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Eco-efficiency of cotton-cropping systems in Pakistan: an integrated approach of life cycle assessment and data envelopment analysis

Asmat Ullah [a,*], Sylvain R. Perret [a,b], Shabbir H. Gheewala [c,d], Peeyush Soni [a]

[a] Asian Institute of Technology, School of Environment, Resources and Development, Bangkok, 12120, Pathumthani, Thailand
[b] Centre de Coopération Internationale en Recherche Agronomique pour le Développement, UMR G-Eau, F-34398, Montpellier, France
[c] The Joint Graduate School of Energy and Environment, King Mongkut's University of Technology Thonburi, 126 Pracha-Uthit Rd., Bangkok, 10140, Thailand
[d] Centre of Excellence on Energy Technology and Environment, PERDO, Bangkok, Thailand

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A B S T R A C T

This study investigates the balance between economic and environmental performances of cotton cropping systems in Southern Punjab, Pakistan. Eco-efficiency analysis was performed using Data Envelopment Analysis to integrate economic and environmental performances, which were assessed through life cycle assessment. All 169 cotton cropping systems were individually analyzed. Special attention was paid to farm size as a possible factor of performances variation. The results show that pesticides and fertilizer use, field emissions, field operations and irrigation are the main sources of environmental impacts. It reveals that production of 1 kg of seed cotton delivered at farm gate generates a global warming potential of 3–3.4 kg CO_{2e} and requires 5–6 L of water. Eco-efficiency estimates of small, medium and large sized farms computed on per hectare basis are 0.86, 0.74 and 0.78, respectively, and 0.51, 0.52 and 0.50 respectively when computed on the basis of kilogram of seed cotton. No significant differences of eco-efficiencies per functional unit were observed across farm size categories. Small farms' higher profits counterbalance their significantly higher levels of eutrophication, and balance its overall eco-efficiency with other farm categories. A trade-off analysis tried to identify the farms that would epitomize sustainable cotton production; it shows that it is almost impossible to combine high economic return with low environmental impacts under current context. However some recommendations have been formulated with regards to pesticides and fertilizers use, which may be significantly reduced with no effect on yield, and potentially reduce environmental impacts.

1. Introduction

Cotton contributes substantially to the national economy of Pakistan and is a key source of livelihood for the rural poor (Pakistan Economic Survey, 2013–2014). It is mainly cultivated under irrigated conditions with a high pest hazard as certain insects are particularly harmful to yields and fibre quality. Cotton production requires huge amounts of resources such as water, fossil energy and agro-chemicals, whose utilization degrades the environment in different ways (Shafiq and Rehman, 2000). The excessive use of fertilizers contributes greenhouse gas emissions and water pollution (IPCC, 2006). In Pakistan, freshwater resources are being contaminated through runoff and leaching of nitrates from agricultural land (Azizullah et al., 2011) and overuse and misuse of chemical pesticides (Tariq et al., 2007). Mechanization has also increased the use of non-renewable energy. The magnitude of these environmental impacts and resource use in different forms varies depending upon the farm management practices, soil properties, and agro-ecosystem conditions (Choudhury and Kennedy, 2005). Also, intensive input use, as a form of insurance for cotton yield and quality, comes with high production costs. Both environmental damages and high costs of cotton production challenge its sustainability and farmers' income in Pakistan; therefore analysing and quantifying jointly environmental impacts and economic performances of cotton production is necessary. The question remains as to how environmental impacts can be reduced while farmer income is sustained. The issue underlying in this research is the trade-off between input use, environmental impact and economic performance in cotton cropping systems of Pakistan.

LCA is a widely used methodology to assess environmental performances of products and processes taking into account the whole life cycle of the products (ISO 14040, 2006; ISO 14044, 2006).

* Corresponding author. Tel.: +66 85 346 4162.
E-mail address: asmat.ait@gmail.com (A. Ullah).

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It helps to identify the environmental impacts hotspots and corresponding decisions can be defined (Baumann and Tillman, 2004). There are limitations to use LCA as a stand-alone methodological approach to sustainability analysis (Vázquez-Rowe et al., 2012). To that aim economic-ecological efficiency or commonly known as eco-efficiency is a useful operational concept. The concept of eco-efficiency refers to a process' increase output value, and lesser negative impacts (World Business Council for Sustainable Development, 2000). Eco-efficiency was defined by OECD. (1998) as the ratio of economic value per environmental impacts. Indicators related to eco-efficiency can be assessed through a product's economic value against its environmental impact (Kuosmanen and Kortelainen, 2005; Van Passel, 2007). Eco-efficiency can help policy-makers to formulate, implement and assess measures to improve the economic activity with reduced amount of negative impacts on environment. Van Passel et al. (2007) stated that eco-efficiency is a useful operational metric to assess farm level sustainability. It may be used as a proxy to sustainability indicator (OECD, 1998). Picazo-Tadeo et al. (2012) argued that any given production process leads to a set of environmental impact indicators (e.g. through the use of life cycle assessment -LCA), hence to a set of eco-efficiency ratios.

Based on the common definition of eco-efficiency, Thanawong et al. (2014) have assessed the eco-efficiency of rice cropping systems in Thailand. The approach provides a reasonable proxy to sustainability analysis, yet it faces the issue of multiple eco-efficiency ratios or indicators (as many as the environmental impact indicators). Interpreting so many indicators may prove cumbersome and, above all, impractical. Therefore integrating both economic and environmental information into a single eco-efficiency indicator may help interpret and compare cases.

Data Envelopment Analysis (DEA) has recently been introduced as a tool to compute such single eco-efficiency score (Kuosmanen and Kortelainen, 2005). Traditionally DEA has been used in industry to evaluate the relative efficiency of decision making units (DMUs) based on commercial inputs and outputs, which is known as technical efficiency (Korhonen and Luptacik, 2004). 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). With the advancement of DEA approach, researchers have started handling the environmentally undesirable outputs into their models as a by-product (e.g. Zhang et al., 2008; Picazo-Tadeo et al., 2011; Avadí et al., 2014), leading to eco-efficiency. Low eco-efficiency score of any given production system always results from low income and/or high environmental impacts. The joint application of LCA and DEA (e.g. Vázquez-Rowe et al., 2012; Mohammadi et al., 2013) has recently emerged as a way to find out trade-off options between environmental impacts and economic return. This approach also helps to compute the potential reduction of environmental impacts through possible reduction of inputs, towards higher eco-efficiency.

This research combines LCA with DEA as an attempt to compute eco-efficiency indicators in a set of cotton cropping systems in Pakistan. To the authors' knowledge, no comprehensive LCA research on cotton has been done in South Asia, let alone research on cotton cropping systems' eco-efficiency. The environmental impacts of a global cotton textile chain have been studied by Steinberger et al. (2009) with LCA, but a single, average production situation was considered, regardless of local diversity.

The objective of our research was to study the sustainability of diverse cotton cropping systems in the Punjab province of Pakistan. The potential influence of farm size as a factor to sustainability was also investigated. Potential environmental impacts were modelled through LCA methodology. Economic performances were assessed, and eco-efficiency scores were computed with DEA.

2. Materials and methods

2.1. Sampling and data collection strategy

Analyses were performed on primary data collected from sampled cotton farming systems of Lodhran and Vehari districts of Southern Punjab, Pakistan, the most suitable area for cotton cultivation (Ali and Abdulai, 2010). Irrigation requirements of cotton are partially fulfilled by surface water and partially by groundwater. Land preparation activities for cotton cultivation are performed mechanically but sowing and cultural management practices (weeding, fertilizing and pesticide spray) are performed either manually or mechanically depending upon farmers' decisions and resources availability. But entire picking of cotton is performed manually. The data were collected using field surveys and structured questionnaire at the farm level. Two hundred cotton farms were selected and surveyed in the two districts. Sampling was done on stratified random basis, in order to select farms of different sizes, which included small (<5 ha) 40 farms, medium (5–20 ha) 68 farms and large (>20 ha) 61 farms. Such classification refers to the land-holding classification of the State Bank of Pakistan. Also, we tried to select systems with different intensification and mechanization levels, as existing in Southern Punjab. Some questionnaires were discarded because of missing data or incoherent information, and 169 cropping systems were eventually used for analyses. Data collection mainly encompassed the consumption of all production factors (inputs per ha) that were used during the cropping season of 2010. In addition, the yields in seed cotton (seed and lint, i.e., un-ginned picked cotton) and the market value of all inputs and the seed cotton were recorded. Gross income, total cost incurred during cotton production, and the value added (net income) were computed for each studied system and used for eco-efficiency estimation.

The Mann–Whitney U-test (two-sided) was used wherever necessary, to determine whether farm size categories possessed significantly different features.

2.2. Environmental impact analysis with LCA

2.2.1. System boundary and specification

Cradle-to-farm-gate approach was used to evaluate the potential environmental impacts of cotton farming systems. The functional unit used refers to the mass of seed cotton produced, delivered at farm gate. The unit used (kg or metric ton) depended upon convenience and adequacy in displaying the results. In this study the potential environmental impacts were computed as per kilogram of seed cotton i.e. seed and lint together. Fig. 1 shows the flow diagram of the studied cotton cropping systems.

2.2.2. Life cycle inventory analysis

Life cycle inventory (LCI) was done with the help of primary data collected through field survey (e.g. input use). Each field operation and input was documented for each system in terms of its type or composition (active ingredients), weight or dose, use time, use schedule, market price and application costs, and fuel consumption as shown in Table 1. Water consumption, both green water (from rainfall and soil stock) and blue water (from irrigation) were modelled based upon the concepts of crop evaporative demand, soil–water relationships, and irrigation system losses. The modelling platform CROPWAT (FAO, 1992), version 8 was used.

2.2.3. Direct field emissions

The direct emissions to air were modelled based on the methods developed by Intergovernmental Panel on Climate Change (IPCC, 2006). Fertilizer-induced emissions were calculated based upon

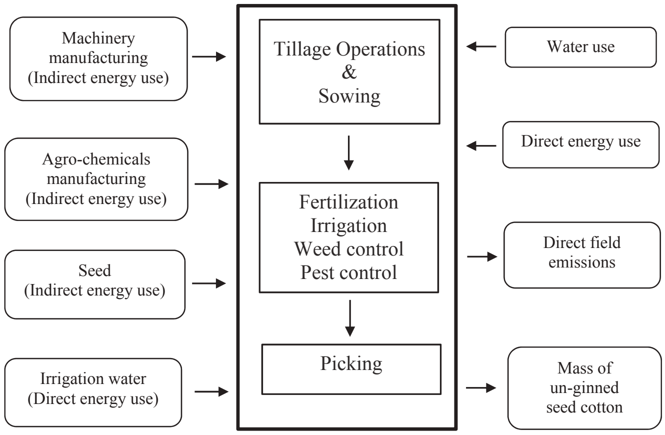

Fig. 1. System boundaries and flow diagram of cotton production systems for LCA from cradle to farm gate.

cropping calendars. Year-round background emissions were also considered, on the basis of common cotton cropping calendar. Cotton cropping and related operations usually covers land over six months (from mid-May to mid-November), wheat being the common winter crop. So yearly background emissions were assessed to reflect the specific contribution of cotton cropping.

Nitrogen (N) and phosphorus (P) balances can be estimated by calculating the difference between respective elements' inputs (fertilization) and outputs (emissions and plant absorption). If N and P stocks in soil are considered constant, each balance consists of:

$$\text{N or P Fertilization} - \text{N or P Emissions} - \text{N or P Plant uptake (exported)} = 0 \quad (1)$$

Under the same cropping systems (cotton–wheat) for years, soil nitrogen and phosphorus contents through time show negligible respective differences. As a consequence, N and P soil stocks were considered constant. Other components such as biological nitrogen fixation (input), and exports by weeds (output) were ignored. All nitrogen and phosphate applications for fertilization were recorded in each cropping system.

2.2.3.1. Nitrogen and phosphorus mass balance. Nitrogen (N) and phosphorus (P) inputs from chemical fertilizer were calculated based on mass content of N and P of the applied fertilizer. Nitrogen and phosphorus uptake and concentration in different parts of cotton plant were adopted from Pettigrew & Meredith Jr. (1997); Boquet & Breitenbeck, (2000); and Murphy et al. (2010) and calculated based on the exported mass of plant parts. Seed cotton and cotton sticks are exported from the field but roots and leaves remain in the field, and ultimately contributing to augmenting soil N content through immobilization in organic matter. However, we considered that mineralization counterbalances such process, under the assumption of constant soil N and organic matter contents through the years. Seed cotton-to-stick weight ratio was considered 0.314 (Aujla et al., 2005). Additionally harvested seed cotton contains approximately 5–10% of trash in the form of plant debris and carpel that is also exported and included as nutrient export (Boquet and Breitenbeck, 2000). Khan et al. (2010) proposed the average lint to seed ratio 0.37.

Nitrogen based emissions to air consist of N_2O, NOx, NH_3 and molecular N_2 (although not a pollutant). The corresponding emission factors of all these emissions are shown in Table 2.

In order to model nitrate emissions (losses to the water compartment), the following assumptions were made: the nitrates absorbed by the plants are counted with exports; the nitrates that are not absorbed remain soluble in the water compartment and will move with drainage, surface run-off and deep percolation. A water balance was modelled in order to evaluate leaching and run-off as media to nitrates losses.

Evapotranspiration ET has been calculated through CROPWAT (FAO, 1992). We used 30-year average monthly data for rainfall (1981–2010), provided by the Meteorological Department of Pakistan. Average irrigation data was provided by the Irrigation Department of Punjab Province of Pakistan.

The average nitrate content of canal irrigation water in Punjab is 3.28 mg L^{-1} (Karim and Veizer., 2000), groundwater and rainwater is 1.9 and 1.42 mg L^{-1} respectively (Farooqi et al., 2007), were used in our water and nitrate balance together with total nitrogen input from fertilizers. The average P content in rainwater 0.4 mg L^{-1}, negligible in groundwater (Farooqi et al., 2007), and 0.76 mg L^{-1} in canal irrigation water (Karim and Veizer., 2000) were used for phosphorus mass balance.

During the cropping period, under limited rainfall, run-off was found negligible. On average, NO_3 concentration in percolating water was found to be 40.7 mg L^{-1}. This figure concurs with the range of nitrate loss reported by Tahir and Rasheed (2008) in Pakistan (11–160 mg L^{-1}).

On the other hand, once the phosphorus balance is calculated (Equation (1)), the remaining P may be considered as water-soluble phosphate salts that are potentially emitted to groundwater and surface water compartments through deep percolation and drainage.

Table 1
Type and sources of data needed for Life Cycle Inventory (LCI).

Data	Area of inventory	Units	Data source
Foreground data (inputs)	- Direct energy consumption (fossil fuel) for field operation	L ha^{-1}	Field survey
	- Electricity (for water pumping)	kWh ha^{-1}	″
	- Seed	kg ha^{-1}	″
	- Fertilizers	″	″
	- Pesticides	kg (a.i)[a] ha^{-1}	″
	- Land occupation	ha per production cycle	″
	- Water consumption	m^3	CropWat (FAO)
Background Processes data	Manufacturing and transportation of machinery, equipment and chemicals	MJ	Eco-invent database
Emissions	- Direct field emission	kg substance/kg seed cotton	Modelled using IPCC guideline
Output	- Yield (seed cotton)	kg ha^{-1}	Field survey
Economic data	- Cost of Inputs	US$ ha^{-1}	Primary data (market prices)
	- Economic value (seed cotton)	US$ ha^{-1}	″

[a] Active ingredients.

Table 2
Nitrogen-based emissions to air and their corresponding emission factors.

Emission	Emission factors	Source	Background emission	Source
N_2O	1%	(IPCC., 2006; Mahmood et al., 2008)	1.22 kg $N-N_2O$ ha^{-1} per year	(Yan et al., 2003)
NO_X	0.66	(Yan et al., 2003; Liu et al., 2010)	0.58 kg $N-NO$ ha^{-1}	(Yan et al., 2003)
NH_3	11.5% (incorporated) and 23.5% if broadcasted.	(Yan et al., 2003)		
N_2	0.09%	(Brentrup et al., 2000)		

2.2.3.2. Pesticides emissions. Different types and quantity of pesticides, mostly insecticides, are applied either manually or mechanically by farmers in cotton cropping systems depending on the level and perception of insect pressure, and outbreaks. Emission of pesticides to air occurs through volatilization either from plant leaf surface, soil surface or through spray drift. The emission factors of different pesticides were adopted from European Environment Agency (EEA, 2009). Pesticides emissions to air were computed by multiplying the mass of active ingredient of the applied doses of pesticides with their corresponding emission factors. After calculating the quantity volatilized, the remaining part has been considered the emission to soil and groundwater compartments.

2.2.4. Life Cycle Impact Assessment (LCIA)

In this stage CML 2001 baseline Life Cycle Impact Assessment method (Guinée, 2001) was selected to calculate mid-point environmental impact indicators as shown in Table 3, using SimaPro 7.2.3. The impact indicators were translated from LCI developed with the help of field data and background processes data retrieved from the ecoinvent database. One additional variable (irrigation water use) was selected as a notably important environmental indicator for water-scarce arid Pakistan. The method and indicators were selected based upon their popularity in LCA studies on agriculture (Abeliotis et al., 2013; Cellura et al., 2012; Khoshnevisan et al., 2014; Romero-Gámez et al., 2012 and Thanawong et al., 2014), and easiness to comprehend by non-specialists in Pakistan. Table 1 shows the environmental impact indicators that have been used.

Considering uncertainty and variability of results, it is crucial to collect best representative operational data and to use the most updated emission models to develop LCI of a product, since it is influential to all calculating processes (Weidema and Wesnaes., 1996). Generally, variability in primary data used in LCI carry a significant standard deviation, which eventually cause differences in the impact assessment. However, we developed individual LCI for each cotton farm and their corresponding potential environmental impact were assessed independently instead of using average values. So variability was addressed; 169 individual systems were analyzed, which effort remain rare and original in LCA + DEA approaches.

Uncertainty rather refers to using secondary data and making assumptions with regards to ex-ante and ex-post inventory calculations (emission models, impact models). In the absence of data, and of locally developed models, we resorted to some regional and possibly outdated models (e.g. Yan et al., 2003), which indeed increases uncertainty in final results.

Table 3
Selected environmental impact categories.

Environmental impact categories	Units
Abiotic depletion potential (ADP)	kg Sb eq
Global warming potential (GWP_{100})	kg CO_2 eq
Acidification potential (AP)	kg SO_2 eq
Eutrophication potential (EP)	kg PO_4^{3-} eq
Human toxicity potential (HTP)	kg 1,4-DB eq
Fresh water aquatic ecotoxicity potential (FETP)	kg 1,4-DB eq
Terrestrial ecotoxicity potential (TETP)	kg 1,4-DB eq
Ozone layer depletion (ODP)	kg CFC-11 eq
Water use (WU)	m^3 H_2O

2.3. Eco-efficiency analyses with DEA

Data envelopment analysis (DEA) is a non-parametric approach, was developed by Charnes et al. (1978) to calculate the relative efficiency of a set of DMUs. It constructs a piecewise linear frontier which represents the best practices and the distance of inefficient DMUs to the frontier is a measure of the relative inefficiency of those DMUs (Cooper et al., 2007).

Several studies have combined LCA and DEA (e.g. Iribarren et al., 2010; Iribarren et al., 2011; Lozano et al., 2009, 2010; Vázquez-Rowe et al., 2010, 2011, 2012; Mohammadi et al., 2013) to analyze eco-efficiency but advocating different perspectives and using five-step or three-step DEA + LCA framework (Vázquez-Rowe and Iribarren, 2014). In this study, we analyzed eco-efficiency of cotton cropping systems using three-step LCA + DEA framework considering environmental impacts as inputs in the input set of DEA model exclusively. The reason is that our main concern was to benchmark the environmental impacts of cotton production systems since we have considered that environmental impacts are mostly associated with agricultural input use.

The DEA approach for our study supposes that the value added or net income denoted by variable v, generated in the production processes of a set of $j = 1, 2, \ldots, J$ DMUs. Additionally, the production processes generate a set of $n = 1, 2, \ldots, N$ environmental impacts, which are denoted by $p = (p_1, p_2, \ldots, p_n)$. Following Kuosmanen and Kortelainen (2005), the production technology is given by:

$$T = [(v, p) : \text{value added v can be generated with environmental impacts p}]$$

To reasonably model the eco-efficiency of the DMU, following Kuosmanen and Kortelainen (2005), Schaffel and La Rovere (2010), Picazo-Tadeo et al. (2011), Gómez-Limón et al. (2012), we attempt to produce a certain amount of net income with as few environmental impacts as possible. The reference technology can provide all feasible relationships among value added and multiple environmental impacts. It can be modelled by simultaneously reducing the environmental impacts through resource use and pollutant emissions reduction while maintaining the output level. The efficiency measure can be computed using the following linear programming model:

$$\begin{aligned} &\text{Minimize } \theta. \\ &\text{Subject to} \\ &v_j \quad \le \sum_{j=1}^{J} \lambda_j v_j \\ &\theta_j p_{nj} \ge \sum_{j=1}^{J} \lambda_j p_{nj} \\ &\sum \lambda_j = 1 \\ &\lambda \ge 0 \text{ and } \quad 0 \le \theta \le 1 \end{aligned} \tag{2}$$

where θ is a scalar, whose value is the eco-efficiency value of the jth farm, and λ is the intensity vector of the weights of efficient DMUs, which helps to project the inefficient DMUs to an efficiency frontier. v_j represents the value added of jth DMU, p_{nj} represents the environmental impact of n category of the jth farm.

The environmental impact va Following, Picazo-Tadeo et al. (2011) riables (from LCA) and net income were used to calculate the eco-efficiency of each DMU. we have avoided the bias of subjective choice of assigning common weights to environmental impacts, and decided DEA aggregation method. Variable returns-to-scale (VRS) model was used since farming is considered as a typical VRS activity. Additionally, impact-specific eco-efficiency of each DMU was analyzed following the methodology developed by Torgersen et al. (1996), using Equation (3).

$$\text{Impact} - \text{specific eco} - \text{efficiency} = \frac{\theta P_{nj} - S^{p}_{nj}}{P_{nj}} \quad (3)$$

where θ denotes the eco-efficiency, P_{nj} denotes the environmental impact n of farms j and S^{p}_{nj} denotes the slack or excess of environmental impact n of farm j. In this equation, the numerator indicates the total amount of potential impact reduction, which consists of the equi-proportional reduction of each environmental impacts and the excess or slack-based specific impact reduction, and the denominator indicates the observed or the actual amount of impact that is generated by farm j. Eco-efficiency analysis was performed using MaxDEA Pro (Gang and Zhenhua, 2013).

In the next stage, the top ten best performing DMUs in terms of high economic return, least production cost and least environmental impacts were considered and compared to check if DMUs can secure high performances in all compartments (being so more sustainable) or if trade-offs are inescapable. This was done through basic comparative decile-based analysis.

3. Results

3.1. Utilization of production factors and direct field emissions

Primary data availability and quality are key requirements to developing sound LCI, and ultimately the computation of results with LCA and DEA methodological approaches (Vázquez-Rowe et al., 2012; Avadí et al., 2014). This LCI developed with the help of different material inputs (land, water, machinery, fuel, fertilizers and pesticides) to each cotton farm, direct field emissions from applied fertilizers and pesticides. Using LCI data, the environmental impacts indicators of each farm i.e DMU was computed through LCA methodological approach. All data related to field operations and production factors are reported in Table 4. Average seed cotton yields amount to 2, 2.2, and 2 metric ton per ha in small, medium and large farms respectively, with statistically significant differences. Yields are also more variable in small farms, and more homogenous in medium farms. Since small farms also have lower production costs, net income is homogenous amongst the farm size categories (Ullah and Perret, 2014).

Table 4 shows that field operations among farm size groups are significantly different except for sowing and electricity consumption. Interestingly, small farms use significantly more irrigation water compared to medium and large farms but medium farms use the least unit area of land to produce certain amount of seed cotton. In terms of land preparation, small farms use more primary tillage operations (i.e. ploughing) compared to medium and large farms. However, in terms of rotary tillage both small and medium farm size group are significantly using higher operations compared to large farms. Larger farms use significantly more crop-care operations and inputs such as pesticides, weeding operations and sulphuric acid (which is used by farmers to de-lint cotton before sowing). In other words, productivity of low-cost resources is low in small farms, which are more productive using costly, manufactured inputs. Conversely, large farms' productivity is low with regards to complex, chemical, costly inputs. Overall, we found that both total costs and net income are higher in medium-sized farms, while their total energy use is also the highest.

Table 5 provides more insights into these results and shows that insecticides (pyrethroids, phenoxy compounds) and Table 6 shows phosphates are the chemical inputs significantly more used by larger farms (hence a lower productivity of these inputs). Table 7 shows the emissions from the different farm categories. It highlights that small farms have higher polluting emissions per FU overall, with significant differences for nitrous oxide, nitrogen oxide (air), and phosphate (water). Phosphate emissions are higher in small farms while they use less P fertilizer per FU due to significantly lower yields, compared to medium and large farms.

Individual life cycle inventory of each cotton farm was used to carry out independent LCIA of each farm using SimaPro. The environmental impact indicators, listed in Table 3, were assessed.

3.2. Environmental impacts

The environmental impact categories with corresponding mean values per kilogram of seed cotton are shown in Table 8. Energy use is included in the Abiotic (resources) Depletion Potential indicator (ADP). Eutrophication potential is significantly higher in small farms (due to higher phosphate and nitrate emissions per FU, and lower yields). Small farms are also showing higher ADP, AP, GWP

Table 4
Statistics of production factors use (per 1000 kg of seed cotton) as per farm size category.

Inventory	Units	Small		Medium		Large		Sig. Diff
		Mean	SD	Mean	SD	Mean	SD	
Land use[a]	Ha	**0.50**	0.30	**0.46**	0.23	**0.50**	0.24	a**, c**
Water use	m^3	**5947**	2386	**4823**	1783	**5019**	1515	a**, b**
Ploughing	ha.hour	**5.50**	3.15	**4.48**	2.78	**4.31**	2.26	a*, b*
Rotary tillage	ha.hour	**1.36**	1.12	**1.52**	1.26	**0.81**	1.07	b**, c**
Field leveling	ha.hour	**0.88**	0.42	**1.17**	0.89	**0.84**	0.65	c**
Sowing	ha.hour	**1.01**	0.78	**1.07**	0.61	**1.00**	0.61	
Cultural management/weeding	ha hour	**1.13**	1.21	**1.64**	2.20	**3.08**	2.51	b**, c**
Mechanical pesticides spray	ha.hour	**1.94**	4.01	**5.73**	6.16	**10.04**	5.33	a**, b**, c**
Electricity	kWh	**568**	319	**487**	212	**503**	187	
Sulphuric Acid	liter	**0.92**	0.82	**1.39**	0.77	**1.66**	0.69	a**, b**, c**

a = Significance difference between small and medium; b = Significance difference between small and large; c = Significance difference between medium and large.
*, ** = significant at 10% and 5% level, respectively using Mann–Whitney U-test.
[a] Land use refers to direct cotton production only, i.e. cotton plots; seed production areas, and required built areas have been ignored.

Table 5
Statistics of pesticides use (as per 1000 kg of seed cotton) as per farm size category.

Inventory	Units	Small		Medium		Large		Sig. Diff
		Mean	SD	Mean	SD	Mean	SD	
Pesticides (unspec.)	kg a.i[A]	**1.80**	1.27	**0.97**	0.76	**1.30**	1.15	
Organophosphates	kg a.i	**0.84**	0.56	**1.06**	0.83	**0.83**	0.64	
Pyrethroids	kg a.i	**0.12**	0.13	**0.18**	0.19	**0.26**	0.26	b**, c**
Pheaxy compounds	kg a.i	**0.70**	0.77	**1.17**	1.28	**1.58**	1.03	a**, b**, c**
Weedicides	kg a.i	**0.84**	0.64	**1.06**	0.96	**1.09**	1.05	

[A]active ingredient.
a = Significance difference between small and medium; b = Significance difference between small and large; c = Significance difference between medium and large.
**Significant at 5% level using Mann–Whitney U-test.

Table 6
Statistics of fertilizers use (as per 1000 kg of seed cotton) as per farm size category.

Inventory	Units	Small		Medium		Large		Sig. Diff
		Mean	SD	Mean	SD	Mean	SD	
Nitrogen-based	kg	**153**	58	**154**	68	**164**	63	
Phosphates	kg	**31**	22	**39**	24	**40**	23	a**, b**

a = Significance difference between small and medium; b = Significance difference between small and large; c = Significance difference between medium and large.
**Significant at 5% level using Mann–Whitney U-test.

and water use. All remaining environmental impacts, related to toxicity potentials, are higher in medium sized farms.

According to our results, production of 1 kg of seed cotton delivered at farm gate generates a global warming potential of 3–3.4 kg CO_{2e} and requires 5–6 L of water, of which 75–80% is irrigation water. Overall, farm size does not play an important role in the level of impacts. Differences remain limited between farm classes, and mostly due to differences in yields.

4. Discussion

4.1. Contribution analysis

Environmental impacts were shown as per farm size category in Section 3; they proved sometimes significantly different, especially from smaller farms as compared to others. Yet, in absolute terms, data were in the same range for all impact categories, with the exception of some toxicities. So, in this section we decided to merge all categories when performing the contribution analysis. Detailed analysis demonstrated that contribution patterns looked very similar amongst categories. So we have shown only contributions across all categories. The approach helps to identify the most important sources of impact that contribute to the overall environmental burden of the cotton production systems. Since general policies can be made based on the general picture (i.e. regardless of farm size), this approach might be helpful.

Fig. 2 represents the contribution of different inputs and field operations to the environmental impacts. Direct field emissions contribute to most toxicity-related, acidification and eutrophication impacts, due to high pesticide and fertilizer use. Irrigation is the major contributor of abiotic resources depletion, global warming potential and ozone depletion potential, due to water use, energy use (through groundwater pumping and fossil fuel consumption).

Fertilizer manufacturing and transportation are contributing much to energy and fossil-fuel use (reflected by ADP and GWP) and to photochemical oxidation potential. They also, with pesticide manufacturing and transport contribute to ozone depletion. Field operations are mainly motorized, so they contribute much to energy use and fossil-fuel combustion (reflected by ADP and GWP). They also contribute significantly to ozone depletion.

Overall, the most important sources of environmental impacts in cotton cropping systems of Southern Punjab are irrigation (through groundwater pumping), fertilizer and pesticide uses, and motorized field operations. Direct field emissions seem particularly harmful (toxicity), due to excessive use of fertilizer and pesticides, leading to high emissions to air and water compartments.

4.2. Eco-efficiency analysis

To compute an eco-efficiency score for each cropping system, we used the values of environmental impacts shown in Table 8 and the net income yielded. Input-oriented eco-efficiency scores have been computed using DEA, which also helped calculate the potential reduction of each environmental impact while maintaining net income. Calculations were done with variables based on FU, i.e. 1000 kg of seed cotton, and also on area basis (per ha).

Table 9 summarises the results of eco-efficiency analysis. Only 13 cropping systems on 169 (DMUs) (i.e. only 7.69%) were found fully efficient, when scores were calculated on per mass basis; all other cropping systems fall below the efficiency frontier, and show excess environmental impacts compared to net income. Average eco-efficiency scores are particularly low when calculations are made on per mass basis.

Table 7
Statistics of field-level nitrogen and phosphorus emissions (as per 1000 kg of seed cotton produced) as per farm size category.

Inventory	Units	Small		Medium		Large		Sig. Diff
		Mean	SD	Mean	SD	Mean	SD	
N_2O emission	kg	**1.99**	0.71	**1.74**	0.58	**1.94**	0.61	a**, c**
NO emission	kg	**1.23**	0.44	**1.08**	0.37	**1.21**	0.38	a*, c*
NH_3 emission	kg	**20.0**	7.6	**17.9**	6.6	**19.6**	6.6	c*
NO_3 emission	kg	**223**	115	**207**	106	**202**	86	
PO_4 emission	kg	**30**	27	**18**	13	**19**	14	a**, b**

a = Significance difference between small and medium; b = Significance difference between small and large; c = Significance difference between medium and large.
*, ** = significant at 10% and 5% level, respectively using Mann–Whitney U-test.

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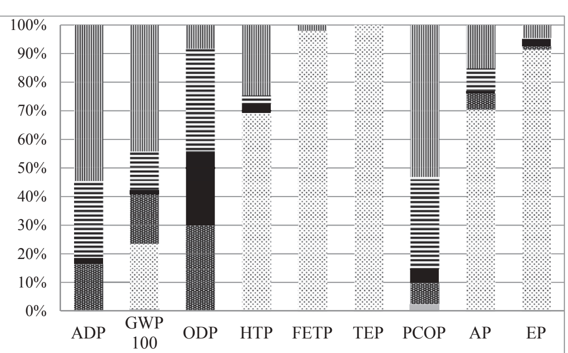
Table 8
Average environmental impacts from the different farm size classes, per kilogram of seed cotton.

Variables	Units	Farm size	Mean	SD	Sig. Diff
ADP	kg Sb eq	Small	0.022	0.010	
		Medium	0.020	0.010	
		Large	0.020	0.007	
		Overall	0.020	0.009	
AP	kg SO_2 eq	Small	0.054	0.021	
		Medium	0.049	0.017	
		Large	0.051	0.017	
		Overall	0.051	0.018	
EP	kg PO_4^{3-} eq	Small	0.067	0.036	a^{**}, b^{*}
		Medium	0.052	0.024	
		Large	0.053	0.021	
		Overall	0.056	0.027	
GWP_{100}	kg CO_2 eq	Small	3.418	1.501	
		Medium	3.059	1.358	
		Large	3.084	1.031	
		Overall	3.153	1.289	
HTP	kg 1,4-DB eq	Small	2.871	1.434	
		Medium	2.889	1.658	
		Large	2.600	1.056	
		Overall	2.780	1.411	
FETP	kg 1,4-DB eq	Small	4.634	8.938	a^{**}
		Medium	6.951	7.219	
		Large	4.306	4.170	
		Overall	5.448	6.866	
TETP	kg 1,4-DB eq	Small	1.196	4.062	a^{**}, b^{*}
		Medium	1.338	2.583	
		Large	0.522	1.663	
		Overall	1.010	2.760	
WU	m^3 H_2O	Small	5.947	2.386	a^{**}, b^{**}
		Medium	4.823	1.783	
		Large	5.019	1.515	
		Overall	5.160	1.912	

a = Significance difference between small and medium; b = Significance difference between small and large; c = Significance difference between medium and large.
*, ** = significant at 10% and 5% level, respectively using Mann–Whitney U-test.

According to a Mann–Whitney U-test, average eco-efficiency scores as per farm size category are not significantly different when calculated on per mass basis. Small farms show significantly higher eco-efficiency scores when scores are calculated on area basis. Overall, this means that small farms generate less environmental impacts from the inputs and resources they mobilize per ha basis to generate an income, compared to other farm size categories.



	ADP	GWP 100	ODP	HTP	FETP	TEP	PCOP	AP	EP
Irrigation	54.50	43.91	8.30	24.62	2.01	0.01	54.26	15.16	4.64
Fertilizers	27.17	13.84	35.85	2.91	0.00	0.02	33.22	7.87	0.19
Pesticides	1.89	1.34	25.99	3.24	0.05	0.00	5.07	0.88	2.66
Field operations	16.44	17.22	29.86	0.00	0.04	0.00	7.44	5.53	1.15
Field emissions	0.00	22.87	0.08	69.21	98.14	99.90	0.33	70.42	91.23
Seed production	0.20	0.82	0.00	0.16	0.06	0.08	2.33	0.12	0.14

Fig. 2. Contribution of cotton cropping inputs and operations to environmental impacts.

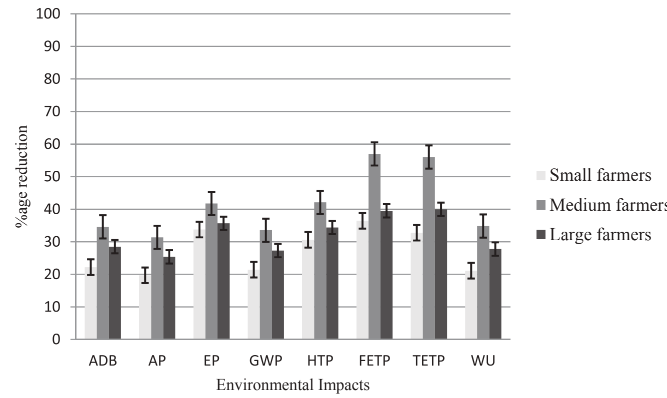


Fig. 3. Percentage potential reductions of environmental impacts per ha.

Table 10 indicates the potential reduction in environmental impacts in non-efficient cropping systems and it has been computed using relative efficiency of each DMU computed through DEA; such reduction would make them reach the efficiency frontier. Potential reductions of the environmental impacts are reached through reducing amount of inputs. Calculations were made on per kg of cotton produced basis. Since the analysis differentiates impacts, one may identify the areas where efforts are most needed. Such results are to be related to the contribution analysis. Results show that potential reduction percentages are fairly homogenous amongst impacts. Overall, all impacts could be halved or further reduced. Toxicity-related impacts are the ones which show significantly higher percentages (>70%). This shows that chemicals use reduction is the most important pathway to lower environmental impacts and higher eco-efficiency.

Fig. 3 reports similar results, yet calculated on per area basis. The trend shown in Table 10 is confirmed. They further highlight that medium sized farms have the highest impact reduction potential, followed by large farms.

4.3. Trade-off analysis

A percentile analysis of performance indicators was performed to investigate trade-off, as the combination of high technical, economic and environmental performances. Among the sampled cropping systems (169 DMUs), the 10% with highest eco-efficiency, the 10% with highest net income, the 10% with lower environmental impacts (several indicators), and the 10% with lower production costs were identified as sub-groups (deciles), then compared with each other. Results are reported in Table 11 and show that there is no overlapping (systems are completely different altogether) between the "high income" decile and the "low production costs", and "low environmental impact" deciles

Table 9
Eco-efficiency scores (averages as per farm size and overall).

	Small		Medium		Large		Overall		Sig. Diff
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	
EE (mass)	**0.51**	0.20	**0.52**	0.25	**0.49**	0.20	**0.51**	0.22	–
EE (area)	**0.86**	0.15	**0.74**	0.16	**0.78**	0.17	**0.78**	0.17	a^{**}, b^{**}, c^{*}

Eco-efficiency (mass) = Eco-efficiency based on the net income per kilogram of cotton.
Eco-efficiency (area) = Eco-efficiency based on the net income per hectare of cotton production.
a = Significance difference between small and medium; b = Significance difference between small and large; c = Significance difference between medium and large.
*, ** = significant at 10% and 5% level, respectively.

Table 10
Potential environmental impact reduction in the different farm size categories computed through relative efficiency to meet full eco-efficiency (calculation on per mass basis).

Farm size	Small		Medium		Large	
Impacts	Mean	SD	Mean	SD	Mean	SD
ADP	**56.23**	20.75	**54.29**	24.08	**56.44**	18.99
AP	**54.95**	19.43	**53.77**	22.43	**56.06**	18.18
EP	**56.28**	21.96	**55.63**	26.68	**56.13**	22.75
GWP	**56.98**	20.47	**54.94**	22.84	**56.16**	18.18
HT	**63.78**	21.59	**62.24**	25.95	**63.51**	18.77
FAET	**69.07**	25.87	**72.99**	27.05	**72.53**	21.31
TET	**66.83**	28.07	**71.31**	29.44	**72.09**	24.81
Water use	**53.08**	21.33	**53.04**	22.37	**55.11**	18.77

respectively, except for 2 DMUs that are common to both "high income" and "low eutrophication" deciles. However it was observed that "highest eco-efficiency" decile are partially overlapping with highest net income and partially with low production cost and low environmental impacts.

The results clearly show that the cropping systems with higher net income are not those with low environmental impacts. A closer look to the given systems shows that the best systems with respect to higher net income are those who are growing their crop earlier and on raised seedbed (ridge cropping). These systems were getting higher yield compared to others and thus higher net income. Ridge cropping (raised seedbeds) requires extra management care and ultimately higher fossil fuel use. These systems are responsible for higher environmental impacts due to extra use of fossil energy for management activities as well as increased amount of agrochemicals due to extended life span of cotton. Further analysis showed that none of the 10% systems with low production cost are eco-efficient. So, in practice, "low production costs" rather refer to "low environmental impacts" than to "higher income" in cotton systems of Southern Punjab.

The descriptive percentile analysis also showed that farm size has no striking impact on the different performances, with the notable exception of "low GWP decile" which is mostly populated with DMUs from large farm size group.

5. Conclusions

In this research the eco-efficiency of irrigated cotton cropping systems in Punjab, Pakistan has been analysed based on the environmental impacts through Life Cycle Assessment (LCA) approach. A wide heterogeneity of practices which influences the environmental impacts and thus eco-efficiency among cotton cropping systems has been confirmed, although they pertain to a relatively homogenous production area (Southern Punjab, Pakistan). Further a specific attention has been given to farm size as a possible factor influencing environmental performances and eco-efficiencies.

The eco-efficiency of small farms has been observed as the highest followed by large and medium farms. On product mass basis, large farms were using more crop-care inputs such as weeding and pesticide sprays and phosphate treatments. It was found that the medium and large sized farms were using higher quantity of pesticides in terms of phenoxy and pyrethroids compound respectively compared to small farms. However, emissions

Table 11
List of cropping systems grouped in deciles with higher net income, lower production cost and lower environmental impacts.

EE	Net income	Total cost	GWP	AP	EP	HTP	TETP	FETP	WU
3	3	1	16	1	3	9	1	1	1
16	13	6	36	5	8	15	9	9	2
17	16	21	102	19	17	39	15	15	8
44	17	24	104	26	25	40	18	19	10
50	37	25	115	30	26	57	26	25	12
56	38	39	128	67	30	79	39	39	39
69	44	40	129	85	61	89	40	40	53
79	50	53	130	102	93	93	56	56	56
90	69	61	131	115	99	99	79	79	65
93	90	85	132	128	102	121	85	85	99
95	94	128	140	130	115	128	89	89	128
104	95	140	150	131	128	130	109	93	130
112	111	153	154	140	130	142	118	109	131
113	112	154	160	142	131	160	121	121	159
128	113	161	165	150	154	162	142	142	160
157	157	162	168	154	159	168	158	163	168
158	164	169	169	165	169	169	160	160	169

Small farms
Medium farms
Large farms

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of N_2O and NO to air and PO_4 to water were higher in small farms (per kg of cotton produced). The main hotspots of environmental impacts are pesticides and fertilizers use, which contribute mostly to global warming, eutrophication and toxicities. The higher eco-efficiency of small farms indicated that small farms make better use of the inputs and resources than medium and large sized farms and that higher economic return (due to lower production costs) offsets the negative impacts of small farms.

Sustainability analysis based upon performance indicators and efficiency scores indicates that trade-off seems inescapable in cotton cropping systems. From empirical data, it appears hardly possible to achieve jointly high economic performance with low environmental impacts. Further, the most profitable systems are not the ones that minimize production costs, while some convergence is observed at system level between lower production cost and lower environmental impacts. Under current technology, farmers' objectives and practices, there is little room to improve together all aspects of sustainability with no trade-offs. It seems that high economic return to production is not compatible with low production costs and low environmental impacts at the moment.

The combination of LCA with DEA is hardly applied in developing contexts and proves extremely fruitful. Eco-efficiency analysis based on value added per individual environmental impact is a common approach. The contribution of this research is that it produced a single value of eco-efficiency (using LCA indicators) for each system, as a proxy to its sustainability. Such score also compensates for the lack of one single environmental impact score per system. The results gained may be of use to scholars, researchers, managers and policy-makers in Pakistan. However, producing such eco-efficiency score for a large and representative enough number of cropping systems is a challenging task. Further research is needed to pre-group cropping systems in typical classes (types) through typology schemes, so that less amount of LCA work be required, especially on inventory. Also, as shown by Ullah and Perret (2014), a combined analysis of eco-efficiency with technical and cost efficiency paves the way to practical advice and solutions to improve both environmental and economic performances at the farm level. Finally, temporal variations always exist regarding input use and yield due to climatic conditions. In this study only one year data have been used. To address this issue 2–3 years data is recommended future studies to make the results generalized.

From the results gained here, it appears that more engaging policy measures and incentives are needed to push trade-offs. In particular, limitations on pesticide use should be considered. The eco-efficiency analysis identified highly eco-efficient farms, which define the efficiency frontier. Such systems have been identified and may be mobilized further through learning programs, such as farmer-to-farmer communication, demonstrations, experiments and capacity building. Some other policy interventions, such taxes on pesticides and fertilisers or banning more lethal products, could be helpful in reducing the impact on the environment.

Throughout this paper, authors consistently referred to the so-called sustainability of cotton cropping systems, while they are well aware that comprehensive sustainability assessment should include also social impacts. As research teams worldwide are currently developing social impact pathways, categories, and ultimately indicators, the methodology presented in the present paper may well apply next to such indicators; all dimensions of sustainability would then be approached.

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