stage bootstrapped truncated regression analysis allow us to identify certain socio-economic causes on empirical bases. Paradoxically, the formal education level of the farmers negatively significantly affects the technical-, cost-, and environmental efficiency levels. However, the efficiency levels can be increased by providing extension and training.

The findings of our study can help to formulate some policy interventions to improve the economic and environmental performances of cotton farms. Extensive training regarding the amount, timing, and application methods of agro-chemicals can help increasing the cost efficiency and environmental efficiency. The environmental efficiency can also be improved through learning programs such as demonstrations and capacity building of farmers. Labor-intensive farming systems may increase the cost and environmental efficiencies and can be a source of employment of rural people. The second-stage efficiency analysis can be extended by introducing the type of soil, yield gap, and pest pressure/incidences. Finally, a similar approach to the environmental efficiency can be refined using the life cycle assessment approach with a more detailed inventory of all environmental impacts.

Acknowledgments This authors wish to express their gratitude to the Higher Education Commission of Pakistan (HEC) and the Centre de Coopération Internationale en Recherche Agronomique pour le Développement (CIRAD) for their financial support to the doctoral research and field work that generated the paper. The authors also thank the three anonymous reviewers, whose valuable comments helped in making substantial improvements in this paper.

Appendix

See Table 9.

Table 9 Correlation matrix of efficiency (2-tailed Spearman's rho correlation coefficients)

	[a]TE_{CCR}	[b]TE_{BCC}	[c]CE	[d]AE	[e]SE	[f]EE_{BCC}	[g]EEwater	[h]EE_{Energy}	[i]$EE_{Nitrogen}$	[j]$EE_{Phosphorus}$	[k]$EE_{Pesticides}$
[a]TE_{CCR}	1										
[b]TE_{BCC}	.356**	1									
[c]CE	.421**	.684**	1								
[d]AE	.370**	.430**	.935**	1							
[e]SE	.971**	.170*	.312**	.324**	1						
[f]EE_{BCC}	.308**	.800**	.657**	.486**	.156*	1					
[g]EE_{Water}	.250**	.698**	.537**	.379**	.106	.902**	1				
[h]E_{Energy}	.436**	.590**	.550**	.450**	.330**	.818**	.726**	1			
[i]$E_{Nitrogen}$	.214**	.661**	.562**	.428**	.083	.855**	.844**	.763**	1		
[j]$EE_{Phosphorus}$	.352**	.667**	.603**	.484**	.232**	.838**	.747**	.812**	.784**	1	
[k]$EE_{Pesticides}$	.294**	.641**	.549**	.435**	.174*	.815**	.738**	.696**	.750**	.766**	1

** = Correlation is significant at 0.01 (2-tailed)

* = Correlation is significant at 0.05 (2-tailed)

[a] Total technical efficiency

[b] Pure technical efficiency

[c] Cost efficiency

[d] Allocative efficiency

[e] Scale efficiency

[f] Environmental efficiency with a variable return to scale

[g] Water use, pressure-specific environmental efficiency

[h] Energy ratio, pressure-specific environmental efficiency

[i] Nitrogen balance, pressure-specific environmental efficiency

[j] Phosphorus balance, pressure-specific environmental efficiency

[k] Pesticide-risk, pressure-specific environmental efficiency

References

Afonso A, St. Auby M (2006) Cross-country efficiency of secondary education provision: A semi-parametric analysis with non-discretionary inputs. Econ Model 23:476–491

Azizullah A, Khattak MNK, Richter P, Hader D (2011) Water pollution in Pakistan and its impact on public health-a review. Environ Int 37:479–497

Banker RD (1984) Estimating most productive scale size using data envelopment analysis. Eur J of Oper Res 17:35–44

Banker RD, Charnes A, Cooper WW (1984) Some models for estimating technical and scale inefficiencies in data envelopment analysis. Manag Sci 30:1078–1092

Barros CP, Assaf A (2009) Bootstrapped efficiency measures of oil blocks in Angola. Energy Policy 37:4098–4103

Barros CP, Garcia-del-Barrio P (2011) Productivity drivers and market dynamics in the Spanish first division football league. J Prod Anal 35:5–13

Callens I, Tyteca D (1999) Towards indicators of sustainable development of firms. A productive efficiency perspective. Ecol Econ 28:41–53

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

Choudhury ATMA, Kennedy IR (2005) Nitrogen fertiliser losses from rice soils and control of environmental pollution problems. Commun Soil Sci Plant Anal 36:1625–1639

Coelli T, Rao DSP, Battese GE (1998) An introduction to efficiency and productivity analysis. Kluwer Academic Publishers, Boston

Cooper WW, Seiford LM, Tone K (2007) Data envelopment analysis: a comprehensive text with models, applications, references and DEA-Solver software, 2nd edn. Springer Science + Business Media, LLC, New York

Dagistan E, Akcaoz H, Demirtas B, Yilmaz Y (2009) Energy usage and benefit-cost analysis of cotton production in Turkey. Afr J of Agric Res 4:599–604

De Koeijer TJ, Wossink GAA, Struik PC, Renkema JA (2002) Measuring agricultural sustainability in terms of efficiency: the case of Dutch sugar beet growers. J of Environ Manag 66:9–17

Economic Survey of Pakistan (2011–12) Government of Pakistan, Finance Division Economic Adviser's Wing, Islamabad, pp. 19

Ellis F (1998) Household strategies and rural livelihood diversification. J of Dev Stud 35:1–38

Fan S, Chan-Kang C (2005) Is small beautiful? Farm size, productivity, and poverty in Asian agriculture. Agric Econ 32(l):135–146

FAO (1992) CROPWAT model. Food and Agricultural Organisation, Rome

Gang C, Zhenhua Q (2013) MaxDEA Pro 6 for data envelopment analysis. available at http://www.MaxDEA.cn

Gómez-Limón JA, Picazo-Tadeo AJ, Reig-Martínez E (2012) Eco-efficiency assessment of olive farms in Andalusia. Land Use Policy 29:395–406

Hussain I, Hussain Z, Sial MH, Akram W, Farhan MF (2011) Water balance, supply and demand and irrigation efficiency of Indus basin. Pak Econ and Soc Rev 29(1):13–38

IPCC (2006) NO_2 emission from managed soil and CO_2 emission from lime and urea application. In: guidelines for national greenhouse gas inventories, volume 4: Agriculture, Forestry and Other Land Use. Geneva

Keating BA, Carberry PS, Bindraban PS, Asseng S, Meinke H, Dixon J (2010) Eco-efficient agriculture: concepts, challenges and opportunities. Crop Sci 50:109–119

Kumar A, Kandpal TC (2007) Renewable energy technologies for irrigation water pumping in India: a preliminary attempt towards potential estimation. Energy 32:861–870

Kuosmanen T (2005) Weak disposability in nonparametric production analysis with undesirable outputs. Am Agric Econ Assos 87:1077–1082

Kuosmanen T, Kortelainen M (2004) Data envelopment analysis in environmental valuation: environmental performance, eco-efficiency and cost-benefit analysis. Discussion Paper, 21. Department of business and economics, University of Joensuu

Mohapatra R, Sen B (2013) Technical, allocative and economic efficiency in sugarcane production: a non-parametric approach. Int J of Adv Res 1:366–374

Nguyen TT, Hoang VN, Seo B (2012) Cost and environmental efficiency of rice farms in South Korea. Agric Econ 43:369–378

Picazo-Tadeo AJ, Reig-Martínez E, Hernández-Sancho F (2005) Directional distance functions and environmental regulations. Resour Energy Econ 27(2):131–142

Picazo-Tadeo AJ, Gómez-Limón JA, Reig-Martínez E (2011) Assessing farming eco-efficiency: a Data Envelopment Analysis approach. J of Environ Manag 92:1154–1164

Picazo-Tadeo AJ, Beltrán-Esteve M, Gómez-Limón JA (2012) Assessing eco-efficiency with directional distance functions. Eur J of Oper Res 220:798–809

Pimentel D (1980) Handbook of energy utilisation in agriculture. CRC Press, Inc., Boca Raton

Proto M, Supino S, Malandrino O (2000) Cotton: a flow cycle to exploit. Ind Crops Prod 11:173–178

Reig-Martínez R, Picazo-Tadeo AJ (2004) Analysing farming systems with data envelopment analysis: citrus farming in Spain. Agric Syst 82:17–30

Simar L, Wilson PW (2000) A general methodology for bootstrapping in nonparametric frontier models. J of Appl Stat 27:779–802

Simar L, Wilson PW (2007) Estimation and inference in two-stage, semi-parametric models of production processes. J of Econom 136:31–64

Tariq MI, Afzal S, Hussain I, Sultana N (2007) Pesticides exposure in Pakistan: a review. Environ Int 33:1107–1122

Torgersen AM, Førsund FR, Kittelsen SAC (1996) Slack-adjusted efficiency measures and ranking of efficient units. J of Prod Anal 7:379–398

Wossink A, Denaux ZS (2006) Environmental and cost efficiency of pesticide use in transgenic and conventional cotton production. Agric Syst 90:312–328