The Technical Efficiency of Australian Irrigation Schemes

by

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1. Introduction

The objective of the following research is to assess the efficiency of Australian irrigation schemes. By measuring irrigation water delivery cost efficiency, the aim is to provide an effective tool for estimating potential cost savings and contribute to the setting of plausible water price limits for Australian irrigation water regulators.

Water resources management reform occupies a prominent place in agricultural policy due to the scarcity of water resources and the associated issue of management efficiency. Managerial inefficiency can further deplete freshwater supplies rapidly. To meet an increasing demand for fresh water the emphasis on water resources exploration must be augmented by more efficient management of existing water schemes.

Australia is no exception, its water reform strategy began in the1980s at the national level following the endorsement of the World Conservation Strategy[1] and the United Nations Conference on Environment and Development in 1992 and the Australian government's adoption of Agenda 21. The release of the Australian Industry Commission's report on Water Resources and Waste Disposal in 1992 accelerated the pace of reform in the Australian water industry. Water reform in Australia is well advanced and is aimed at ensuring the sustainability of the country's limited water endowment, a key component of which is the introduction of economic instruments which treat water as an economic good. Market reform has become the core of the reform of the Australian water industry.

However, water was, and still is in many countries, viewed as having some of the characteristics of a public good although it has many characteristics of an economic good. So it is unsurprising that 76% of Australia's major irrigation schemes are operated by State governments or public authorities. Fresh water is the wellspring of life itself, being produced by nature rather than by humankind. So from an economic viewpoint, water has several characteristics that make the role of its development and management more essential than other goods available for mankind. First, by supplying water to one individual other individuals should not be prevented from accessing it. Second, water projects are usually associated with large investment and most capital markets do not have the capacity to finance such huge investments over time, so that water provision is often a naturally monopolistic industry. Third, water allocation is often used as a way of encouraging fairer income distribution, food security and the settlement of remote regions by governments, which bestow political social welfare and ecological benefits on water. Finally, the physical nature of water makes it costly to transport and allocate. These characteristics of water make water pricing a highly political and economically sensitive aspect of water reform and makes price regulation crucial in the process of water marketisation. Obviously, market failure caused by the naturally monopolistic property of water could damage the public interest and the unique importance of water to human society's life and environment make such damage untenable politically. Water providers only operate water provision when it is profitable. Thus, the question for regulators to consider is whether operating cost savings are in principle feasible. DEA, the technique which measures internal managerial efficiency, identifies better practises and sets plausible targets, thereby providing operating cost savings which can be factored into the setting of reasonable pricing limits by water regulators.

2. DEA Theory, Models and Applications

Data envelopment analysis (DEA) was developed by Charnes, Cooper, and Rhodes (1978, 1979, 1981) based on M.J. Farrel's contribution to productive efficiency. In his classic paper, M.J. Farrell (1957) argues that the measurement of productive efficiency is of theoretical and practical importance; a satisfactory efficiency measure allows both empirical testing of theoretical arguments and economic planning to improve the productivity of particular industries. Farrell's approach, largely inspired by Koopmans (1951), was developed for multiple outputs and reformulated as a mathematical programming problem by Charnes et al. (1978). Since then DEA has been widely applied to assessing the productive efficiencies of organisational units such as bank branches, schools, hospitals and public sector agencies which perform a given function and are relatively homogeneous. DEA has several manifestations. Different interpretations actually encompass a number of alternative approaches to efficiency measurement. The measurement of relative efficiencies of decision-making units (DMUs) present only the first and perhaps more obvious kind of information provided by a DEA assessment. A number of other ways of elaborating further on the performance of individual units and how the units can be more efficient are indicated by DEA technology: constructing peer groups, identifying efficient operating practices, target setting, identifying efficient strategies, monitoring efficiency changes over time, and resource allocation.

In their original study, Charnes et al (1978) describe the DEA methodology as a

> "mathematical programming model applied to observed data [that] provides a new way of obtaining empirical estimates of extremal relationships such as the production functions and/or efficiency production possibility surfaces that are the cornerstones of modern economics".

Based on Farrell's idea linking the estimation of technical efficiency and production frontiers, Charnes, Cooper, and Rhodes generalised the single-output/input ratio measure of efficiency of a single DMU in terms of a fractional liner-programming formulation transforming the multiple output/input characterisation of each DMU to that of a single "virtual" output and virtual input. The relative technical efficiency of any DMU is calculated by forming the ratio of a weighted sum of outputs to a weighted sum of inputs, where the weights (multipliers) for both outputs and inputs are to be selected in a manner that calculates the Pareto efficiency measure of each DMU subject to the constraint that no DMU can have a relative efficiency score greater than unity.

In DEA modelling, the relative efficiency of each DMU is estimated in comparison with all other DMUs, using the observed values of outputs and inputs of each DMU. In a DEA analysis, the relative efficiency score of each DMU is maximised subject to the condition that the set of weights obtained in this manner for each DMU must also be feasible for all the other DMUs included in the calculation. Those DMUs which have a DEA efficiency score equal to unity are efficient relative to all other DMUs and form the piece wise production frontier and the others which have efficiency score less than 1 are relatively inefficient falling inside the frontier. For each inefficient DMU, DEA identifies corresponding efficient DMUs, which form a peer group for it and the sources and level of inefficiency as well. The level of inefficiency can be achieved by comparing each of the inputs and outputs with that of a single reference efficient DMU or a convex combination of a set of peer group DMUs located on the efficient frontier that have the same level of inputs and same or higher level outputs.

As previously stated DEA models vary in the following ways: in relation to scale conditions as to whether these are constant or variable; in relation to the models orientation as to whether it is an input or output oriented model and to the mathematical form of the objective function which can be piecewise linear, log-linear or Cobb-Douglas forms. An inefficient DMU can be made fully efficient by projection onto a point on the envelopment surface and this particular projected point location is dependent upon the DEA model employed in the analysis. Thus, DEA models provide various choices for the analyst, and can be employed to meet different demands corresponding to each situation.

In the DEA literature, quite a number of extensions to the basic DEA model have been discussed. They are developed to overcome the incompleteness or inconsistencies of data, or to refine particular models and to take into account managerial and organisational factors. These extensions include the DEA model for non-discretionary variables, the DEA model for categorical variables and the DEA model for panel data. Regardless of their origin, these extensions are now accepted as valuable additions to the methodology of DEA.

Although the DEA approach has been widely and successfully used in different areas, its application to the water industry, particularly to irrigation water management is surprisingly rare. However, the Office of Water Services of UK (OFWAT) adopted the DEA approach as one method for addressing what operating cost savings are in principle feasible in relation to urban water providers and for water pricing regulation after a massive program of privatisation of publicly owned assets in the 1980s (Emmanuel Thanassoulis, 2000). In its Periodic Review in 1994 (1994 a, b, c, ORWAT), the annual price change limits for each urban water provider are announced as $\text{RPI} + K_i$. Where RPI is the retail price index which measures price inflation in the UK economy and K_i the permitted provider-specific variation from RPI, determined by OFWAT. It is composed two parts. The first component of the K-factor is the expected cost-saving led by economy-wide technical progress in the water-industry, and the second component reflects the scope for water provider-specific savings which result from operating efficiency improvement. Although the technique used by OFWAT was not free from the inherent problem of the DEA approach, which is the confounding of inefficiency with random shocks and statistical noise, it does not incorporate nondiscretionary variables (uncontrollable variables for DMUs), and provides an effective way to set reasonable pricing regulation for a market-oriented water industry. In the research project by London Economics (July 1995), the DEA approach is applied to measure the performance of the water industry for the Tasmanian water and sewerage sector, in which some uncontrollable factors were taken into account.

Compared to the urban water supply, pricing regulation for irrigation water provision is more significant because irrigation water makes up over 70 percent of total water utilisation in Australia and most countries in the world. In the foreseeable future, the growth of agricultural production to meet the demands of a rapidly increasing population will largely depend on the augmentation of irrigated fields. At the same time irrigation activities could cause more serious environmental problems via export of salt, nutrients, herbicides and pesticides. Irrigation water is an issue concerning food provision and environmental preservation and improvement.

3. Specification of DEA Models for Technical Efficiency Measurement of Australian Irrigation Schemes

DEA models differ in the emphasis of their orientation and on the assumption of returns to scale. The DEA measurement of efficiency can be addressed with or without certain orientations. Input-oriented DEA models strive to maximise the proportional decrease in input variables while remaining within the envelopment space (production possibility set), but output-oriented DEA models maximise the proportional increase in the output variables while remaining within the envelopment space. Instead of considering the amount of proportional increase or decrease, an additive DEA model equivalently characterises input and output orientation in terms of the resultant proportion of the inputs or outputs after the increase or decrease has been effected. Thus the possible improvement of an inefficient DMU could be achieved by either focusing on a proportional input reduction or proportional output augmentation or both simultaneously. Generally speaking, the input-oriented model is suited to the measurement of cost saving efficiency while an output-oriented model is better for revenue efficiency evaluation, thus an input-oriented DEA model is chosen to service the purpose of this study because of its emphasis on cost savings. In terms of the assumption of returns to the scale, DEA models are distinguished as constant returns to scale models (CRS) or variable returns to scale models (VRS). Although from the economic viewpoint and from the public interest, cost efficiency measurement should always be taken under constant returns to scale in a pricing regulation context thereby encouraging water providers to operate at the most economic scale, a variable return to scale (VRS) model may be adopted to measure cost efficiency because operating scale is often uncontrollable for DMUs in the short and medium term. The difference in operating scale between the irrigation schemes included in this study is remarkably large. So, potential cost savings will be measured according to the nature of the returns which characterise efficient operation and this may not be the most efficient scale. In the sense of acknowledging the scale inefficiency of each scheme, cost efficiency is also assessed at constant returns to scale (CRS) after the input and output variables are identified. Under VCR the envelopment surface presents convexity as a consequence of the constraint ($\mathbf{1}\lambda = 1$) in the model. It ensures that the inefficient DMUs are measured in comparison with those efficient DMUs on the efficient frontier operating at the same scale size as themselves, the efficiency measured is 'pure technical efficiency' without considering the impact of the operating scale size of each DMU. The input-oriented VRS DEA model adopted in this study for cost saving efficiency is an input-oriented VRS model as follows:

Input-oriented BCC model BCC_P^I :

$$\min_{\theta,\lambda,S+,S-} \quad TE_c = \theta - \varepsilon\,(\mathbf{1}s^+ + \mathbf{1}s^-) \qquad \text{(M1)}$$

$$\begin{aligned}
\text{s.t.} \quad & Y\lambda - s^+ = Y_o \\
& \theta X_0 - X\lambda - s^- = 0 \\
& \mathbf{1}\lambda = 1 \\
& \lambda, s^+, s^- \geq 0
\end{aligned}$$

where TE_c is the cost technical efficiency score and the variable θ is the (proportional) reduction applied to all inputs of DMU_0 (the DMU being evaluated) to improve efficiency, λ is the value of constructing a composite unit with inputs $Y\lambda$ and outputs $X\lambda$ outperforming DMU_0, ε allows the minimisation over θ to preempt the optimisation involving the slack variables s^+ and s^- , the variables s^+ and s^- represent the excess inputs and output slacks and are the distance between an inefficient DMU(X_0, Y_0) and its projected point ($\hat{X}_0 = \theta X_0 - s^-$, $\hat{Y}_0 = Y_0 + s^+$) on the envelopment surface of efficiency frontier. As can be seen, an input-oriented BCC model (Banker et al. 1984), focuses on the maximal movement toward the frontier through a proportional reduction of inputs, given the output level. When cost efficiency is measured at constant returns to scale, the convexity constraint $\mathbf{1}\lambda = 1$ is dropped from the BCC model and is identified as an input-oriented CCR (Charnes, Cooper and Rhodes, 1978) model as follows:

Input-oriented CCR model CCR_P^I :

$$\min_{\theta,\lambda,S+,S-} \quad TE_c = \theta - \varepsilon(\mathbf{1}s^+ + \mathbf{1}s^-) \qquad \text{(M2)}$$

$$\text{s.t.} \qquad Y\lambda - s^+ = Y_o$$
$$\theta X_0 - X\lambda - s^- = 0, s^+, s^- \geq 0$$

The absence of the convexity constraint makes the efficient frontier pass though the origin and enlarges the feasible region for the CCR model, so the efficiency score derived from the CCR model is lower than that obtained from the BCC model. In the DEA approach, CCR (M2) efficiency is defined as (global) technical efficiency since it takes no account of scale effects, and the BCC (M1) efficiency is expressed as the (local) pure technical efficiency under variable returns to scale in such circumstances. The relationship between M1 and M2 is demonstrated later by referring to M5which explores the scale efficiency of irrigation schemes involved in this study.

One additional methodological step is required. An OLS regression model is used to disentangle the possible effect of the uncontrollable variable pipeline length (PL) on the cost technical efficiency score. The OLS regression model is specified as follows:

$$TE_{ci} = \beta_1 + \beta_2 PL_i + \mu_i \qquad \text{(M3)}$$

where TEci is the cost technical efficiency of DMU_i (irrigation schemes) obtained from the model M1, PL_i is the irrigation water supply pipeline length of DMU_i which is incorporated into the output variable length of carrier (LC) and μ_i is a random term with zero mean and constant variance σ^2. Using the parameter estimates of model M3, the cost technical efficiency score can be adjusted by disentangling the impacts of pipeline utilisation on the irrigation water delivery cost efficiency. So, the adjusted technical efficiency of irrigation water delivery cost of an irrigation scheme is defined from the estimated residual of (M3) as follows:

$$\begin{aligned} \hat{\mu}_i &= TE_{ci} - (\hat{\beta}_1 + \hat{\beta}_2 PL_i) && \text{if } \hat{\mu}_i < 100 \\ &= 100 && \text{if } \hat{\mu}_i \geq 100 \end{aligned} \qquad \text{(M4)}$$

4. The Choice of Input and Output Variables

In DEA analysis, the identification of input and output variables is fundamental and those environmental factors affecting the efficiency of transformation of controllable inputs into outputs should also be accounted for in the assessment. Irrigation schemes in general involve activities from water catchment to headworks, to irrigation supply, to drainage and to downstream catchment (ANCID, 2000). Some irrigation schemes also provide additional services such as headworks, catchment, land and water management plans as part of their business. However, the delivery of water to meet the requirement of irrigation and other purposes is the primary focus of the water provider's business operations. The DEA analysis applied here will focus on irrigation water delivery excluding other activities of irrigation water schemes. In order to identify suitable input and output variables for this purpose, it is necessary to delineate the irrigation water delivery function from other activities of the irrigation scheme as shown in Figure 1.

Figure 1 here

Irrigation water delivery begins with water input coming from the reservoirs or bore holes and ends at the point where water is delivered to farms. Inputs in this stage include capital investment in renewing and maintaining infrastructure such as water mains plus operating expenditure such as labour cost. Since the investment capital required in renewing and maintaining infrastructure is mainly incurred by the state, investment is beyond the control of the DMUs. Thus it is appropriate to regard operating expenditure as an input variable. It contains all the variable resources expended in supplying irrigation water from scheme reservoirs or other water resources to farms. With similar staff and materials prices, operating expenditures are generally clearly identifiable and uniformly defined across all irrigation schemes. Therefore, once environmental conditions and output levels are taken into account, any remaining cost differences will reflect the discrepancy of operating efficiency between irrigation schemes. It is worth noting that most of the irrigation schemes in this study do supply water for live stock and for domestic utilisation and the operating cost for delivering stock and domestic water is not separable from the cost of irrigation water delivery. The concept of irrigation water delivery cost in this study will include expenditures on live stock and the domestic water supply. This does not affect the relative efficiency analysis in this study, since live stock and the domestic water supply are not excluded from irrigation water delivery.

Five potential output variables are identified in the explanation of differences in operating cost between irrigation schemes. They are water delivery (WD), people employed for water delivery (PE), the length of irrigation water carrier (LC), the irrigated area (IA) and the number of customers (NC).

WD reflects the major part of water delivery outputs. Most Australian irrigation schemes measure their flow to each farm by a metering device. An average of 92% of irrigation supply points are metered, and only a small proportion of these schemes do not meter their groundwater delivery. These use a combination of surface and groundwater. The variable PE represents labour cost and is an important aspect of the total water delivery cost. It is often a major index of managerial efficiency. LC reflects the geographical dispersion of irrigation water delivery and influences its operating cost obviously. Some irrigation schemes use pipelines as water carriers to deliver water under certain physical circumstances. Pipeline utilisation costs more than surface channel and is often beyond the control of the irrigation schemes' management. IA and NC capture the scale size of water distribution and so they are expected to influence operating cost. The correlation coefficients matrix indicates that the potential output variables are relatively highly intercorrelated, as shows on Table 1

Table 1 here

Subsets of output variables are constructed to decide which potential output variables should be taken into account for measuring the cost efficiency of irrigation water delivery, rather than using the full set of potential output variables. The subset of output variables which gives a fairer reflection of scheme efficiency will be used for the cost saving analysis. The potential output variable sets are shown on Table 2.

Table 2 here

By applying the data set described in the next section to M1 with five subsets of potential output variables in Table 2 respectively, the DEA scores of operating cost technical efficiency of the 43 irrigation schemes and their efficiency ranks are shown in Appendix B

(Efficiency Scores and Ranks of Five Subsets of Potential Output Variables). Prior to discussing these results, we examine the sensitivity of estimated DEA scores to changes in the potential output sets -- in this study (Table 2). Of the 43 schemes, 33 changed rank across the five output subsets, however 16 changed rank by no more than 2 places, 14 changed rank by 3-5 places and the average degree of rank change is 2.26. Only one scheme (Murrumbidgee) changed its relative efficiency substantially by 46.65% and rank by 10 places when LC and IA are taken as output variables. This follows as it has the largest OC of all schemes, (1.2 times its peer scheme the Murray Irrigation scheme on the efficient frontier) but a relatively lower level of WD, LC and LA, which are only 70.5%, 73% and 23% of that for the Murray Irrigation scheme. Another scheme, Eton, changes its efficiency score by 11% and rank by 6 places, when IA replaces NC as one of the output variables. The DEA approach demonstrates that the output variable IA makes a crucial contribution (75%) to the determination of Eton's cost technical efficiency when its IA is only 32.17 % of the average IA of all schemes, and NC makes no contribution (0%) when it is only 26.9% of the average level of all schemes costs. However, the efficiency rank for most schemes across five subsets is relatively stable. Namely, for the majority of irrigation schemes it makes little difference to their efficiency rating and ranking which one of the output subsets in Table 2 is used.

Because of the large variance of operating cost per customer, the number of customers (NC) does not effectively reflect cost efficiency. For instance, the scheme Jemalong has only one customer, its operating cost is AU$ 71525.8, average cost per customer is 71525.8, but for the Wimmera-Mallee scheme, these indexes are 6755, 362561.3 and 53.67 respectively. The output variable irrigation area (IA) should not be taken into account for two reasons when cost saving efficiency is measured. The high correlation of IA with WD (correlation coefficient is 0.86) and given the inability to reflect the influence of water for live stock and household on the operating cost, IA is excluded. Thus, the potential output variables WD, PE and LC are adopted to measure the irrigation scheme water delivery cost efficiency. As a final step an OLS regression model is used to test and verify the choice of the subset output variables as follows:

$$\begin{array}{lllllll}
\hat{OC}_i = 290750 & + & 2.69WD_i & + & 2037.6PE_i & - & 262.72LC_i & & \text{(M5)} \\
\text{se} = (0.4672) & & (0.8408) & & (3205) & & (68.27) & r^2 = 0.8966 & \\
t = (3.458) & & (5.641) & & (6.357) & & (-3.848) & df = 39 & \\
p = (0.001) & & (0.000) & & (0.000) & & (0.000) & &
\end{array}$$

Given the confidence limit of 95 percent, the t-test for all independent (output) variables is statistically significant. The impact of LC on the OC is negative due to average scale of LC for all irrigation schemes is over the most economic scale size[2].

4. Data

The irrigation water delivery data set used in this study is obtained from the 'Benchmarking Report, 1998/1999 Australian Irrigation Water Provider ' issued by the Australian National Committee on Irrigation and Drainage (ANCID) in 2000. The DMUs are limited to 46 irrigation schemes around Australia, which represent most of the significant irrigation water providers nationally. Three irrigation schemes (Lower Murray, Boyne River, Pioneer Valley) are discarded from the samples because operating cost are unavailable. The descriptive statistics for the irrigation scheme data set is represented in Table 3. (Detailed data and information see Appendix A)

Table 3 here

5. Empirical Results and Discussion

Once the foregoing set of three output variables was chosen, the cost technical efficiency of irrigation schemes can be computed by using the DEA input-oriented model

BCC (M1). As explained in section 3, the DEA scores should be adjusted by model M4 because the contribution of the variable LC to the efficiency score may be attributable to the possible impacts of the uncontrollable variable PL which is incorporated into LC when the DEA score is calculated by M1. It must be borne in mind that $\hat{\beta}$ is negative in M4 due to the utilisation of pipeline increase operating cost (input) by reducing the cost efficiency score. So, the efficiency score adjustment by M4 is aimed to make up the efficiency score reduction caused by the utilisation of pipeline to measure 'true' technical efficiency. Surprisingly the result of model M3 does not indicate that the utilisation of pipeline has significant effects on the DEA cost technical efficiency score although the average operating cost of irrigation schemes using pipeline over 50% of the length of carrier is higher than irrigation schemes which do not use pipeline (see the impact of using over 50% pipeline of LC on the operating cost, Figure 32, Page 57, 1998/99 Australian Irrigation Water Provider, Benchmarking Report, February 2000). Thus, the adjusted DEA cost technical scores are the same as the unadjusted scores in this study.

The DEA scores for every irrigation scheme at constant returns to scale are also given in Table 4, scale efficiency therefore can be measured by the DEA input-oriented model under constant returns to scale:

$$SE_i = \frac{\theta_i^{*}{}_{CCR}}{\theta_i^{*}{}_{BCC}} \qquad (i = 1, 2, \ldots 43) \qquad \text{(M5)}$$

where SE_i is the scale efficiency of the ith irrigation scheme, θ^{*}_{CCR} and θ^{*}_{BCC} are the cost technical efficiency score at variable returns to scale and constant returns to scale by M1 and M2 respectively. The cost efficient scores by the CCR model (M2) are equal or lower than that of BCC model (M1) because of their scale inefficiency.

After cost efficiency of every scheme is measured and adjusted accordingly, the potential operating cost savings (PCS) of irrigation water delivery can be estimated from:

$$PCS = \Sigma\, PCS_i = \Sigma\, (100 - \theta^*_{i\,BCC})\, OC_i \qquad (i = 1, 2 \ldots. 43) \qquad (M6)$$

where $\theta^*_{i\,BCC}$ is the DEA efficiency score for the ith irrigation scheme generated from M4. Given the current price in 1998/1999, the total potential cost savings of irrigation water delivery across the 43 irrigation schemes in this study is about AU$ 17.5 million a year for 1998/1999, which is 37.29% of the total operating cost of 43 irrigation schemes. The potential operating cost savings for each individual scheme is shown in Table 4. No doubt, this potential cost saving has a substantial influence on the final price determined for irrigation water and has obvious financial impacts on the public interest and company profits.

Variable returns to scale are assumed in this research because of the large quantitative difference in inputs and outputs and the consideration of scale size is generally beyond the control of irrigation scheme management in the short or medium term. (see Appendix B: scale difference between irrigation schemes). Thus, scale efficiency is not incorporated in price determination on the basis of variable returns to scale (VRS), although from the public interest view point efficiency assessment should be subject to constant returns to scale irrespective of scale conditions applying to individual schemes. The inefficiency consequence of operating on non-economic scales should not be transferred to the consumers in the price. However, the operating scale efficiency of irrigation schemes can be measured by the DEA method as shown in this study and so the scale efficiency target can be established in the long term. This would encourage schemes to move to the most productive operating scale.

The results from M1, M2 and M5 suggest that a scheme which is technically efficient by M1 is not necessarily efficient according to M2, because it is probably scale inefficient, namely the scheme is operating at increasing or decreasing returns to scale. At the same time, an inefficient scheme by M1 is certainly inefficient for M2. In all samples of this study, only the Wimmera-Mallee and Ord River schemes are efficient for both M1 and M2. They are technical and scale efficient. The Murray irrigation, Murrumbidgee, Emerald, Proserpine and G-MW Torrumbarry schemes are 'purely' efficient but not 'globally' technically efficient because of scale inefficiency, indicating they are not operated at constant returns to scale. Of these, the Murrumbidgee and Proserpine schemes only reached 46.8 and 20.04 of their scale efficiency separately. However, there is the possibility of them producing more cost savings by moving their operating scale to the most economic scale size.

Table 4 here

As table 4 indicates 83.72% irrigation schemes are not technically efficient and 63.89% of them have technical efficiency scores below the average technical efficiency score 49.96. At the same time, the average scale efficiency scores of scale inefficient schemes reached 72.29. Further, 56.1% of the schemes have scale efficiency score exceeding the average efficiency score. This result suggests that it is managerial inefficiency rather than short to medium term uncontrollable operating scale size which is the major problem for most Australian irrigation schemes. Improvement of internal managerial efficiency should be the first option for reducing operating costs for the Australian irrigation water industry.

Although privatisation is the key component of water resource management reform in Australia, there is no significant difference of water delivery efficiency between private and publicly-run schemes in this study. The average efficiency score of publicly-run schemes is 51.87, about 10 points higher than that of privately-run schemes, but the percentage of efficient schemes among total privately-run schemes is 25% exceeding 10% of publicly-run schemes. It also worth noting that in the comparison of the average efficiency score of irrigation schemes with live stock and the domestic water supply and the schemes without live stock and household water supply, there is no significant differences in DEA score. This is evident where schemes supplying stock and household water have average DEA score of 49.11, while those not doing so have scores of 51.58 (see Table 5). The difference of 2.47 is not significant.

In terms of regional efficiency scores, the average efficiency scores of New South Whales (NSW) 67.19 and Victoria (VIC) 60.39 are higher than total average efficiency score 49.96, the average efficiency scores of Queens Land (QLD) 48.77 and West Australia (WA) 47.34 are close to the total average efficiency score, South Australia (SA) and Tasmania (Tas) have average efficiency scores 17.02 and 10.41respectively much lower than the total average level. Upon closer inspection, it is clear that South Australia and Tasmania have relatively lower operating costs (input), 93.9% and 78.84% of average level of inefficient schemes group respectively, but much lower WD, PE and LC (output) level, which are 40.26%, 57.42% and 32.72% of the average level for SA and 3.53%, 12.54% and 19.13% Tas. These rates are even lower when the South Australia and Tasmania schemes are compared with the efficient schemes group. However, the 'pure' technical and scale efficiency of South Australia schemes are all higher than that of Tasmania (see Table 5).

Table 5 here

8. Conclusion

This paper has applied the basic DEA model to Australia's major irrigation schemes to assess water delivery cost efficiency and the potential cost savings under variable returns to scale. It introduces OLS regression models to support the identification of output variables of the DEA model and to disentangle the impacts of uncontrollable factors on DEA efficiency. DEA efficiency scores at constant returns to scale are also estimated in order to analyse the scale efficiency of each irrigation scheme rather than to determine potential cost savings. The DEA analysis in this study focuses on the major stage of irrigation water provision instead of the whole process.

The major finding that 83.72% schemes are not technically efficient and 63.89% of Australian schemes have efficiency scores below the average level 49.96, compare with an average scale efficiency score of 72.29, indicating that managerial rather than scale inefficiency is the major problem for Australian irrigation schemes. By improving technical efficiency, potential cost savings account to AU$ 17 million, which is over one third of the total operating cost of 43 major Australian irrigation schemes in 1998/1999. The results prove that DEA analysis is a powerful tool for water industry regulators who seek to defend the public interest against the potential abuse of monopoly power and to encourage water providers to improve efficiency. On the other hand, it should always be remembered that DEA analysis does not indicate how technical efficiency can be improved and if improvement is possible or not, although it can identify the level and sources of inefficiency for each of the inputs and outputs. As a non-parametric approach to efficiency measurement, it does not require imposition of a specific functional form, such as a regression equation, which relates the independent variables to the dependent variables but it does have some disadvantages in handling statistical 'noise' and outliers in the data.

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Figure 1: Irrigation Water Supply Operation System

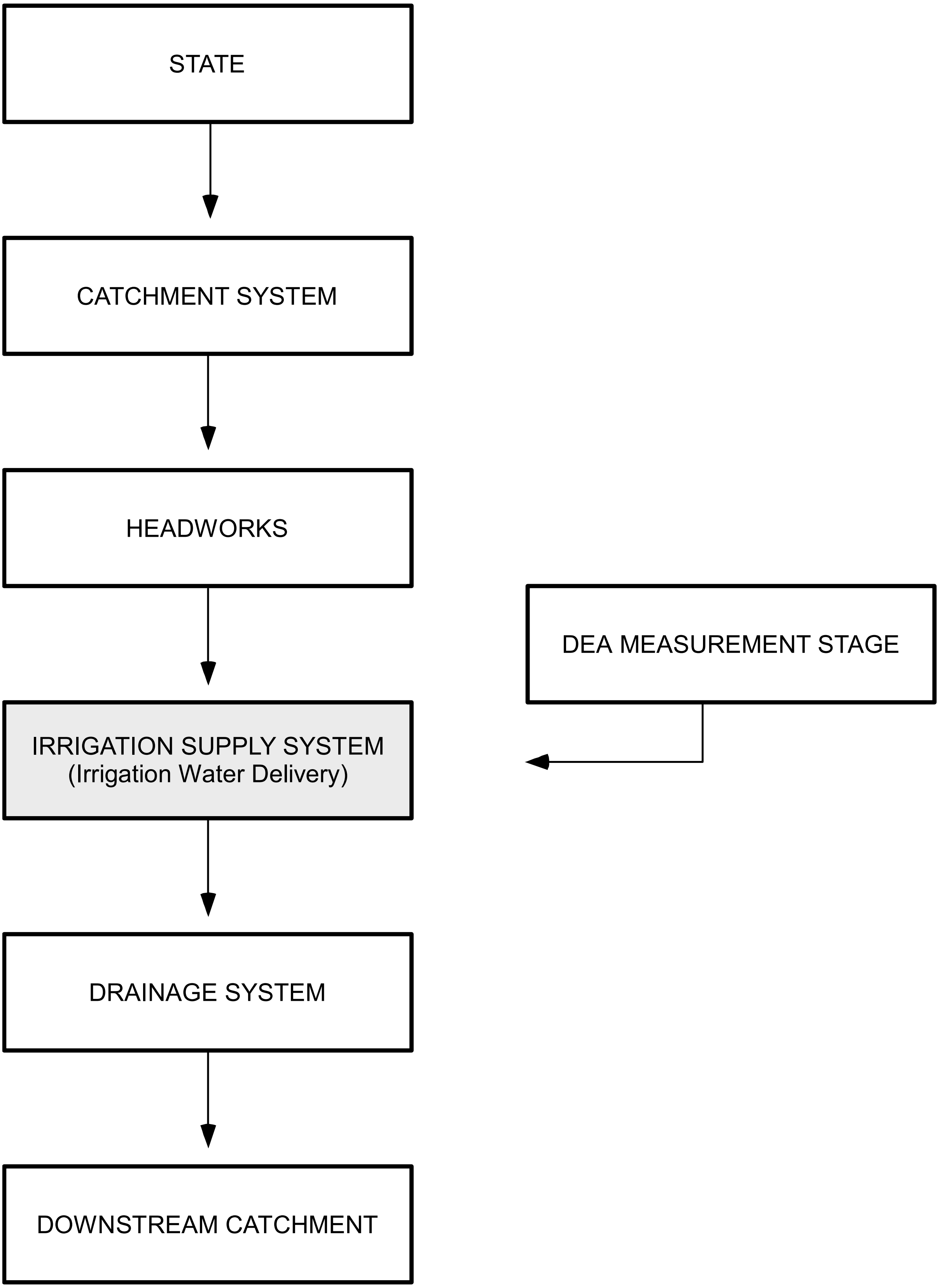

Table 1 Correlation Matrix of Variables 43 Observations

OC	1.0000					
WD	0.88831	1.0000				
PE	0.84708	0.76364	1.0000			
LC	0.33233	0.35188	0.66405	1.0000		
IA	0.70942	0.85835	0.54041	0.34418	1.0000	
NC	0.41868	0.42638	0.69860	0.82442	0.32035	1.0000
	OC	WD	PE	LC	IA	NC

Table 2 Potential Output Subsets

1. WD, PE and NC
2. WD, PE and IA
4. WD, PE and LC
4. WD, LC and IA
5. WD, PE, LC and NC

Table 3 Descriptive Statistics of Maine Australian Irrigation Schemes for Water Delivery Cost Saving Efficiency Measurement (Sample Size = 43)

	Mean	**Std. Dev.**	**Variance**	**Minimum**	**Maximum**
Outputs:					
WD	0.14207E+06	0.23911E+06	0.57172E+11	1039.0	0.11678E+07
PE	29.860	44.471	1977.7	2.0000	243.00
LC	725.16	1440.2	0.20742E+07	21.000	8810.0
IA	46631.	0.12405E+06	0.15388E+11	723.00	0.79676E+06
NC	997.40	1358.3	0.18448E+07	1.0000	6755.0
Input:					
OC	0.101903E+07	0.13521E+07	0.18283E+13	40230	0.66517E+07

2. This explanation is simply one of several, some of which would suggest that the influence of LC is negative. There is no a prior restriction on the parameter associated with LC.

Table 4 Efficiency Score by BCC (M1) and CCR (M2)Potential Cost Saving and Scale Efficiency Score

	Score (M1)	**Adjusted Score (M4)**	**Inefficiency**	**OC (AU$)**	**Potential Cost Saving (AU$)**	**Score (M2)**	**Scale efficiency**
Coleambally	87.4	87.4	12.6	2088490	263149.74	72.35	83.22
Jemalong	25.93	25.93	74.07	715251.8	529787	22.17	85.5
Murray Irrigation	100	100	0	5593546	0	69.8	69.8
Murrumbidgee	100	100	0	6651690	0	46.8	46.8
West Corurgan	22.63	22.63	77.37	1215028	940067.16	20.91	92.4
Barker-Barambah	42.15	42.15	57.85	163044.6	94321.3	21.92	54.62
Bundagerg	21.84	21.84	78.16	1714846	1340323.63	21.62	98.99
Burdekin River	50.46	50.46	49.54	2870530	1422060.56	43.5	86.21
Condamine	69.31	69.31	30.69	323864.7	99394.08	61.48	88.7
Dawson	22.05	22.05	77.95	444070.1	346152.64	16.12	73.12
Emerald	100	100	0	297236.3	0	98.04	98.04
Eton	25.25	25.25	74.75	251247.2	187807.28	12.87	50.97
Logan	23.43	23.43	76.57	227217.6	173980.52	9.78	41.74
Lower Marray River	50.07	50.07	49.93	88996.48	44435.94	14.86	32.49
Mareeba-Dimbulah	33.04	33.04	66.96	884152.9	592028.78	32.29	94.58
Proserpine	100	100	0	40230.08	0	20.04	20.04
South Burdekin	71.86	71.86	28.14	197784	55656.42	58.42	80.87
St George	53.47	53.47	46.53	667172.4	310435.32	52.73	98.62
Warrill	19.94	19.94	80.06	290085.5	232242.45	9.47	47.79
Central Irrig (SA)	29.16	29.16	70.84	1201769	851333.16	28.75	98.35
Golden Heights	11.19	11.19	88.81	535150.1	475266.8	5.56	49.68
Sunlands	9.92	9.92	90.08	674516.1	607604.1	5.56	56.05
Cressy-Longford	18.93	18.93	81.07	279009.4	226192.92	6.82	36.03
Southeast (Tas)	3.77	3.77	96.23	1193010	1148033.52	0.99	29.2
Winnaleah	8.54	8.54	91.46	564012.4	515845.74	2.76	32.32
First Mildura	27.84	27.84	72.16	874885.8	631317.59	26.53	95.24
G-MW Murray Valley	90.32	90.32	9.68	1614177	156252.33	77.97	88.31
G-MW Shepparton	60.6	60.6	39.4	1009196	397623.22	60.54	96.67
G-MW Cent. Goulburn	80.72	80.72	19.28	2044903	394257.3	69.22	86.23
G-MW Rochester	76.58	76.58	23.42	1080034	252943.96	72.58	94.27
G-MW Pyramid-Boort	66.77	66.77	33.23	1302636	432865.94	61.96	92.8
G-MW Torrumbarry	100	100	0	2261638	0	83.39	83.39
G-MW Nyah	34.75	34.75	65.25	186978.4	122003.42	18.89	54.36
G-MW Tresco	49.81	49.81	50.19	109000.2	54707.2	19.73	44.17
G-MW Woorinen	63.01	63.01	36.99	92014.02	34035.99	29.54	57.21
Bacchus Marsh	52.84	52.84	47.16	88999.68	41972.25	17.47	32.38
Macalister	49.31	49.31	50.69	1015403	514707.78	49.09	99.55
Werribee	39.79	39.79	60.21	184594.4	11144.29	24.19	60.79
Sunraysia	13.65	13.65	86.35	3002638	2592777.91	13.57	99.41
Wimmera-Mallee	100	100	0	362561.3	0	100	100
Carnarvon	10.03	10.03	89.97	761250	684896.63	6	80.74
Ord River	100	100	0	686700	0	100	100
South West (WA)	31.99	31.99	68.01	1033739	703045.89	30.98	96.84
				46883298	**17480670.76**		

Table 5 Average Efficiency Scores

A.		**B.**		**C.**	
a. Public-run schemes	51.87	a. Schemes with stock and domestic water supply	49.11	a. Schemes in NSW	67.19
b. Private-run schemes	41.59			b. Schemes in OLD	48.77
				c. Schemes in SA	17.02
		b. Schemes without stock and domestic water supply	51.58	d. Schemes in TAS	10.41
				e. Schemes in VIC	60.39
				f. Schemes in WA	47.34

Footnote 1.

The World Conservation Strategy (WCS) was commissioned by the United Nations Environment Programme (UNEP) which together with the World Wildlife Fund (WWF) provided the financial support for its preparation and contributed to the evolution of its basic themes and structure. This document presents the aim of the WCS. It explains the contribution of living resource conservation to human survival and to sustainable development, identifies the priority conservation issues and the main requirements for dealing with them and proposes ways for effectively achieving the Strategy's aim.

Appendix A.

Overview of Major Irrigation Schemes in Australia (data source: 1998/1999 Australian Irrigation Water Provider, Benchmarking Report, ANCID)