Technical efficiency of water use and its determinants, study at small-scale irrigation schemes in North-West Province, South Africa

Stijn Speelman[a] *, Marijke D'Haese[b], Jeroen Buysse[a] and Luc D'Haese[a]

[a] Department of Agricultural Economics, Ghent University, Coupure links 653, 9000 Ghent, Belgium
[b] Development Economics Group, Wageningen University, Hollandseweg 1, 6706KN Wageningen, The Netherlands

*Corresponding author: Stijn.Speelman@ugent.be

Paper prepared for presentation at the 106[th] seminar of the EAAE

Pro-poor development in low income countries:
Food, agriculture, trade, and environment

25-27 October 2007 – Montpellier, France

Efficiency of water use and its determinants at small-scale irrigation schemes in North-West Province, South Africa

Abstract

This paper analyses the efficiency with which water is used in small-scale irrigation schemes in North-West Province in South Africa and studies its determinants. In the study area, small-scale irrigation schemes play an important role in rural development, but the increasing pressure on water resources and the approaching introduction of water charges raise the concern for more efficient water use. With the Data Envelopment Analysis (DEA) techniques used to compute farm-level technical efficiency measures and sub-vector efficiencies for water use, it was shown that under Constant Returns to Scale (CRS) and Variable Returns to Scale (VRS) specification, substantial technical inefficiencies, of 49% and 16% respectively, exist among farmers. The sub-vector efficiencies for water proved to be even lower, indicating that if farmers became more efficient using the technology currently available, it would be possible to reallocate a fraction of the irrigation water to other water demands without threatening the role of small-scale irrigation. In a second step, Tobit regression techniques were used to examine the relationship between sub-vector efficiency for water and various farm/farmers characteristics. Farm size, landownership, fragmentation, the type of irrigation scheme, crop choice and the irrigation methods applied showed a significant impact on the sub-vector efficiency for water. Such information is valuable for extension services and policy makers since it can help to guide policies towards increased efficiency.

1. Introduction

Water scarcity is a growing problem in many countries, hence irrigation systems, being a main consumptive user, experience pressure to release water for other uses and to find ways in which to improve performance (Malano et al., 2004). The North West province in South Africa is such a water-stressed region. Moreover, because rainfall is low (<500mm per year) and extremely variable in space and time there, irrigation is a key factor indispensable for agricultural production (Ashton and Haasbroek, 2002). As in many areas in South Africa, economic development among the previously disadvantaged communities is low in Zeerust Municipality, and, given the high levels of unemployment (STATSA, 2003), small-scale irrigation schemes are of great importance for the livelihood of many families there.

It is believed that small-scale irrigation schemes could play an important role in rural development because of their potential to provide food security, income and employment opportunities (Perret and Touchain, 2002). On the other hand, performance and economic success of these schemes have been poor, which raises questions on their level of efficiency (Perret, 2002). Moreover, the new water policy regards water as an economic good and thus charges will be levied on its use. Currently water use of farmers at small-scale irrigation schemes is subsidized. However, these subsidies will gradually decrease and in the future farmers will have to pay to ensure cost recovery (DWAF, 2004), hence small-scale irrigators will face two new problems in the future: firstly, less water will be allocated to the agricultural sector, due to the increasing water scarcity, and secondly, they will have to pay for the water they use. In other words, they will have to deal with a reality where water becomes a limited input for which they have to pay. The impact of this new reality is unclear, but it will definitely have an impact on the production system and stress the importance of using water in a more efficient way.

This paper analyses the efficiency with which water is used in small-scale irrigation schemes and studies its determinants, with data of a sample of 60 farmers in Zeerust Municipality being used. Although the sample is relatively small, the case study will provide insights that reflect the typical situation of rural areas in South Africa. It is nevertheless difficult to ascertain whether the use of water is efficient or not, since irrigated agriculture is a multiple input-multiple output process. Furthermore, it is important not to consider water as a resource in an isolated manner (Malana and Malano, 2006; Rodríguez Díaz et al., 2004b). Studies on efficiency differentials among farms often use simple measures, such as yield per ha or output per m³, which are easy to calculate and understand. However, such measures tell very little about the reasons for any observed differences among farms. Output per m³, for example, does not take into account the differences in non-water inputs among farms (such as labour, fertilizers etc…) (Coelli et al., 2002).

In the first step of the analysis in this paper, a Data Envelopment Analysis (DEA) is used to calculate more consistent measures of efficiency (Fraser and Cordina, 1999). This is a systems approach widely used in management science and economics, in which the relationships between all inputs and outputs are taken into account simultaneously (Raju and Kumar, 2006). The method enables the relative efficiency of a farm to be determined and to examine its position in relation to the optimal situation. Moreover, this methodology allows not only technical, but also subvector efficiencies to be calculated, which can be used to specifically monitor the efficiency of water use.

A second step of the study consists of analysing the determinants of efficiency measures (Reig-Martinez and Picazo-Tadeo, 2004). Separate Tobit models are estimated as a function of various attributes of the farmers/farms within the sample (Chavas et al., 2005;

Binam et al., 2003), allowing a pointing out of which aspects of the farms' human and physical resources might be targeted by public investment to improve efficiency (Wadud and White, 2000).

Although there have been several studies that have analysed the efficiency of agricultural production in developing countries (Haji, 2006; Malana and Malano, 2006; Chavas et al., 2005; Abay et al., 2004; Binam et al., 2004; Dhungana et al., 2004; Binam et al., 2003; Coelli et al., 2002, Wadud and White, 2000), most of them have focused on mono-cropping of major food crops like rice, maize or wheat or on cash crops like coffee and tobacco. However, these studies have not specifically focused on the use of water. The novelty of this paper is that it has a clear focus on water of which the sub-vector efficiencies are calculated and analysed. This is highly relevant given the growing water scarcity and the future introduction of water pricing. It is of significant importance for policy makers, because it not only creates awareness concerning inefficiencies in water use, but also provided insight into possible improvements by exploring the determinants of these inefficiencies.

The remainder of the paper is organised as follows. The next section elaborates on the efficiency concepts and their measurement and discusses the theoretical background for DEA and in section 3, data collection is described. Obtained efficiency scores are presented with the determinants of inefficiency in section 4 and discussed in section 5. Section 6 provides some conclusions.

2. Methodology

2.1 Efficiency measures

Efficiency refers to the global relationship between all outputs and inputs in a production process (Rodríguez Díaz et al., 2004b). The performance of a farm can be evaluated based on different efficiency measures, namely technical, allocative[1] and economic efficiency.

This study is limited to the calculation of technical efficiencies. More specifically, we use the measures that originate from the seminal work on technical efficiency by Farell (1957), where technical efficiency is defined as the ability of a farm to produce the maximum feasible output from a given bundle of inputs, or to use minimum feasible amounts of inputs to produce a given level of output. These two definitions of technical efficiency lead to what is respectively known as the 'output-oriented' and the 'input-oriented' efficiency measure (Coelli et al., 2002; Dhungana et al., 2004; Rodríguez Diaz et al., 2004a; Rodríguez Díaz et al., 2004b). Input-oriented models were chosen in this study to reflect the reality where the main aim is not to increase production but to use different resources more efficiently (Rodríguez Diaz et al., 2004a).

Technical efficiency itself can be further decomposed into two components: scale efficiency and pure technical efficiency. The former relates to the most efficient scale of operation in the sense of maximising average productivity. Pure technical efficiency, however, is obtained when separating the scale effect from the technical efficiency.

For calculating the efficiency of an individual input, sub-vector efficiency measures are introduced, in order to generate technical efficiency measures for a subset of inputs rather than for the entire vector of inputs. The concept looks at the possible reduction in a subset of inputs, holding all other inputs and output constant (Oude Lansink and Silva, 2004; Oude Lansink and Silva, 2003; Oude Lansink et al., 2002; Färe et al., 1994).

[1] Allocative efficiency is another frequently used measure of efficiency. It is defined as the ability of a farm to equate marginal value product and marginal cost (Dhungana et al. 2004). In other words a farm is allocative inefficient if it does not utilise the inputs in optimal proportions, given the observed input prices, and hence does not produce at minimum possible cost (Coelli et al., 2002; Abay et al., 2003). The product of technical and allocative efficiency provides yet another efficiency measure, namely the overall economic efficiency (Coelli, 1998).

2.2 The Use of DEA to measure efficiencies

Two major approaches to measure efficiency have evolved, namely parametric and non-parametric approaches, with the stochastic frontier production function approach and the DEA methodology respectively as most popular techniques.

The DEA methodology has some important advantages over the econometric approach to efficiency measurement. Firstly, because it is nonparametric there is no need to make assumptions concerning the functional form for the frontier technology or the distribution of the inefficiency term. Secondly, the approach permits the construction of a surface over the data, which allows the comparison of one production method with the others in terms of a performance index. In this way DEA provides a straightforward approach to calculating the efficiency gap that separates each producer's behaviour from best productive practices, which can be assessed from actual observations of the inputs and outputs of efficient firms (Haji, 2006; Reig-Martinez and Picazo-Tadeo, 2004, Malano et al., 2004; Wadud and White, 2000). Furthermore, when using DEA, efficiency measures are not significantly affected by a small sample size, as long as the number of inputs is not too high in comparison to the sample size. (Thiam et al 2001; Chambers, 1998). Oude Lansink et al. (2002) finally argue that calculating sub-vector technical efficiencies using a stochastic frontier approach would be highly problematic. The disadvantages of DEA, however, are that it is deterministic and sensitive to measurement errors and other noise in the data, although several studies comparing both methodologies have shown that results from both methods are highly correlated (Alene and Zeller, 2005; Thiam et al., 2001; Wadud and White, 2000). In this study DEA approach is preferred because of its flexibility and the possibilities of calculating sub-vector efficiencies

DEA is based on the notion that a production unit employing less input than another to produce the same amount of output can be considered as more efficient, with a production frontier constructed and an efficiency measure obtained simultaneously. The frontier surface is assembled piecewise by solving a sequence of linear programming problems, one for each farm, with each farm related to this frontier. The frontier created envelops the observed input and output data of each farm.

The model is presented here for a case where there is data on K inputs and M outputs for each of the N farms. For the i-th farm, input and output data are represented by the column vectors x_i and y_i, respectively. The *KxN* input matrix, X, and the *MxN* output matrix, Y, represent the data for all N farms in the sample.

The DEA model to calculate the technical efficiency (TE) is in this case (equation 1):

$$Min_{\theta\lambda}\theta,$$

subject to
$$\begin{aligned} & -y_i + Y\lambda \geq 0, \\ & \theta x_i - X\lambda \geq 0, \\ & N1'\lambda = 1, \\ & \lambda \geq 0 \end{aligned}$$

Where θ is a scalar, *N1* is a *Nx1* vector of ones, and λ is an *Nx1* vector of constants. This is solved once for each farm, where the value of θ obtained is the technical efficiency score for the i-th farm, a score which will always lie between zero and one, one indicating that the farm lies on the frontier and is efficient. It should also be noted that equation 1 has a variable returns to scale (VRS) specification which includes a convexity constraint ($N1'\lambda=1$). Without that constraint, equation (1), would have constant returns to scale specification (CRS). Using that specification, it is assumed that farms are operating at their optimal scale (Fraser and Cordina, 1999). In the case of agriculture, increased amounts of inputs do not proportionally increase the amount of outputs. For instance, when the amount of water to crops is increased, a linearly proportional increase in crop volume is not necessarily obtained, one reason why the variable return to scale option might be more suitable for our problem (Rodriguez-Diaz et al., 2004b). Coelli et al. (2002) and Haji (2006) on the other hand found that for small farms like the ones considered in this study, little scale economies could be realised, hence both specifications will be modelled. In addition, a comparison of both scores is interesting because it provides information on scale efficiency (SE). Coelli et al. (2002) showed that the relation is as follows:

$SE= TE_{crs}/TE_{vrs}$

Using the notion of sub-vector efficiency proposed by Färe et al. (1994), the technical sub-vector efficiency for the variable input k is determined for each farm i by solving following programming problem (equation 2):

$$Min_{\theta\lambda}\theta^{k},$$

subject to
$$\begin{aligned}
&-y_i + Y\lambda \geq 0,\\
&\theta^{k} x_i^{k} - X^{k}\lambda \geq 0,\\
&x_i^{n-k} - X^{n-k}\lambda \geq 0,\\
&N1'\lambda = 1,\\
&\lambda \geq 0
\end{aligned}$$

Where θ^k is the input k sub-vector technical efficiency score for farm i. The terms x_i^{n-k} and X^{n-k} in the third constraint refer to x_i and X with the kth input (column) excluded, whereas, in the second constraint, the terms x_i^k and X^k include only the kth input. All other variables are defined identically as in equation 1.

A graphical representation of the measurement of technical efficiency and sub-vector efficiency using DEA shows the intuitive interpretation of the method (figure 1). The problem takes the i-th farm A and then seeks to radially contract the input vector, x_i, as much as possible, while remaining within the feasible input set. The inner-boundary of this set is a piecewise linear isoquant determined by the frontier data points (the efficient farms in the sample: F1 and F2). The radial contraction of the input vector x_i produces a projected point on the frontier surface (A^0). This projected point is a linear combination of the observed data points, with the constraints in equation 1 ensuring that the projected point cannot lie outside the feasible set. The overall technical efficiency measure of farm A relative to the frontier is given by the ratio $\theta = 0A^0/0A$. The sub-vector efficiency for input X_1 is also presented in figure 1, in which X_1 is reduced while holding X_2 and output constant. In the graph, A is projected to A' and sub-vector efficiency is given by the ratio $\theta^l = 0'A'/0'A$.

<INTRODUCE FIG 1 ABOUT HERE>

2.3 Identifying determinants of efficiency using Tobit analysis

After calculating the efficiency measures, the next step is to identify the determinants of inefficiency, something commonly done by estimating a second-stage relationship between the efficiency measures and suspected correlates of efficiency (Barnes, 2006; Chavas et al., 2005; Binam et al., 2003; Iráizoz et al., 2003). Since the efficiency parameters vary between 0-1, they are censored variables and thus a Tobit model needs to be used (equation 3):

$$\theta^{k*} = \beta_0 + \beta_1 z_1 + \beta_2 z_2 + \ldots \beta_j z_j + e$$
$$= Z\beta + e$$

$$\theta^k = \theta^{k*} \text{ if } 0 < \theta^{k*} < 1$$
$$= 0 \text{ if } \theta^{k*} < 0$$
$$= 1 \text{ if } \theta^{k*} > 1$$

Where θ^k is the DEA sub-vector efficiency index for water used as a dependent variable and Z is a vector of independent variables related to attributes of the farmers/farms within the sample. The variables included in the Tobit model are discussed in the following section. The estimation of the Tobit model is based on maximum likelihood procedures (Verbeek, 2000). For Tobit estimates to be consistent it is necessary that residuals are normally distributed (Holden, 2004). Therefore, a normality test is necessary. In this case the conditional moment test for normality in censored data will be used.

2.4 Data collection

Data was collected from small-scale irrigation schemes situated in Zeerust Municipality (North-West Province, South Africa) from July to September 2005. The municipality is located in the Central District Council of North West Province and shares a border with Botswana. The surface area of the municipality is 7192 km² with a population of 136 000 (AGIS, 2005; Zeerust Local Municipality, 2004).

Most Zeerust residents are engaged in economic activities like agriculture, hunting, forestry, fishing and wholesale or retail of goods and services. The rest of the population is either unemployed or spread in various small businesses (Zeerust Local Municipality, 2004).

Questionnaires were used to collect data, with a total of 60 farmers interviewed, spread over 13 small-scale irrigation schemes. Extension staff of the North West Province Agricultural Department acted as interpreters. Random sampling was applied in selecting schemes and individual farmers, but representativeness was maintained by adapting the number of respondents at each scheme to the number of farmers operational within them.

During the interviews information was gathered on the irrigation schemes, household characteristics, farm activities, quantities and costs of inputs used in production (capital, variable and overhead), quantities and value of output, the quantity of water consumed and irrigation practices. In general this type of farmers does not keep records concerning their farming activities, so data gathered during interviews was based on recollections of farmers. The expert knowledge of the extension staff was used as a supplement to the recollections of the farmers, something that was particularly helpful for the estimation of the water use and the prices of their produce.

For the different outputs both quantities and corresponding prices were obtained. Total output was then converted into monetary terms, the inputs considered in the efficiency analysis including land (hectares), irrigation (m^3), labour (man days), fertilizers (expenses) and pesticides (expenses). Table 1 reports the sample description of the data.

<INTRODUCE TABLE 1 ABOUT HERE>

In the Tobit analyses various farmer/farm specific factors were regressed on the sub-vector efficiencies for water, factors including those of a demographic nature, such as age of the farmer (in years), gender (dummy variable taking 1 if farmer was female and 0 otherwise) and household size (number of members in the household), as well as socio-economic characteristics like education (dummy variable taking 1 if farmer minimally attended primary education and 0 otherwise), cultivated area (total area in ha), landownership (dummy taking 1 if land is privately owned and 0 if it consisted communal land), crop choice (farmers profit per m^3 of water used)[2] and a land fragmentation index (Simpson index, defined as the sum of the squares of the plot sizes, divided by the square of the farm size, with higher values of this index indicating more fragmentation). Since three irrigation techniques were identified within the sample (sprinkler, hose, and bucket irrigation), two dummies for irrigation methods were also included. Furthermore three types of institutional contexts for irrigation schemes were recognised (food gardens[3], typical small-scale schemes and individual farmers irrigating), therefore 2 dummies for these arrangements were also included. The descriptive statistics for the variables included in the Tobit model are presented in table 2.

[2] As a quantitative proxy for the compilation of crops selected by the farmers the overall profit per m^3 of water was used.

[3] Parallel to typical small-scale irrigation schemes founded by government, a second type of schemes originating from civil society (communities, NGO's) has evolved. The plots at these schemes are usually very small and the main objective is to provide some additional food or income to the persons working there.

<INTRODUCE TABLE 2 ABOUT HERE>

3. Results

Both the CRS and the VRS DEA models for overall technical efficiency (equation 1) are estimated using the program DEAP (Coelli, 1996). Sub-vector efficiencies were modelled in GAMS using the methodology proposed by Färe et al. (1994) and the modelling suggestions of Kalvelagen (2004).

Table 3 gives the frequency distribution of the efficiency estimates obtained by the DEA methods. The average overall technical efficiencies for the CRS and the VRS DEA approaches are 0.51 and 0.84 respectively, indicating that substantial inefficiencies occurred in farming operations of the sample farm households. Under the observed conditions, about 14% and 39% of farms were identified as fully technical efficient under the CRS and VRS specification respectively. The large differences between the CRS and VRS measures further indicated that many farmers did not operate at an efficient scale and that adjusting the scale of operation could improve the efficiency.

<INTRODUCE TABLE 3 ABOUT HERE>

The sub-vector efficiencies for water demonstrated even larger inefficiencies. Average water efficiency was only 0.43 under CRS and 0.67 under VRS. Figure 2 gives a graphical representation of the cumulative efficiency distributions for the different measures. Again it is clear that under both returns to scale specifications more farms were highly inefficient in the use of water compared to overall technical efficiency.

<INTRODUCE FIG 2 ABOUT HERE>

Table 4 gives the correlation statistics between sub-vector efficiency for water and the overall technical efficiency, which help us to determine the relationship between the two efficiency measures. Under CRS, technical efficiency and sub-vector efficiency were highly positively correlated. Under VRS, however, correlation was still positive but only moderate. A paired sample t-test to analyse the equality between sub-vector efficiencies and overall efficiencies was statistically significant. Furthermore, sub-vector efficiencies for water were significantly lower then overall technical efficiency measures, both under CRS and VRS specification, (table 5).

<INTRODUCE TABLE 4 AND 5 ABOUT HERE >

The second part of the analysis consists of identifying the characteristics that determine the sub-vector efficiencies for water of these smallholder farms. Two separate Tobit regressions for CRS and VRS specifications were estimated using LIMDEP version 8, the results of which are presented in table 6.

<INTRODUCE TABLE 6 ABOUT HERE>

The conditional moment test for normality in censored data indicated that the normality hypothesis could not be rejected. Furthermore, two fit measures are reported for the regressions: an ANOVA based fit measure R^2_{ANOVA} and a decomposition based fit measure R^2_{DECOMP} [4]. For both regressions, the fit was more than satisfactory.

The joint significance of all variables within the model was assessed using three test statistics, namely the Lagrange multiplier statistic (LMstat), the likelihood ratio statistic (LR) and the Wald statistic. All three statistics confirmed that both Tobit models were significant.

Concerning the individual variables, the results of the models with CRS and VRS specification showed consistency. Personal farmer's characteristics like gender, age[5], education, household size were not significant, whereas cultivated area, landownership, the scheme type dummy for food gardens and the crop choice were significant in both models. The cultivated area negatively influenced water efficiency, while the other significant variables had a positive effect on the efficiency measures. Under the VRS specification fragmentation was also highly significant and had a negative effect on the sub-vector efficiency for water. The dummies for the irrigation methods, on the other hand, had a negative effect under both specifications, but were only significant under the CRS specification.

---

[4] In the case of Tobit models these fit measures are best suited to be used as a substitute for the Ordinary Least Squares R^2, because both mimic R^2 and converge to it as censoring probability goes to zero. They are composed as follows: The R^2_{ANOVA} takes the variance of the estimated conditional mean divided by the variance of the observed variable. The R^2_{DECOMP} takes the variance of the conditional mean function around the overall mean of the data in the numerator (Greene, 2002).

[5] A non-linear relationship was also checked without significant result.

4. Discussion

The results of the DEA show that substantial inefficiencies occur among smallholder irrigators within the study area, which is consistent with a recent meta-analysis by Bravo Ureta et al. (2007). They showed that in less developed countries, mean values of technical efficiency per study averaged at about 0.74. Moreover, given the poor performance of the type of irrigation schemes in the area mentioned in several studies (IPTRID, 2000; Shah et al., 2002, Perret, 2002), substantial efficiencies were expected.

Secondly, results show that scale inefficiencies are significant (0.6 on average) with nearly all farms operating at increasing returns to scale, which implies that most farms should be larger than they presently are to produce efficiently under the present factor mix. Large scale inefficiencies were also reported by Binam et al. (2003) for coffee farmers in Ivory Coast, by Abay et al. (2004) for tobacco farmers in Turkey and by Shafiq and Rehman (2000) for cotton farmers in Pakistan. Haji (2006) on the other hand found that in more traditional farming systems like the ones of smallholder farmers in Eastern Ethiopia, scale inefficiencies were nearly absent and similar conclusions were drawn by Alene et al. (2006) for intercropping in Southern Ethiopia.

Thirdly, the results indicate that farms have a poor performance in terms of water use efficiency. As indicated by Nsanzugwanko et al. (1996), this might be explained by the absence of pricing mechanisms for water. Farmers at this moment have no financial incentive to limit their water use or to invest in water saving technologies. The gradual introduction of a water pricing scheme for this type of farmers, which is planned for the coming years, can probably be a trigger for more efficient use. Another interesting implication of these results is that there appears to be a considerable scope for reducing the water use, even with the technology currently available. This means that if efficiency improves, it should be possible to reallocate a fraction of the water to other water demands without really endangering production or the role small-scale irrigation might play for rural development. Besides, correlation tests showed that poor performance regarding water use efficiency and overall technical efficiency are strongly linked. This can be explained by the vital role irrigation water plays in the production systems under study. However, this finding also implies that the introduction of water prices can be a threat to the viability of the poorer performers, because they will be most affected by this additional cost. If those farmers fail to improve their water use efficiency, their farming activities might become financially unviable.

Fourthly, the results of the Tobit models show that cultivated area, landownership, the scheme type dummy for food gardens and the proxy for crop choice have a significant impact on the sub-vector efficiency for water, under both specifications. Owner-operators seem to be more efficient in their water use, but one has to be careful with this conclusion, given their small number in the sample. Nevertheless, if this finding could be confirmed, it indicates the importance of land rights and can be an additional argument for land reforms, which make people owner of the land they work on. The cultivated area had a negative impact on the sub-vector efficiency for water. Haji (2006) also reported such a negative impact on overall technical efficiency, attributing it to the labour intensive character of the type of vegetable production he studied. In our study, however, this finding seems inconsistent with the increasing returns to scale for overall technical efficiency found in the DEA outcomes, but it should be reminded that the Tobit model only considers the sub-vector efficiency. Apparently, the relationship between cultivated area and the totality of farming activities is different from that between cultivated area and the use of one input. This was also confirmed in a Tobit model, where cultivated area had a significant positive impact on overall technical efficiency (result not presented in this paper). Further investigation on this matter is needed.

Finally, the institutional context of the schemes seems to be of relevance. Efficiency of water use is higher for farms in food garden schemes, which is in accordance with a study in South Africa by IPTRID (2000) that discussed the large potential of such food garden schemes in vegetable production. The highly significant and positive effect of crop choice on sub-vector efficiency for water supports the call for selecting crops with high higher profits per m^3 of water used or for water saving irrigation technology. Iráizoz et al. (2003) found a similar result for the relationship between technical efficiency and partial productivity indices like output per unit of land and output per unit of labour. Fragmentation has a negative effect under the variable returns to scale specification, indicating that, for a certain size of operation, the sub-vector inefficiency effects for water are lower if the farm is less fragmented, something due to the fact that irrigation can be managed more efficiently on larger plots (Wadud and White, 2000). However, under constant returns to scale specification, where farms operating at different scales are compared, the effect of fragmentation is not significant. This can partly be explained by the efficiency differences between the different types of schemes occurring in the area, which apparently neutralizes the effect of fragmentation. Earlier it was shown that the food garden schemes were more efficient compared to the other two types and typically these smaller schemes have a higher degree of fragmentation.

Other variables are not significant, education, for example, having no significant impact on the sub-vector efficiency for water. This is consistent with studies such as those of Haji (2006), Coelli et al. (2002) and Wadud and White (2000). The explanation that this could be due to the low average education level in the sample given by Coelli et al. (2006) is also acceptable for this study. Dhungana et al. (2004) and Binam et al. (2004) in contrast reported a significant positive effect of education on efficiency for some of the regressions they performed, possibly due to a slightly higher average education level in their samples.

Farmer's age does not contribute significantly to a higher level of efficiency either. A possible explanation is that two effects neutralize each other: older more experienced farmers have more knowledge on their land and traditional practices, but are less willing to adopt new ideas. Sometimes one of the two effects dominates, accounting for the mixed results in literature for the effect of age: negative in the study of Wadud and White (2000) and Binam et al. (2003), but positive in the study of Dhungana et al. (2004). In this study experience was not measured, so an age-experience interaction term could not be included to test the hypothesis above.

Consistent with Haji (2006) and Dhungana et al. (2004) the effect of family size is negative, but, as in Coelli et al. (2002), this effect is not significant. Finally, looking at gender no significant effect can be shown. This is in line with Chavas et al. (2005) and Dhungana et al. (2004).

5. Conclusions

The study used a DEA approach to measure the technical and sub-vector efficiency for water of vegetable producing small-scale irrigators in North West Province in South Africa. Detailed survey data collected in 2005 on 60 sampled farmers spread over 13 small-scale irrigation schemes were used to compute the efficiency measures. The results indicate that the mean technical efficiency under the CRS and VRS is 51% and 84%, respectively; the large difference between the two being a sign of substantial scale inefficiencies. The majority of the farmers were operating at increasing returns to scale, implying that larger farm sizes would be more efficient.

The sub-vector efficiencies for water are with 43% (CRS) and 67% (VRS), even lower than overall technical efficiencies. This might be an indication that farmers have little incentives to use water in an efficient manner, in the absence of a water price. The gradual introduction of a water pricing scheme for this type of farmers, which was planned for the coming years, could be a trigger for more efficient use. Because of the large correlation between sub-vector efficiencies for water and the overall technical efficiency, the effect of introducing water prices can however also be negative, endangering the viability of the poor performers. Study of the economic efficiency of the farmers can shed some light on this.

On the other hand, these low efficiencies suggest that substantial decreases in water use can be attained given existing technology, without compromising the key role in rural development played by small-scale irrigation. In this way there is room for lifting part of the increasing pressure on water resources by reallocating a fraction of the irrigation water elsewhere.

In a second step, the relationship between the sub-vector efficiency for water and various attributes of the farm and farmer was examined. The results of the Tobit models can help policy makers or extension services to better aim efforts to improve water use efficiency. If the significant positive effect of landownership on the sub-vector efficiency could be confirmed for a larger sample, this would, for instance, emphasize the importance of land rights, supporting land reforms where people are made owner of the land they work. Another practical example is the positive and significant effect of crop choice on the sub-vector efficiency, which should incite extension services to encourage farmers to select crops with higher profit per m^3 of water or water saving irrigation techniques to improve water use efficiency.

Finally, it should be noted that this article focused on technical efficiency measures. Additional research on allocative and economic efficiency can further determine the scope for production improvements and can add to our understanding of the effect on efficiency of the introduction of a water price.

More research would also be needed to generalise the results. This paper builds on information of 60 farmers, spread over a significant number of irrigation schemes, but a similar approach in other irrigation schemes in rural areas could provide an interesting comparison.

References

Abay, C., Miran, B., Gunden, C., 2004. An analysis of input use efficiency in Tobacco production with respect to sustainability: The case study of Turkey. Journal of Sustainable Agriculture 24(3), 123-143.

AGIS, 2005. AGIS Atlas 2005, ARC institute for soil, climate and water, South Africa.

Alene, A.D., Manyong, V.M., Gockowski, J., 2006. The production efficiency of intercropping annual and perennial crops in southern Ethiopia: A comparison of distance functions and production frontiers. Agricultural systems 91, 51-70.

Alene, A.D., Zeller, M. 2005. Technology adoption and farmer efficiency in multiple crops production in eastern Ethiopia: A comparison of parametric and non-parametric distance functions. Agricultural Economics Review 6, 5-17.

Ashton, P., Haasbroek, B., 2002. Water demand management and social adaptive capacity: A South African case study. In: Turton A., Henwood R., (Ed.), Hydropolitics in the Developing World: A Southern African Perspective. African Water Issues Research Unit, Pretoria, pp.187-204.

Barnes, A.P., 2006. Does multi-functionality affect technical efficiency? A non-parametric analysis of the Scottish dairy industry. Journal of Environmental Management, 80, 287-294.

Binam, J.N., Sylla, K., Diarra, I., Nyambi, G., 2003. Factors Affecting Technical Efficiency among Coffee Farmers in Côte d'Ivoire: Evidence from the Centre West Region. R&D Management 15, 66-76.

Binam, J.N., Tonyè, J., Wandji, N., Nyambi, G., Akoa, M., 2004. Factors affecting the technical efficiency among smallholder farmers in the slash and burn agriculture zone of Cameroon. Food Policy, 29, 531-545.

Bravo-Ureta, B.E., Solis, D., Moreira Lopez, V.H., Maripani, J.F., Thiam, A., Rivas, T., 2007. Technical efficiency in farming: a meta-regression analysis. Journal of Productivity Analysis 27, 57-72.

Chambers, R.G., Fare, R., Jaenicke, E., Lichtenberg, E., 1998. Using dominance in forming bounds on DEA models: the case of experimental agricultural data. Journal of Econometrics 85, 189-203.

Chavas, J., Petrie, R., Roth, M., 2005. Farm household production efficiency: evidence from the Gambia. American Journal of Agricultural Economics 87, 160-179.

Coelli, T., Rahman, S., Thirtle, C., 2002. Technical, Allocative, Cost and Scale Efficiencies in Bangladesh Rice Cultivation: A non-parametric Approach. Journal of Agricultural Economics 53 (3) 607-627.

Coelli, T., Rao, P.D.S., Battese, G.E., 1998. An introduction to efficiency and productivity analysis. Kluwer academic publishers. Boston.-

Coelli, T., 1996. A Guide to DEAP Version 2.1: A data envelopment analysis (computer) program. CEPA Working Papers n°8/96, University of New England, Australia.

Dhungana, B.R., Nuthall, P.L., Nartea, G.V., 2004. Measuring the economic inefficiency of Nepalese rice farms using data envelopment analysis. The Australian Journal of Agricultural and Resource Economics 48 (2), 347-369.

DWAF, 2004. Water Resources Strategy Paper. Department of Water Affairs and Forestry, Republic of South Africa.

Färe, R., Grosskopf, S., Lovell, C.A.K., 1994. Production frontiers, Cambridge, Cambridge University Press.

Farrell, M.J. 1957. The measurement of productive efficiency. Journal of the royal statistical society A 120, 253-281.

Fraser, I., Cordina, D., 1999. An application of data envelopment analysis to irrigated dairy farms in Northern Victoria, Australia. Agricultural Systems 59, 267-282.

Green, W.H., 2002. LIMDEP version 8, Econometric Modeling Guide, volume 2. Econometric Software, Inc.

Haji, J. 2006. Production Efficiency of smallholders' vegetable-dominated Mixed Farming System in Eastern Ethiopia: A non-parametric Approach. Journal of African Economies 16(1), 1-27.

Holden, D., 2004. Testing the Normality Assumption in the Tobit Model. Journal of Applied statistics 31, 521-532.

IPTRID, 2000. Affordable irrigation technologies for smallholders: opportunities for technology adaptation and capacity building, South Africa. Programme formulation report No.6, International Programme for Technology and Research in Irrigation and Drainage, FAO , Rome.

Iráizoz, B., Rapún, M., Zabaleta, I., 2003. Assessing the technical efficiency of horticultural production in Navarra, Spain. Agricultural Systems, 78, 387-403.

Kalvelagen, E., 2004. Efficiently solving DEA models with GAMS. http://www.gams.com/~erwin/dea/dea.pdf.

Malana, N.M., Malano, H.M. 2006. Benchmarking productive efficiency of selected wheat areas in Pakistan and India using data envelopment analysis. Irrigation and drainage 55, 383-394.

Malano, H., Burton, M., Makin, I., 2004. Benchmarking performance in the irrigation and drainage sector: a tool for change. Irrigation and drainage 53, 119-133.

Nsanzugwanko, M.D., Battese, G.E., Fleming, E.M., 1996. The technical Efficiency of small agricultural producers in Central Ethiopia. Centre for Efficiency and Productivity Analysis working papers n°5/96. University of New England, Australia.

Oude Lansink, A., Pietola, K., Bäckman, S., 2002. Efficiency and productivity of conventional and organic farms in Finland 1994-1997. European Review of Agricultural Economics 29 (1), 51-65.

Oude Lansink, A., Silva, E., 2003. CO_2 and energy efficiency of different heating technologies in Dutch Glasshouse Industry. Environmental and Resource Economics 24, 395-407.

Oude Lansink, A., Silva, E., 2004. Non-parametric production analysis of pesticides use in the Netherlands. Journal of productivity analysis 21, 49-65.

Perret, S., Touchain, E., 2002. A simulation-based approach to access the economic viability of smallholding irrigation schemes in South Africa. CIRAD-Tera, Research report 02/02. Pretoria, South Africa.

Perret, S., 2002. Water policies and smallholding irrigation schemes in South Africa: a history and new institutional challenges. Water Policy 4 (3), 283-300.

Raju, S.K., Kumar, N.D., 2006. Ranking Irrigation Planning Alternatives Using Data Envelopment Analysis. Water Resources Management 20, 553-566.

Reig-Martinez, E., Picazo-Tadeo, A.J., 2004. Analysing farming systems with Data Envelopment Analysis: citrus farming in Spain. Agricultural Systems 82, 17-30.

Rodríguez Díaz, J.A., Camacho Poyato, E., López Luque, R., 2004a. Applying Benchmarking an Data Envelopment Analysis (DEA) Techniques to irrigation districts in Spain. Irrigation and Drainage 53, 135-143.

Rodríguez Díaz, J.A., Camacho Poyato, E., López Luque, R., 2004b. Application of Data Envelopment Analysis to Studies of Irrigation Efficiency in Analusia. Journal of irrigation and drainage engineering 130, 175-183.

Shafiq, M., Rehman, T., 2000. The extent of resource use inefficiencies in cotton production in Pakistan's Punjab: an application of Data envelopment analysis. Agricultural Economics 22, 321-330.

Shah, T., van Koppen, B., Merrey, D., de Lange, M., Samad, M., 2002. Institutional Alternatives in African Smallholder Irrigation: Lessons from International Experience with Irrigation Management Transfer. Research Report 60. International Water Management Institute, Colombo, Sri Lanka.

Thiam, A., Bravo-Ureta, B.E., Rivas, T.E., 2001. Technical efficiency in developing country agriculture: a meta analysis. Agricultural Economics 25, 235-243.

Verbeek, M., 2000. A guide to modern econometrics. John Wiley & Sons, Chichester.

Wadud, A., White, B., 2000. Farm household efficiency in Bangladesh: a comparison of stochastic frontier and DEA methods. Applied Economics, 32, 1665-1673.

Zeerust Local Municipality, 2004. Integrated Development Planning. Zeerust Local Municipality, South Africa.

Figures

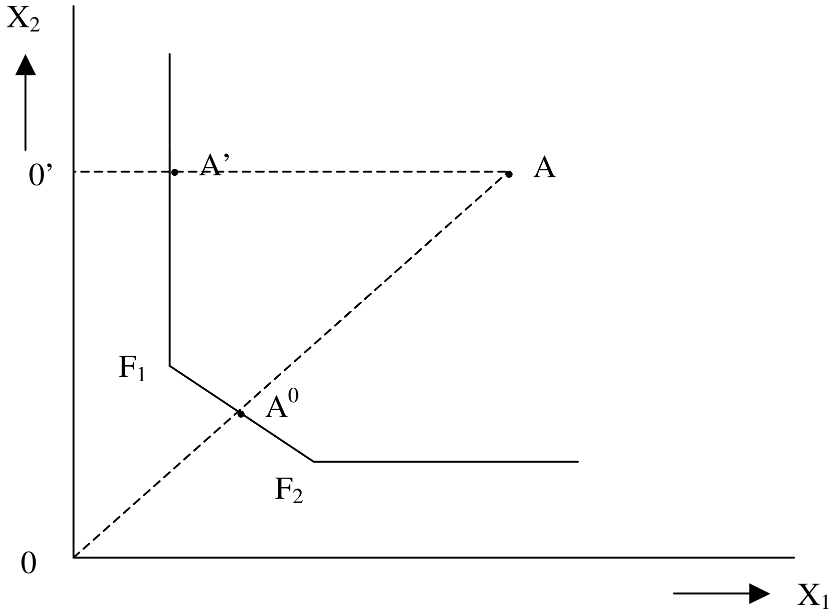

Figure 1. Graphical representation of the measurement of technical efficiency and sub-vector efficiency using DEA for an example with two inputs and one output (adapted from Oude Lansink et al., 2002)

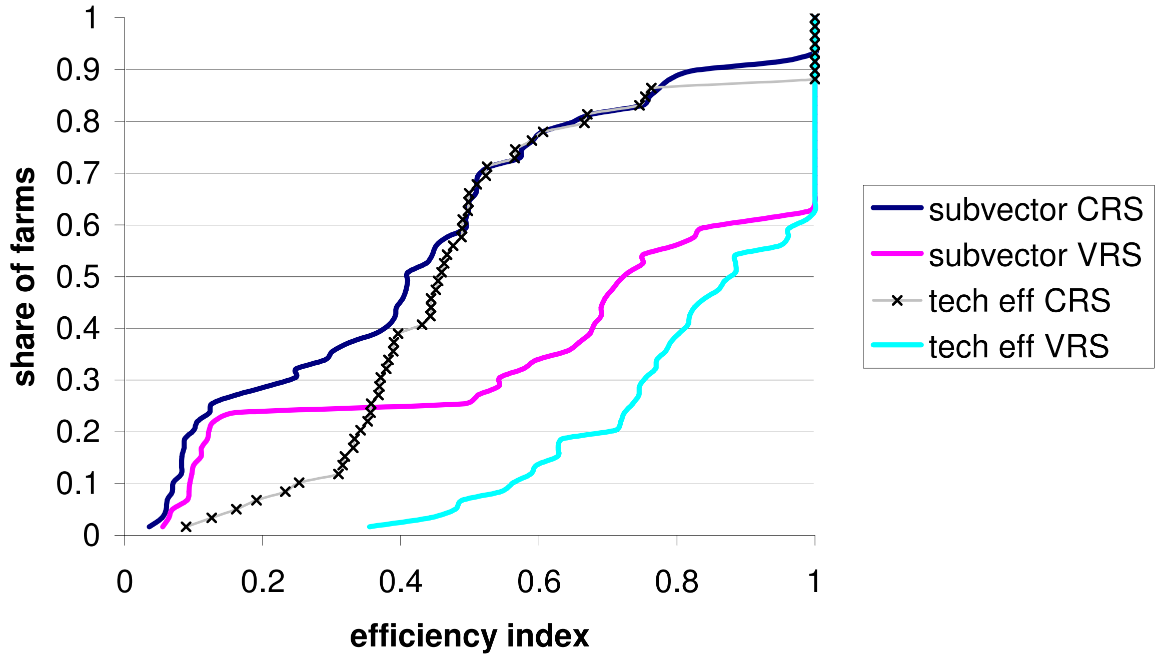

Figure 2: Cumulative efficiency distribution for technical and subvector efficiency for water under VRS and CRS specification

Table 1 Descriptive statistics on outputs and inputs used in efficiency analysis.

	Unit	Average	St. dev.	Minimum	Maximum
Output	rand[6]	2816	11348	150	87200
Inputs					
Land	ha	0.16	0.40	0.01	2.8
Water	m^3	1287	3299	82.9	2215
Labour	man days	29	76	5.6	599
Expenditure on pesticides	rand	72	82	0	360
Expenditure on fertilizers	rand	64	91	0	487

[6] At the time of the data collection the exchange rate was 1 Rand = 0.1504 US$

Table 2. Summary statistics for variables included in the Tobit regressions

	Mean	St dev	Min	max
Quantitative variables				
Farmers' age	58	13	27	86
Household size	6	3	1	19
Cultivated area (ha)	1.018	1.210	0.011	6.6
Simpson fragmentation index	0.700	0.260	0.000	0.889
Crop choice (R/m³)	1.236	1.352	0.000	7.405
Qualitative variables (number of respondents in each category)				
Gender	Male	Female		
	32	27		
Education	No education	Primary or more		
	29	30		
Landownership	Private	Communal		
	3	56		
Irrigation technique	Hosepipes	Buckets	Sprinkler	
	35	21	3	
Type of irrigation institution	Food garden	Small scale scheme	Private small farm	
	37	18	3	

Table 3: Overall technical and water-subvector efficiencies under constant and variable returns to scale specifications

	Tech CRS		Tech VRS		Water subvec CRS		Water subvec VRS	
Efficiency score	N° farms	% of farms	N° farms	% of farms	N° farms	% of farms	N° farms	% of farms
0-10	1	2	0	0	11	19	7	12
10-20	3	5	0	0	5	8	7	12
20-30	2	4	0	0	4	7	0	0
30-40	17	29	1	2	6	10	0	0
40-50	16	27	3	5	12	20	1	2
50-60	6	10	4	7	7	12	5	9
60-70	3	5	3	5	3	5	7	12
70-80	3	5	11	19	4	7	6	10
80-90	0	0	10	17	1	2	2	3
90-100	0	0	4	7	1	2	2	3
100	8	14	23	39	5	9	22	37
Average score	0.51		0.84		0.43		0.67	

Table 4. Pearson correlations between efficiency measures

	Tech CRS	Tech VRS	Sub-vector CRS	Sub-vector VRS
Tech CRS	1			
Tech VRS	0.506 ***	1		
Sub-vector CRS	0.703***	0.140	1	
Sub-vector VRS	0.448***	0.349***	0.731***	1

Note: *** indicates a 99% significance level

Table 5. Paired samples t-tests demonstrating the difference between overall technical efficiency and sub-vector efficiency

	Mean difference	Std dev.	t-statistic
CRS: sub-vector- overall technical efficiency	-0.08	0.21	-2.849***
VRS: sub-vector- overall technical efficiency	-0.17	0.34	-3.912***

Note: *** indicates a 99% significance level

Table 6. Tobit estimates on determinants of sub-vector CRS and VRS efficiency

Dependent variable	Sub-vector CRS efficiency		Subvector VRS efficiency	
	coefficient	St dev	coefficient	St dev
Constant	0.0778	0.1529	0.4898*	0.2589
Gender (1=female)	-0.0204	0.0379	0.0655	0.0708
Age of farmer (years)	-0.0006	0.0014	0.0033	0.0027
Education dummy (1=primary or more)	-0.0240	0.0414	0.0492	0.0780
Household size (number)	-0.0072	0.0061	-0.0125	0.0113
Cultivated area (ha)	-0.0577***	0.0173	-0.1066***	0.0325
Landownership (1= owner of land)	0.6614***	0.1845	0.6605***	0.2114
Dummy irrigation method (1= hoses)	-0.2688***	0.0798	-0.0705	0.1444
Dummy irrigation method (1= buckets)	-0.3267***	0.0859	-0.2259	0.1557
Fragmentation index (index)	0.1147	0.0862	-0.5907***	0.1629
Dummy scheme (1=typical small-scale)	0.4208***	0.1477	0.2923	0.2150
Dummy scheme (1= food garden)	0.4981***	0.1504	0.5668***	0.2060
Crop choice (R/m³)	0.1679***	0.0137	0.1333***	0.0261
R^2ANOVA	0.789		0.512	
R^2DECOMP	0.816		0.575	
LMstat	80.12		53.28	
LR (p-value)	99.51 (0.000)		57.43 (0.000)	
Wald (p-value)	269.62 (0.000)		97.17 (0.000)	
Test value CM Normality test (p value)	1.665 (0.435)		0.491 (0.782)	

Note: *** indicates a 99% significance level and * indicates a 90% significance level