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Measuring Environmental Performance of Irrigated Cotton Enterprises

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Abstract

Irrigation enterprises are often branded with poor environmental record in relation to the intensity of their water use, and their impact on increased water and soil salinity. One novel way of looking at environmental performance of agricultural enterprises is to measure their environmental efficiency. This is achieved using methods similar to the traditional technical efficiency measurement. This study evaluates the environmental efficiency of a sample of irrigated cotton enterprises in the Mooki Catchment, located in northern New South Wales. Deep drainage, which adds to the aquifer recharge and can thereby contribute to salinisation problems, is treated as an environmentally detrimental output. Using Data Envelopment Analysis, eco-efficiency of cotton enterprises is estimated and relative efficiency rankings are determined for each of the considered cotton areas in the catchment. These results are then evaluated in relation to the biophysical characteristics at the sample cotton enterprises to help identify the particular features of an area which may influence outcomes that are both environmentally sound and economically efficient. With the identification of the most and least efficient cotton irrigation areas in the region, policymakers can construct a relative ranking system to best determine policy directions in order to achieve economic and environmental objectives.

Keywords: Cotton, Irrigation, Deep Drainage, Environmental Efficiency

1. Introduction

As a result of increasing environmental awareness and declining natural resource availability, agricultural industries in Australia and irrigation enterprises in particular, are under pressure to increase their environmental performance. Two key areas of environmental performance for irrigated enterprises are under special scrutiny: the quantity of water extracted from the river systems for irrigation purposes which threaten the survival of the riverine eco-system, and the salinity impact caused by the irrigation enterprises.

One of the most important irrigation enterprises in Australia is cotton which is a valuable fibre commodity and important commercial crop mostly grown inland in northern New South Wales and southern Queensland. Despite its economic significance, cotton production is notoriously renowned as a water-intensive industry. According to the NSW Irrigator's Council (2002), approximately 80% of NSW cotton production was irrigated, which was substantially above the state average of 29% of total agricultural production that was irrigated in 2001/02. One of the key environmental concerns with cotton is that deep drainage of irrigation water below the root zone contributes to increased salt mobility, as well as potentially rising groundwater tables, which can combine to significantly increase salinity impacts (Ghasemmi et al. 1995). Deep drainage will always occur with irrigation, but is especially significant with surface irrigation methods (Meyer 2005), that are widespread in the cotton production in NSW (Lee 2007).

One way of determining environmental efficiency is to contrast the amount of deep drainage from irrigation with the economic value added in cotton enterprises. For a given economic outcome (yield/profit), the enterprise that has a low deep drainage is more environmentally efficient compared to enterprises who exhibit high deep drainage. By comparing the cotton enterprises according to their environmental efficiency score it factors such as land category, soil texture, and others can be identified as particularly affecting the level of environmental efficiency. Therefore, with the identification of the most and least efficient cotton irrigation areas in the region, policymakers can construct a relative ranking system to best determine policy directions in order to achieve economic and environmental objectives.

The aim of this study is to estimate the environmental efficiency of a sample irrigated cotton-producing enterprises, with an emphasis placed on deep drainage loss as an environmentally detrimental output. The main objective of this study is to determine the type of cotton enterprises within the region that are most efficient, in terms of their use of environmental assets, both in the sense of economic value adding based on water extractions, and in the sense of their salinity impact. Hence, by comparing the efficiencies of all cotton enterprises, one should in principle be able to find out specific areas where the application of water produces the highest benefit and where irrigation practices are the most efficient.

2. Literature Review

An extensive amount of literature exists on measurement of production efficiency from the earlier articles by Koopmans (1951), Farrell (1957), Charnes *et al.* (1978), Färe *et al.* (1985), to the more recent work incorporating environmental indicators by Tyteca (1996), Kortelainen and Kuosmanen (2004), and Daraio and Simar (2005). The more recent works have attempted to measure overall productive efficiency whilst also accounting for some environmental factors which might influence the production process, essentially in the form of 'undesirable outputs,' under a notion of 'eco-efficiency'.

Modern efficiency measures can be attributed to the pioneering work of Farrell (1957). By drawing upon the ideas of resource utilisation and allocation as presented by Debreu (1951) and Koopmans (1951), Farrell (1957) proposed a simple efficiency measure that could account for multiple inputs. Farrell suggested the use of either a parametric or a non-parametric approach. Both parametric and non-parametric approaches have been used across various applications, and the consensus remains that neither approach is better than the other – primarily because of the trade-offs they are affected by (Galdeano-Gómez, 2007). Parametric approaches have the advantage of allowing for random error and for formal statistical testing. On the other hand, non-parametric approaches, such as Data Envelopment Analysis (DEA) have an advantage over parametric approaches because they provide a good measure of relative productivity and are therefore suitable for benchmarking and ranking of all units when no *a priori* or functional form is pre-defined.

Apart from the traditional Farrell measure of efficiency, there are various other measures that can be adopted to measure the efficiency of production – dependent on the focus of the efficiency analysis being sought. To measure performance of agricultural production activities such as irrigation efficiency, environmental efficiency approaches can be related to studies in agricultural production and can also describe efficiency in terms of environmental impacts. However, a variety of environmental performance indices have been proposed in the past, based on adjustments of conventional measures of productive efficiency. These indices can be categorized as those which are measured using deterministic techniques, which can be either parametric or nonparametric, and those which are estimated using stochastic techniques, which are exclusively parametric. These indices can also be categorized on the basis of whether they treat the environmental effects as inputs or outputs.

Färe *et al.* (1989) treated environmental effects as undesirable outputs developing a hyperbolic efficiency measure that evaluates producer performance in terms of the ability to obtain an equiproportionate increase in desirable outputs and reduction in undesirable outputs. They developed a measure of a strongly disposable technology (applicable if undesirable outputs are freely disposable) and on a weakly disposable technology (applicable when it is costly to dispose off undesirable outputs, perhaps due to regulatory action). They proposed a nonparametric mathematical programming technique know as Data Envelopment Analysis (DEA) to construct strong-disposal and weak-disposal best-practice production frontiers, and to calculate a hyperbolic efficiency measure. Ball et al. (1994) and Tyteca (1997) provided empirical applications of the DEA model proposed by Färe et al. (1989).

Färe *et al.* (1993) also defined environmental effects as undesirable outputs and used a parametric mathematical programming technique similar to goal programming to calculate the parameters of a deterministic translog output distance function. This enables them to calculate a hyperbolic efficiency measure and to calculate shadow prices of the undesirable outputs.

Kortelainen and Kuosmanen (2004) defined the concept of eco-efficiency as the ratio of economic value added to the environmental pressure (or damage index) and developed a general measurement framework based on production theory and activity analysis approach (i.e., Data Envelopment Analysis). The difference between the earlier production economic approaches and this approach is that they focussed on environmental pressures rather than specific undesirable outputs.

Reinhard *et al.* (2000) showed environmental efficiency could be estimated using both Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA). But SFA allows the estimation of environmental efficiency scores only in the two environmentally detrimental input cases while DEA is able to calculate environmental efficiency for every environmentally detrimental input model.

3. The Model for the Study

In this study DEA approach is chosen within the context of irrigation decision making units because it can be used to determine the relative efficiency of a productive activity. This then allows for the determination of its position relative to the optimal situation by providing a numerical quantification of the direction to which future irrigation decisions should be targeted. Charnes et al. (1994) note that there are several DEA models that can be applied for efficiency measurement. In this study we will focus on the use of the basic DEA model which was proposed by Charnes, Cooper and Rhodes in 1978 (Liem 2007). The model (defined here as CCR) is well established and it offers a theoretically sound framework for conducting performance analysis. For commensurability, it has been proposed that the efficiency of target j_0 can be obtained by solving the following model with *n* DMUs; and each DMU has *t* outputs and *m* inputs:

$$\max h_o = \frac{\sum_{r=1}^{t} u_r y_{rj_o}}{\sum_{i=1}^{m} v_i x_{ij_o}} \tag{1}$$

$$\text{subject to} \quad \frac{\sum_{r=1}^{t} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \le 1, \quad \begin{matrix} j = 1, \dots, n \\ u_r, v_i \ge 0 \end{matrix}$$

where u_r = the weight of output *r*
v_i = the weight of input *i*
y_{rj} = the amount of output *r* of DMU_j ; j = 1, ..., n
x_{ij} = the amount of input *i* of DMU_j ; j = 1, ..., n

The above model can be converted from a fractional program to a linear program (adopted henceforth), thus allowing it to be solved using linear optimisation techniques. The linear form for each DMU in this case becomes:

$$\max h_o = u_1 y_o + \dots + u_r y_{ro} \tag{2}$$

$$\begin{aligned} \text{subject to} \quad & v_1 x_{1o} + \dots + v_i x_{io} = 1 \\ & u_1 y_{1j} + \dots + u_r y_{rj} \le v_1 x_{1j} + \dots + v_i x_{ij} \\ & v_1, v_2, \dots, v_i \ge 0 \\ & u_1, u_2, \dots, u_r \ge 0 \end{aligned}$$

By virtue of the constraints, the optimal objective value h_o is at most one, since the weights assigned to u_r and v_i also should not exceed one for every DMU. Therefore, by definition, a DMU will be CCR-efficient if the optimal $h_0 = 1$ and there exists at least one optimal point (v^*, u^*) with u^*, $v^* > 0$. Otherwise, the DMU will be considered CCR-inefficient.

For this study an input oriented CCR model was adopted as input oriented model refers to the capacity of a DMU to reduce input proportionately without a reduction in output. However, for one input and one output case the linear form of the above model can be expressed for each DMU as:

$$\max h_o = u y_o \tag{3}$$

$$\begin{aligned} \text{subject to} \quad & v x_o = 1 \\ & u y_j \le v x_j \\ & v \ge 0 \\ & u \ge 0 \end{aligned}$$

For every inefficient DMU, the DEA model can be used to identify a set of corresponding DMUs that can be utilised as potentially improving-benchmarks – that is, it can compute the projected values to make the corresponding input or output efficient. However, as highlighted by Yilmaz and Harmancioğlu (2007), the DEA remains a primarily diagnostic tool and does not prescribe any immediate strategies to make inefficient DMUs efficient. Such improvement strategies will require a combination of the efficiency results evaluated in conjunction with technical knowledge associated with production decisions, including land types, irrigation methods, and the quantity and quality of the water supplied.

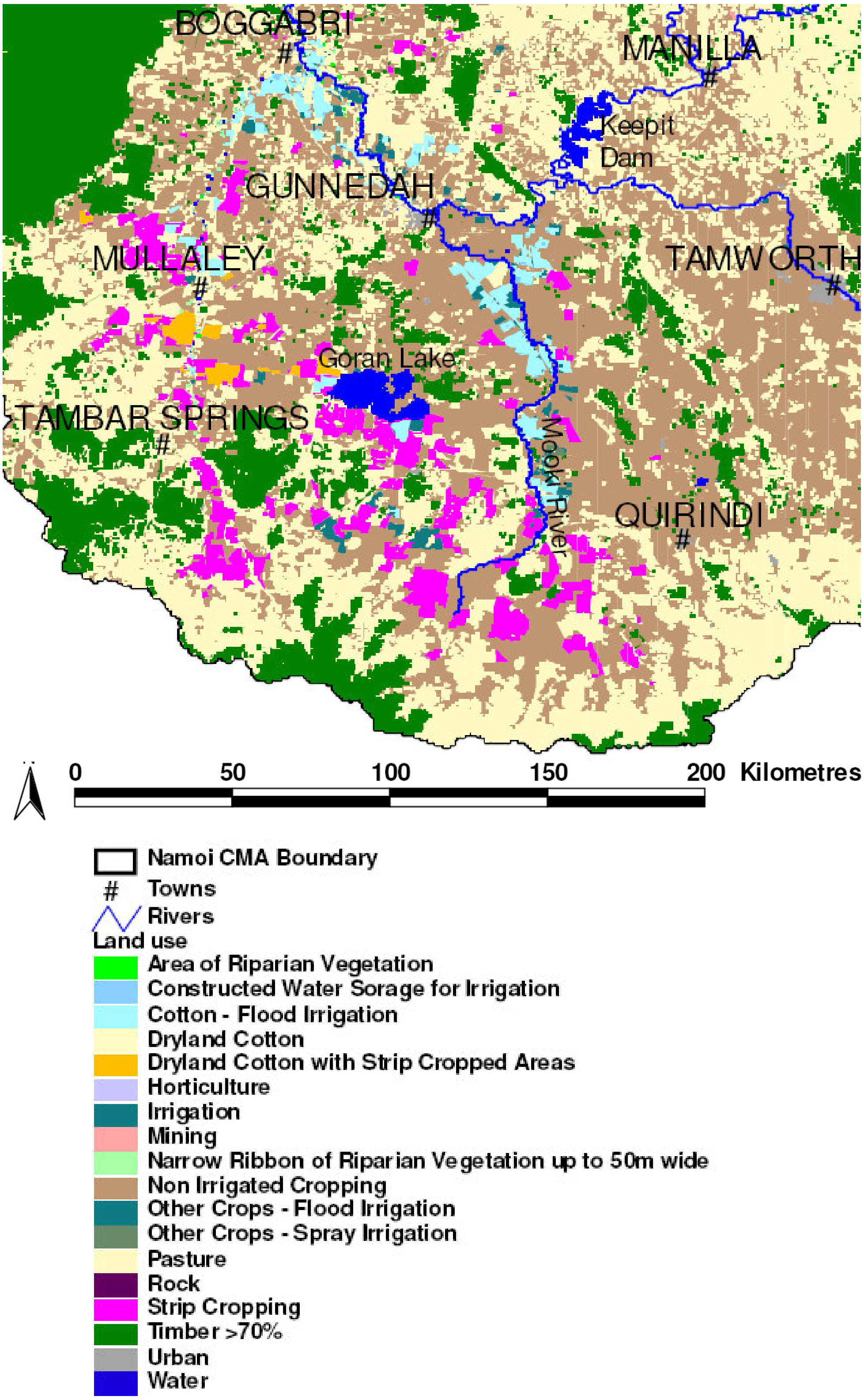
4. Method and Data

The Namoi catchment is located in northern NSW – bounded by the Great Dividing Range in the east, the Liverpool Ranges and the Warrumbungle Ranges in the south, and Mount Kaputar in the north. It encompasses an area of approximately 42,000 square kilometres, across a lineal distance of over 350 kilometres. The major tributaries of the Namoi River include Cox's Creek and the Mooki, Peel, Cockburn, Manilla and McDonald Rivers (Namoi CMA 2006a). This study will focus on data collected in the Lower Namoi, in particular, from a sample of cotton growing areas located along the Mooki River. The data were reported in a recent PhD dissertation (Lee 2007).

The data set consists of 53 observations, collected in terms of Hydrological Response Units (HRU), but for the purpose of this study henceforth defined as a Decision Making Unit (DMU). Lee (2007) used a bio-physical model Soil and Water Assessment Tool (SWAT), to divide the catchment into multiple sub-basins, then using Geographical Information Systems (GIS), this was further divided into HRUs that consist of homogenous land use, management and soil characteristics (Gassman *et al.* 2007). These HRUs correspond directly to the DMUs in the present analysis. For each DMU, one input; irrigation water applied valued in per hectare terms, as well two outputs; cotton yield (or net profit), and environmentally detrimental deep drainage are estimated. Figure 1 and Figure 2 show the study area in terms of current land use in the region, as well as the spatial location of each of the DMUs.

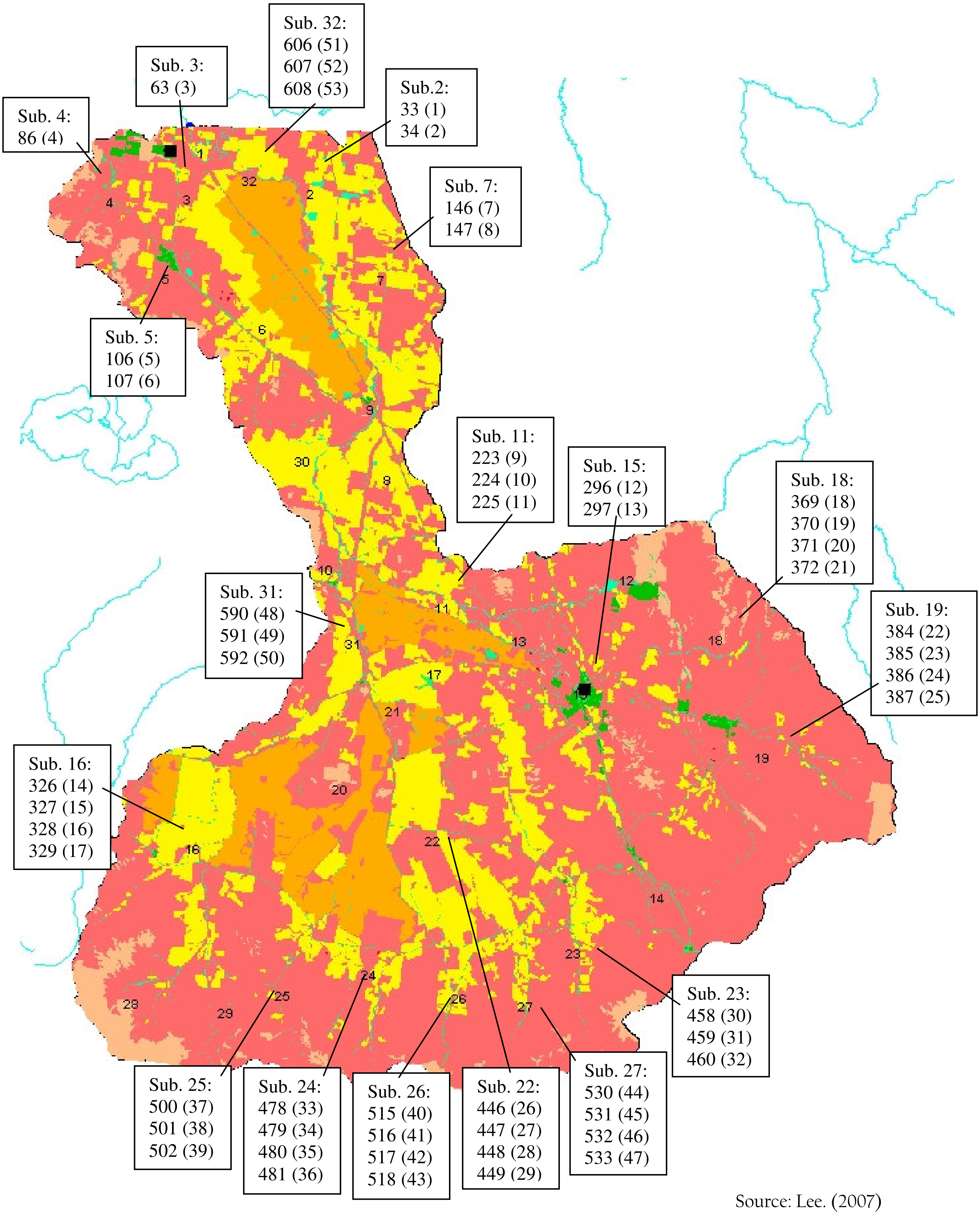
Using these data, the model outlined above was run by specifying eco-efficiency in terms of economic value added (cotton yield) as an output, and environmental damage (deep drainage) as an input. This specification calculates efficiency using the eco-efficiency approach, sp that running a DEA would require that the economic value added be considered as the output variable and the environmental damage be considered as an input variable. For this study the Coelli (1996) DEAP 2.1 package was used to estimate the CRS models for the sample of 53 DMUs (ie. cotton irrigated areas). This involved solving a linear mathematical program for every DMU to determine an efficiency score.

Figure 1: Section of the Namoi CMA current land use map



Source: Namoi CMA (2006b)

Figure 2: Location of HRUs for Mooki catchment delineated in SWAT



Source: Lee. (2007)

Legend: Shaded areas = land uses; Sub. = Sub basin; Numerals = HRUs with irrigated cotton; Numerals in parenthesis = DMUs corresponding with HRUs

Table 1: Sub-catchment characteristics described in SWAT

Sub-catchment	HRU	DMU	CHARACTERISTICS			
			Average slope steepness (m)	Hydrological classification	Soil classification *(CLAY:SILT:SAND)*	Depth (mm)
2	33	1	0.005	D	D (60:30:10)	200
	34	2		C	E (55:35:10)	
3	63	3	0.048	C	E (55:35:10)	200
4	86	4	0.018	C	E (55:35:10)	200
5	106	5	0.010	D	D (60:30:10)	200
	107	6		C	E (55:35:10)	
7	146	7	0.037	D	D (60:30:10)	200
	147	8		C	E (55:35:10)	
11	223	9	0.016	D	D (60:30:10)	200
	224	10		C	E (55:35:10)	
	225	11		D	F (60:30:10)	
15	296	12	0.052	D	D (60:30:10)	200
	297	13		D	F (60:30:10)	
16	326	14	0.093	D	D (60:30:10)	200
	327	15		D	B (15:5:80)	
	328	16		C	C (15:15:70)	
	329	17		D	F (60:30:10)	
18	369	18	0.041	D	D (60:30:10)	200
	370	19		C	G (35:45:20)	
	371	20		C	E (55:35:10)	
	372	21		C	C (15:15:70)	
19	384	22	0.021	D	D (60:30:10)	200
	385	23		C	E (55:35:10)	
	386	24		C	C (15:15:70)	
	387	25		D	F (60:30:10)	
22	446	26	0.020	D	H (40:35:25)	200
	447	27		C	G (35:45:20)	
	448	28		C	E (55:35:10)	
	449	29		C	C (15:15:70)	
23	458	30	0.073	D	D (60:30:10)	200
	459	31		C	E (55:35:10)	
	460	32		D	F (60:30:10)	
24	478	33	0.058	D	D (60:30:10)	200
	479	34		C	G (35:45:20)	
	480	35		C	E (55:35:10)	
	481	36		C	C (15:15:70)	
25	500	37	0.073	D	D (60:30:10)	200
	501	38		C	E (75:15:10)	
	502	39		D	F (60:30:10)	
26	515	40	0.071	D	D (60:30:10)	200
	516	41		D	H (40:35:25)	
	517	42		C	G (35:45:20)	
	518	43		C	E (55:35:10)	
27	530	44	0.079	D	D (60:30:10)	200
	531	45		D	H (40:35:25)	
	532	46		C	G (35:45:20)	
	533	47		C	E (55:35:10)	
31	590	48	0.029	D	D (60:30:10)	200
	591	49		C	E (55:35:10)	
	592	50		D	F (60:30:10)	
32	606	51	0.002	D	D (60:30:10)	200
	607	52		C	E (55:35:10)	
	608	53		D	F (60:30:10)	

Source: Lee, 2007

5. Results and Discussion

Using the DEA approach, eco-efficiency of cotton enterprises was estimated and Table 2 presents efficiency scores for each of the Decision Making Units (DMUs). Figure 3 also illustrates the distribution of eco-efficiency score graphically. Results imply that DMU8 distinguished itself as an efficient (efficiency score of unity) within the 53 DMUs sample set. Two other DMUs (DMU9 and DMU51) came close, with an eco-efficiency score of 0.952. The score can be interpreted as an indication that these two DMUs could decrease environmental damage in form of deep drainage by 4.8% [(1-0.952) x 100%] by efficiency improvement. Moreover, this suggests that opportunities for deep drainage reductions with currently used technology were relatively limited for these DMUs. Significant efficiency improvements would seem to require adoption of technologies and policy measures that were not applied in these enterprises.

The relative rankings of all DMUs in the sample are presented in Table 2**.** By identifying the most efficient enterprises, it is possible to hypothesise about the underlying reasons for better performance of the leading DMUs than to the inefficient ones.

Figure 3. Histogram of eco-efficiency scores

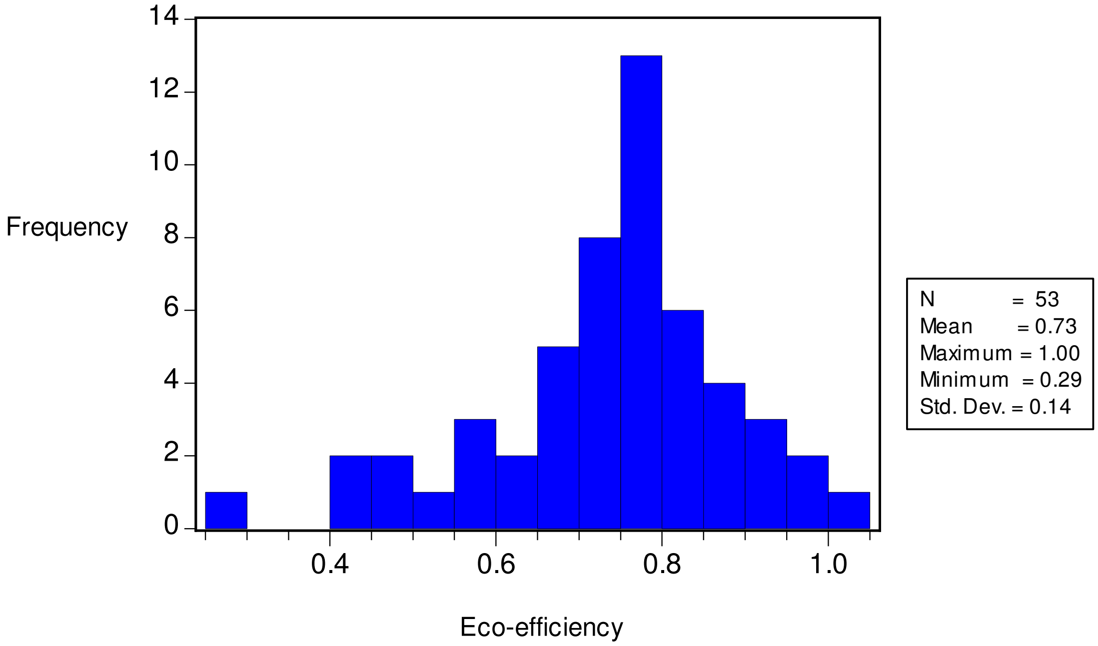


Table 2. Eco-efficiency results obtained from DEA analysis

DMU	Eco-efficiency	Rank	Irrigation water used (ML/ha)	Deep drainage (PERC/ mm)	Cotton yield (bale/ha)
1	0.775	26	6.770	1.350	7.480
2	0.873	8	5.030	1.100	6.860
3	0.879	7	5.110	1.100	6.910
4	0.868	9	5.000	1.100	6.820
5	**0.412**	**52**	**8.670**	**2.440**	**7.190**
6	0.903	6	5.290	1.100	7.100
7	0.567	47	7.500	1.940	7.860
8	**1.000**	**1**	**5.420**	**1.100**	**7.860**
9	**0.952**	**3**	**7.740**	**1.100**	**7.480**
10	0.716	34	5.030	1.100	5.630
11	0.716	33	5.000	1.100	5.630
12	**0.292**	**53**	**8.110**	**2.950**	**6.150**
13	**0.442**	**51**	**7.020**	**2.050**	**6.480**
14	**0.469**	**50**	**8.170**	**1.850**	**6.200**
15	**0.480**	**49**	**6.740**	**1.630**	**5.590**
16	0.789	19	5.480	1.100	6.200
17	0.837	12	5.010	1.100	6.580
18	0.683	40	5.800	1.270	6.200
19	0.802	15	5.020	1.100	6.300
20	0.755	29	5.000	1.140	6.150
21	0.711	35	5.000	1.100	5.590
22	0.525	48	8.360	1.590	5.960
23	0.807	14	6.090	1.100	6.340
24	0.645	43	5.190	1.100	5.070
25	0.716	30	5.000	1.100	5.630
26	0.602	44	5.500	1.220	5.250
27	0.782	23	5.030	1.100	6.150
28	0.802	16	5.000	1.100	6.300
29	0.723	32	5.020	1.100	5.680
30	0.789	22	6.380	1.100	6.200
31	0.681	42	5.010	1.100	5.350
32	0.650	43	5.150	1.100	5.110
33	0.717	29	6.540	1.210	6.200
34	0.861	10	5.670	1.100	6.770
35	0.795	17	5.000	1.100	6.250
36	0.729	31	5.100	1.100	5.730
37	0.795	18	5.510	1.100	6.250
38	0.831	13	5.010	1.100	6.530
39	0.844	11	5.040	1.100	6.630
40	0.765	28	5.460	1.100	6.010
41	0.589	45	5.070	1.180	4.970
42	0.777	25	5.000	1.100	6.110
43	0.789	20	5.000	1.100	6.200
44	0.771	27	5.110	1.100	6.060
45	0.583	46	5.000	1.170	4.870
46	0.777	24	5.000	1.100	6.110
47	0.789	21	5.000	1.100	6.200
48	0.689	38	8.550	1.210	5.960
49	0.687	39	5.110	1.100	5.400
50	0.747	30	5.730	1.100	5.870
51	**0.952**	**2**	**5.820**	**1.100**	**7.480**
52	**0.915**	**4**	**5.080**	**1.100**	**7.190**
53	**0.903**	**5**	**5.000**	**1.100**	**7.100**

Note: The highlighted DMUs are the most and least efficient DMUs.

The estimated eco-efficiencies are summarized in Table 3. It shows the average efficiency scores are about 73% which are within an accepted range in irrigated cotton production as previous efficiency studies have shown (Shapiro 1983, Chakraborty et al. 2002 and Tennakoon and Milroy 2003). The lowest efficiency score was 0.29 while 8% cotton enterprises have an efficiency score of above 0.8. This result shows that there is considerable variability among DMUs in the sample region. However, this can be attributed to a number of reasons, such as physical factors (i.e., soil quality, salinity levels, topography, and distance from river), irrigation technologies, water allocations, and other factors. Another important factor could be the size of the sample used, as well as the variations within the sample itself. For this study size does not a factor since comparisons within the sample are based on per hectare terms and do not necessarily incorporate operating cost.

Table 3: DEA environmental efficiency scores

Parameters	Environmental efficiency (EE)
Mean	0.735
Standard Deviation	0.144
Minimum	0.292
Maximum	1.000
EE = 1	1 (1.9%)
EE > 0.9	5 (9.4%)
EE > 0.8	10 (18.9%)
EE > 0.7	21 (39.6%)
EE > 0.6	7 (13.2%)
EE > 0.5	4 (7.6%)
EE < 0.5	5 (9.4%)

To highlight potential discrepancies regarding location, the sample region was categorised into upstream and downstream regions. As depicted in Figure 2, the downstream category consists of DMUs 1 to 11 and 48 to 53, whilst the upstream category consists of DMUs 12 to 47. Based on this category, the DEA program was run separately for each category and a summary of the results is shown in Table 4.

Table 4: DEA environmental efficiency scores under upstream and downstream Regions

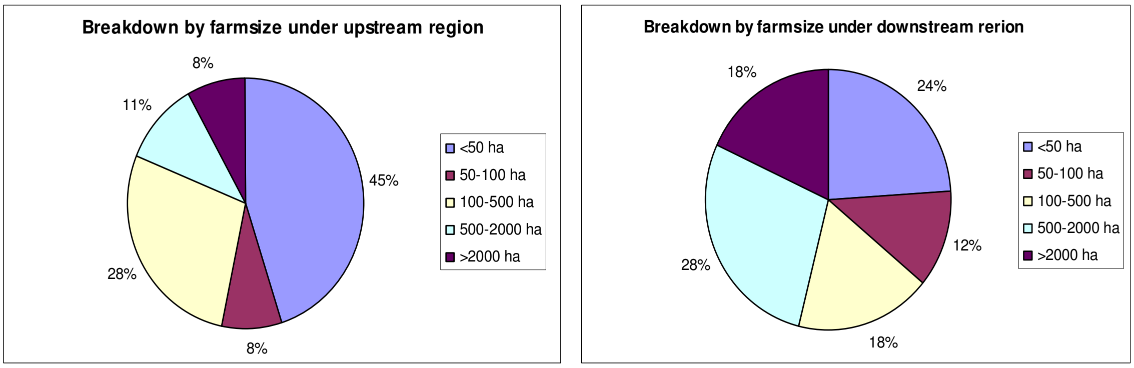
Parameters	Environmental efficiency (EE)	
	Upstream	Downstream
Mean	0.819	0.797
Standard Deviation	0.152	0.155
Minimum	0.339	0.412
Maximum	1.000	1.000
EE > 0.9	41.7%	29.4%
EE > 0.8	22.2%	17.6%
EE > 0.7	11.1%	23.5%
EE < 0.7	22.2%	23.5%

Results show that overall average efficiency scores are higher when location was considered as a factor into the analysis – in particular, upstream DMUs generally performed better than downstream DMUs. The average efficiency score of upstream DMUs was 0.819 while this score was 0.797 for downstream DMUs. More than 40% of the upstream cotton enterprises were observed who had an eco-efficiency score of 0.9 whereas only 29% downstream enterprises had that level of eco-efficiency.

Again, when the sample in each category was breakdown according to farm size, it was found that the majority of DMUs under downstream region consisted of smaller cotton producers whilst in contrast, a significant proportion of average-sized to larger cotton producers were located in the upstream region shown in Figure 4.

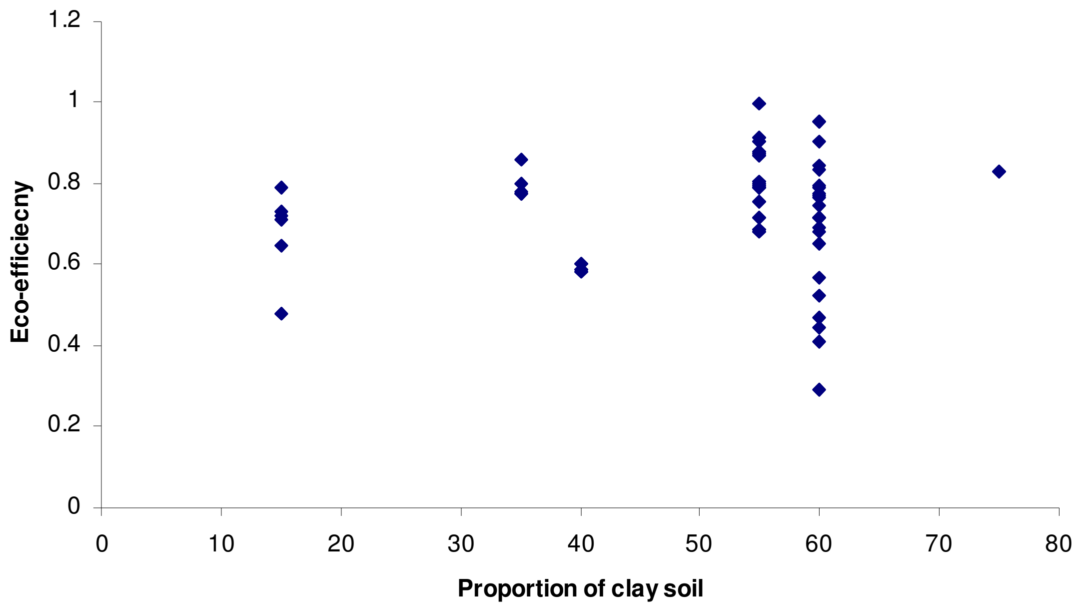
It was also observed that all the efficient DMUs occurred where cotton production areas were smaller than 50 hectares in the upstream region, but were more dispersed across farm sizes up to the lower end of the average cotton area in the downstream region.

Figure 4: Breakdown of data set according to farm size, as categorised by upstream and downstream regions



There might be some other possible explanation for the observed eco-efficiency differences across the cotton enterprises, i.e., soil texture. A hypothesis was drawn to test that high clay content soil contributed less deep drainage than other soil types. But, the result from analysing the correlation (correlation coefficient of only 0.094) between eco-efficiency score and the soil clay content shows that there is only a weak positive correlation which is supported by the Figure 5. This result reveals that there are some other factors such as irrigation method, management factors that might contribute to the deep drainage.

Fig 5. Correlation between eco-efficiecny and clay content soil



6. Conclusions

The study placed an emphasis on eco-efficiency rather than traditional technical efficiency measurement of agricultural production and estimated environmental efficiency of cotton enterprises using a DEA approach. The overall eco-efficiency of cotton enterprises in the study region was found to be 74% which may be considered as reasonable although the efficiency score showed considerable variation across DMUs. Therefore, relative rankings were also determined for each enterprise and this result was then compared against biophysical characteristics from previous studies and catchment data to identify potential characteristics that may influence outcomes that are both environmentally sound and economically efficient. However, it can be concluded that benchmarking might be helpful for setting targets and finding the weaknesses of current practices. By learning from the experiences and best allocation decisions of other efficient farms, even the relatively efficient farms can also further improve their efficiency.

7. Policy Implications

The Mooki sub-catchment is an unregulated tributary within the overall Namoi catchment area, thus creating incentives for producers to extract water from the River and irrigate beyond sustainable levels. This may have severe environmental consequences on the region – for example, altered river flows and salinity. As a result, policymakers may view these externalities as an opportunity to impose environmental charges to help drive water reform and efficiency objectives. A catchment planning approach can be adopted to improve the holistic accountability of current cotton irrigators in the region. Hence, benchmarking can provide a useful gauge for the determination of realistic environmental targets and threshold limits.

By identifying the most and least efficient DMUs in a particular region, policymakers can use a relative ranking system to best determine policy directions – to achieve economic and environmental objectives. Moreover, incorporating environmental efficiency in the biophysical information, it would be possible to determine the potential enterprises which are superior in respect of both environment and economic perspective.

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