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USE OF DATA ENVELOPMENT ANALYSIS AS A MULTI CRITERIA DECISION TOOL – A CASE OF IRRIGATION MANAGEMENT

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Abstract- In this paper, the use of Data Envelopment Analysis (DEA) as a tool for Multiple Criteria Decision Making (MCDM) is investigated for assessing various irrigation management strategies in terms of economic, environmental and social criteria. To carry out this task, an irrigation management research project report is used for the comparison of various MCDM and DEA rankings as well as providing the required data. The DEA methods called Charnes-Cooper-Rhodes (CCR), Banker-Charnes-Cooper (BCC) and Reduced-CCR (RCCR) are employed by the integration of criteria weights through the addition of assurance regions to improve discriminating power of the analysis, and to reach the ranking of strategies. The results indicate that DEA constitutes a valuable approach to be used alternatively or in addition to MCDM, and incorporating managerial preferences into the DEA methods provide correlated results with MCDM techniques.

Keywords-Data Envelopment Analysis, MCDM, Irrigation Management

1. INTRODUCTION

As the fresh water resources are declining in quantity and deteriorating in quality, water resources management is of greater importance than ever before and it is agreed by all that integrated management is the way forward. Integrated water resources management is the concept of managing water sectors subject to various objectives in an integrated manner while considering social, economic, environmental and technical dimensions. On the other hand, all water related objectives cannot be easily traded off with each other due to their complicated and often conflicting nature. This multiplicity overburdens decision makers (DMs) in finding the “most satisfactory decision”. Therefore, MCDM methodologies have been gaining more attention in water resources management. DEA is a linear programming methodology to measure the relative efficiencies of a homogenous set of Decision Making Units (DMUs) when the production process presents a structure of multiple inputs and outputs. Despite large number of MCDM methodologies available [1], the application of DEA as a discrete alternative MCDM tool is also an admissible way to achieve reasonable decisions. Some specific examples of DEA including the efficiency studies of the water companies in UK [2], the irrigation districts in Buyuk Menderes Basin [3], dam locations [4] and the reservoir system in Paraguacu River Basin [5] can be cited in recent literature. In this study, the evaluation of DEA as a MCDM tool is investigated through calculating efficiency scores of the alternatives dealing with irrigation management strategies. The data used is taken from the report of *Euro-Mediterranean Forum of Economic Institutes*

[6]. The DEA results are compared with the results achieved by the report in the application of the various MCDM models. The DEA is also employed by the integration of criteria weights through the addition of assurance regions for the DEA methods. The main relationship between DEA and MCDM can be summarized as defining the *maximizing criteria* as *outputs* and the *minimizing criteria* as *inputs.* Since it is a freeware for academic use and able to incorporate weight restrictions, the software Efficiency Measurement System (EMS) [7] is used in computations.

2. MULTI CRITERIA EVALUATION

In MCDM context, the selection is achieved by evaluating the alternatives where each alternative is described by its performance on each of a number of criteria. The aim of MCDM is to provide support to the decision maker in the process of making the choice among the available alternatives and may include the generation of a proposed "compromise" solution and/or some form of preference ranking. The problem of discrete alternative multiple criteria evaluation is formulated by considering a set of alternatives A = (a_1, a_2,.,a_n) and a set of criteria G = (g_1, g_2,.,g_m), where *n* is the number of alternatives and *m* is the number of criteria. The comparison of various alternatives is based on their values for each criterion. In most approaches, the multi criteria evaluation for an alternative *a* is presented by the vector $g(a)=(g_1(a), g_2(a),..,g_m(a))$, where $g_j(a_i)$ is the performance of the alternative $a \in$A on criterion g_j. The MCDM methods can be classified into five main categories [8] as outranking type techniques, distance-based techniques, value or utility type techniques, direction-based techniques and mixed techniques. In this study, since the comparison of the results are based on the outranking and distance-based techniques, namely ELECTRE-3, ELECTRE-4 (ELimination Et Choice Translating Reality; outranking) and CP (Compromise Programming; distance-based), the main properties of these methods are introduced below however the mathematical structures of these methods are beyond the scope of this article. A detailed description of MCDM methods is available in Pomerol and Romero [1] and Rogers et al. [9].

In ELECTRE-3, the required information are the weights of the criteria used in the comparison of alternatives, indifference (q_j) and preference (p_j) thresholds and veto thresholds on the criteria which are determined with DMs. The evaluation procedures of ELECTRE-3 model comprise the constitution of the threshold function, disclosure of concordance and discordance indexes, outranking degree and the ranking of alternatives. Each of the g_j, taken together with two thresholds denoted by q_j and p_j constitutes a pseudo-criterion [10]. Using thresholds, the method seeks to establish an outranking relation *S*. An outranking relation of *a S b* implies that *a* is preferred to *b* if *a* is at least as good as *b* on a majority of criteria and it is not significantly bad on any other criteria. By establishing such a relation between each and every pair of alternatives, the dominated alternatives can be eliminated and the non-dominated solutions can be obtained.

Although the ELECTRE-4 method is similar to ELECTRE-3, the main difference between these methods is that while the DM's weights are directly used in the calculation of concordance indices in ELECTRE-3, ELECTRE-4 does not require such weights. However, this does not mean that the criteria weights are assumed to be equal. A set of credibility degrees similar to ELECTRE-3 is defined to classify the alternatives based on the ascending and descending distillations. The method can be particularly useful when the DM is not able to assign a set of preference weights to reflect specific requirements of a given decision making problem [11].

CP is a mathematical programming technique for multi criteria problems that rank alternatives according to their closeness to a so called “ideal point” [12]. The best alternative is the one whose point is at the least distance from the ideal point in the set of efficient solutions. Minimization of this closeness is a surrogate of the standard maximization of the criterion function. The distance measure used in CP is the family of L_j-metrics. The expression is used to compute the families of distance metrics (L_j) for a set of *n* criteria and *m* alternatives and with a parameter *p* to implicitly express the DM’s attitude to balance criteria (p = 1), to accept decreasing marginal utility (p > 1), or to search for absolutely dominant solution (p = ∞). Whichever parameter value is used, an alternative with minimum L_j–metric is considered as the best.

3. DATA ENVELOPMENT ANALYSIS

3.1. Theory

DEA is a productivity analysis model for measuring the relative efficiencies of a homogenous set of DMUs based on their multiple inputs and outputs. The efficiency score in the presence of multiple inputs and outputs is defined as:

$$\text{Efficiency} = \frac{\text{weighted sum of outputs}}{\text{weighted sum of inputs}} \tag{1}$$

Assuming that there are *n* DMUs, each with *m* inputs and *s* outputs, the relative efficiency score of a test DMU *p* is obtained by solving the following model, known as CCR, proposed by Charnes et al. [13].

$$\max \quad \frac{\sum_{k=1}^{s} u_k y_{kp}}{\sum_{j=1}^{m} v_j x_{jp}}$$

$$\text{s.t.} \quad \frac{\sum_{k=1}^{s} u_k y_{ki}}{\sum_{j=1}^{m} v_j x_{ji}} \le 1 \quad i=1,2,\ldots,n \quad ; \quad u_k, v_j \ge 0 \quad k=1,2,.,s \quad j=1,2,.,m \tag{2}$$

where, y_{ki} : amount of output *k* produced by DMU *i*, x_{ji} : amount of input *j* utilized by DMU *i*, u_k : weight given to output *k* and v_j: weight given to input *j*. The above fractional equation can be converted to a linear program problem as follows.

$$\max \sum_{k=1}^{s} u_k y_{kp}$$

$$\text{s.t.} \sum_{j=1}^{m} v_j x_{jp} = 1 \; ; \; \sum_{k=1}^{s} u_k y_{ki} - \sum_{j=1}^{m} v_j x_{ji} \le 0 \quad i=1,2,.,n \; ; \; u_k, v_j \ge 0 \quad k=1,2,.,s \quad j=1,2,.,m \tag{3}$$

Equation 3 is solved *n* times to identify the relative efficiency scores of all DMUs. Each DMU selects input and output weights that maximize its efficiency score thus an *efficient frontier* is constructed by the combination of efficient units. In general, a DMU is considered to be efficient if it possess a score of 1, and a score less than 1 implies that it is inefficient. The other basic DEA model that differs from CCR model by scale assumptions is the Banker Charnes Cooper (BCC) model. As shown in Figure 1, the envelopment surface can take the form of constant-return-to-scale (CRS) or variable-return-to-scale (VRS) as evaluated in the CCR model and the BCC model, respectively.

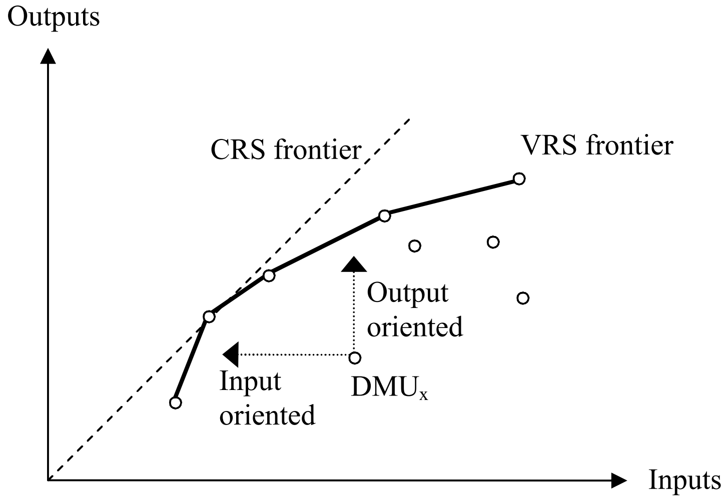

Figure 1. Envelopment surfaces and orientation

The models with CRS envelopment surface assume that an increase in inputs will result in a proportional increase in outputs (e.g. a doubling of all inputs will double output). However, it is rare for markets to function the production process with CRS surface. The DEA model for variable-returns-to-scale (VRS) was developed to cater for such non-proportionality [14], and reflects the fact that production process may exhibit increasing, constant and decreasing returns to scale. In other words, the VRS model allows an increase in input values to result in a non-proportional increase of output levels. The VRS frontier envelops the DMUs by connecting the outermost DMUs, including the one approached by the CRS surface. Moreover, in the BCC model, the efficiency scores of DMUs are bigger than or equal to scores of CCR. In addition to above classical DEA methods, Andersen and Petersen [15] developed a new procedure to build up the ranking ability of DEA which is a reduced version of CCR model. The resulting model being the reduced version of the CCR is entitled as RCCR or *superefficiency*. In this model, the test DMU *p* is removed from the constraint set thus the DMU can achieve an efficiency score of greater than 1, which provides a method for ranking efficient and inefficient units.

The DEA models have been developed to measure the efficiency in two different ways, namely input-oriented and output-oriented. The output-oriented model refers to the capacity of a DMU to achieve the maximum volume of production (output) with the available inputs, while the ability to maintain the same capacity of production using a minimum of inputs is known as the input-oriented model (Figure 1). Input-oriented efficiency scores range between 0 and 1 whereas output-oriented efficiency scores range from 1 to infinity. In both cases, 1 is the efficient score. Since we focus on sustainability of water resources, naturally to be consistent with research, an input-oriented model is constituted in this study.

3.2. Weighting and ranking in DEA

Two important subjects should be considered in the DEA models. First, all DEA models allow for unrestricted weight flexibility in determining the efficiency scores of DMUs. This allows units to achieve relatively high efficiencies by indulging inappropriate input and output weights. Weight restrictions allow for the integration of managerial preferences in terms of relative importance levels of various inputs and outputs. The use of assurance regions (AR) approach, described in detail by Thompson et al. [16], for weight restrictions is denoted as being more prevalent and reflecting marginal rates of substitution in the literature. The process of setting AR is to define upper and lower bounds for each input and output weight. The lower (α) and upper (β) bounds for each weight can be determined by decreasing and increasing the weight with a given percentage (e.g. 10%), respectively. The analysts can also determine the bounds with a series of questions to DMs as Wong and Beasley [17] mentioned: (a) "Do you think that the importance of input measure *i* in evaluating DMUs could be as low (as high) as z%?"; or (b) "Should, as a matter of policy, the importance of input measure *i* in evaluating DMUs be allowed to be as low (as high) as z%?". Once the upper and lower bounds of all inputs are determined, the AR constraints reflecting the DM preference range on input weights (Equation 4) can be added to the linear programming problem, thus the efficiency scores indicate more reliable and reasonable results.

$$v_i \geq \frac{\alpha_i}{\beta_j} v_j \ , \ v_i \leq \frac{\beta_i}{\alpha_j} v_j \qquad (4)$$

Second, the traditional DEA models do not allow for ranking DMUs, specifically the efficient ones. To address this issue, a number of techniques namely, cross-efficiency ranking method [18], super-efficiency ranking technique [15] and benchmarking ranking method [19] have been proposed for better discrimination among alternative scores.

4. APPLICATION

4.1. The alternatives and criteria

The data used in this study is provided from the research project report that suggests a suitable strategy for water pricing in Euro-Mediterranean agriculture by considering not only economic, but also technical, environmental and social aspects of water resources management in Greece [6]. The report provides useful methodologies that can be used as economic tools to allow the policy decision makers to evaluate the different alternative strategies in order to reorient the water management of the agricultural sector towards sustainability; constructs a MCDM set of water pricing policies, which can be adapted to every Mediterranean basin country, taking into account of course the specialties of each country and also proposes ways to control water demand in the agriculture.

A total of 36 alternatives obtained by the combination of four major factors are introduced as (i) various irrigation schemes (with 3 sub factors – surface, sprinkler, drip), (ii) price of water (with 3 sub factors – moderate, high, very high), (iii) crop distribution (with 2 sub factors – existing, less cotton more fruits/vegetables per acre), (iv) kind of fertilizers used (with 2 sub factors – chemical, green). For example, alternative 1 (A1) is obtained by the integration of surface irrigation scheme, moderate price of water, existing cropping pattern and the use of chemical fertilizers. Details on the acquisition of the data, the definitions of the criteria, the detailed explanation of alternative formulation and the evaluation process can be found in the project report.

In order to find the best possible strategies, 7 criteria are identified including 4 minimizing (initial cost often paid by the state (CR1), maintenance cost (CR2), irrigation water volume used (CR3), effect of pollution (CR4)) and 3 maximizing (profitability of crops (CR5), efficiency of water use (CR6), social impact including employment (CR7)). Although there are three groups of DMs who prioritize economic effects, environmental effects and social effects; the results of MCDM methods are given by the criteria weights of economy inclined DMs' weights that are represented by: initial cost, 0.10; maintenance cost, 0.10; water volume used, 0.10; effect of pollution, 0.06; profitability of crops, 0.30; social impact, 0.25; water use efficiency 0.09.

Three different MCDA techniques, namely, ELECTRE-3, ELECTRE-4 and CP have been applied for the selection of the most preferred alternatives. In two outranking techniques the preference thresholds are fixed as 0.5 to consider the subjectivity in the data. Distillation coefficients employed in ELECTRE-3 method are –0.15 and 0.3, and distillation coefficient employed in ELECTRE-4 is 0.1. On the other hand, the CP has been used for three levels of p ($p = 1,2,\infty$) reflecting the attitude of decision maker with respect to compensation between deviations.

In this study, the decision matrix of the relevant report which is used for DEA computations is given in Table 1. It should be noted that, different from the original, the data of the minimizing criteria are obtained by reversing the specified data to evaluate the inputs. The {I} and {O} signs are used for the DEA that indicate if the criterion is in respect to minimization (input) or to maximization (output).

4.2. Application of DEA

The CCR, BCC and RCCR models are applied to the same data with and without the additional weight restrictions. To incorporate these constraints, it is needed to determine upper and lower bounds for all criteria. Since the given criteria weights are single scalar values, it is assumed that the lower and upper dispersions are equal and defined the upper (β)/lower (α) bounds by increasing/decreasing by 10%. For example, the given criteria weight for the first minimizing criterion (initial cost) is 0.10. Ten percent of this value is 0.01, thus the lower and upper bounds of that criterion are calculated 0.09 and 0.11, respectively. Here, all the criteria are assumed to have the same percentage of dispersion on their bounds for a given level of dispersion, and if the (α) and (β) of the criteria are exactly determined by the DMs, these bounds can be used for the criteria ranges.

Table 1. The data used for DEA

Alternative	CR1 {I}	CR2 {I}	CR3 {I}	CR4 {I}	CR5 {O}	CR6 {O}	CR7 {O}
A1	0.556	0.500	0.625	0.714	2.800	1.800	2.800
A2	0.455	0.500	0.625	0.556	3.000	1.800	3.200
A3	0.500	0.556	0.714	0.714	2.600	1.600	3.000
A4	0.417	0.556	0.714	0.556	2.800	1.600	3.400
A5	0.556	0.500	0.625	0.714	2.600	1.800	2.200
A6	0.455	0.500	0.625	0.556	2.800	1.800	2.600
A7	0.500	0.556	0.714	0.714	2.400	1.600	2.400
A8	0.417	0.556	0.714	0.556	2.600	1.600	2.800
A9	0.556	0.625	0.556	0.714	2.400	2.000	2.000
A10	0.455	0.625	0.556	0.556	2.600	2.000	2.400
A11	0.500	0.714	0.625	0.714	2.200	1.800	2.200
A12	0.417	0.714	0.625	0.556	2.400	1.800	2.600
A13	0.714	0.500	0.556	0.625	3.000	2.000	2.600
A14	0.556	0.500	0.556	0.500	3.200	2.000	3.000
A15	0.625	0.556	0.625	0.625	2.800	1.800	2.800
A16	0.500	0.556	0.625	0.500	3.000	1.800	3.200
A17	0.714	0.500	0.556	0.625	2.800	2.000	2.000
A18	0.556	0.500	0.556	0.500	3.000	2.000	2.400
A19	0.625	0.556	0.625	0.625	2.600	1.800	2.200
A20	0.500	0.556	0.625	0.500	2.800	1.800	2.600
A21	0.714	0.625	0.500	0.625	2.600	2.200	1.800
A22	0.556	0.625	0.500	0.500	2.800	2.200	2.200
A23	0.625	0.714	0.556	0.625	2.400	2.000	2.000
A24	0.500	0.714	0.556	0.500	2.600	2.000	2.400
A25	0.714	0.455	0.500	0.556	3.200	2.200	2.600
A26	0.556	0.455	0.500	0.455	3.400	2.200	3.000
A27	0.625	0.500	0.556	0.556	3.000	2.000	2.800
A28	0.500	0.500	0.556	0.455	3.200	2.000	3.200
A29	0.714	0.455	0.500	0.556	3.000	2.200	2.000
A30	0.556	0.455	0.500	0.455	3.200	2.200	2.400
A31	0.625	0.500	0.556	0.556	2.800	2.000	2.200
A32	0.500	0.500	0.556	0.455	3.000	2.000	2.600
A33	0.714	0.556	0.455	0.556	2.800	2.400	1.800
A34	0.556	0.556	0.455	0.455	3.000	2.400	2.200
A35	0.625	0.625	0.500	0.556	2.600	2.200	2.000
A36	0.500	0.625	0.500	0.455	2.800	2.200	2.400

5. RESULTS

The efficiency scores of all DEA models applied are summarized in Table 2 where the highlighted numbers show the efficiency scores equal to or higher than 1. In the CCR, BCC and RCCR models, the results do not give distinguishing comments because 12 and 15 of the 36 alternatives have a score of 1 in CCR and BCC models, respectively. On the other hand, the RCCR efficiencies seem a little bit different. This confirms the expectations that CCR and BCC alone is not a good discriminator among alternatives, and the RCCR model is insufficient for a full ranking. However, incorporating weight restrictions can be concluded as a procedure not only to judge the decision makers preferences but also to improve the discrimination power of DEA. It is clearly seen that *alternative 26* is the only efficient DMU in all models.

Table 2. The efficiency scores determined

Alternatives	CCR	BCC	RCCR	CCR/w	BCC/w	RCCR/w
A1	0.8577	0.9394	0.8577	0.7453	0.8565	0.7453
A2	**1.0000**	**1.0000**	**1.0162**	0.9045	0.9466	0.9045
A3	0.8459	0.9052	0.8459	0.7117	0.8254	0.7117
A4	**1.0000**	**1.0000**	**1.1591**	0.8552	0.9024	0.8552
A5	0.7927	0.9394	0.7927	0.6509	0.8565	0.6509
A6	0.9740	**1.0000**	0.9740	0.7966	0.9466	0.7966
A7	0.7796	0.9052	0.7796	0.6176	0.8254	0.6176
A8	0.9601	**1.0000**	0.9601	0.7523	0.9024	0.7523
A9	0.8257	0.9154	0.8257	0.5987	0.8365	0.5987
A10	**1.0000**	**1.0000**	**1.0080**	0.7329	0.9212	0.7329
A11	0.8196	0.9009	0.8196	0.5628	0.8013	0.5628
A12	**1.0000**	**1.0000**	**1.0197**	0.6867	0.8737	0.6867
A13	0.8264	0.9091	0.8264	0.7378	0.8384	0.7378
A14	0.9226	0.9508	0.9226	0.9027	0.9369	0.9027
A15	0.7724	0.8472	0.7724	0.7152	0.8219	0.7152
A16	0.9444	0.9589	0.9444	0.8709	0.9114	0.8709
A17	0.8264	0.9091	0.8264	0.6542	0.8384	0.6542
A18	0.8915	0.9508	0.8915	0.8036	0.9369	0.8036
A19	0.7058	0.8472	0.7058	0.6246	0.8219	0.6246
A20	0.8867	0.9589	0.8867	0.7670	0.9114	0.7670
A21	0.8333	0.9091	0.8333	0.5986	0.8145	0.5986
A22	0.9130	0.9524	0.9130	0.7399	0.9107	0.7399
A23	0.7384	0.8521	0.7384	0.5702	0.7967	0.5702
A24	0.9192	0.9589	0.9192	0.6973	0.8764	0.6973
A25	**1.0000**	**1.0000**	**1.0000**	0.8312	0.9009	0.8312
A26	**1.0000**	**1.0000**	**1.1178**	**1.0000**	**1.0000**	**1.0554**
A27	0.8485	0.9091	0.8485	0.8046	0.8873	0.8046
A28	**1.0000**	**1.0000**	**1.0847**	0.9757	0.9834	0.9757
A29	**1.0000**	**1.0000**	**1.0000**	0.7413	0.9009	0.7413
A30	**1.0000**	**1.0000**	**1.0000**	0.9002	**1.0000**	0.9002
A31	0.8264	0.9091	0.8264	0.7122	0.8873	0.7122
A32	0.9788	**1.0000**	0.9788	0.8654	0.9834	0.8654
A33	**1.0000**	**1.0000**	**1.0000**	0.6822	0.8773	0.6822
A34	**1.0000**	**1.0000**	**1.1341**	0.8367	0.9786	0.8367
A35	0.8333	0.9091	0.8333	0.6548	0.8646	0.6548
A36	**1.0000**	**1.0000**	**1.0295**	0.7967	0.9530	0.7967

The results of MCDM techniques and weighted DEA models are given in Table 3, which represents the ranking pattern of alternatives. The rank orders are not exactly the same for each technique. It can be seen that *alternative 26* is best followed by *alternative 28* in the MCDM and in the DEA models. In ELECTRE-4 method, *alternatives 26, 28* are tied at rank 1, and *alternatives 2, 30, 32* occupy second position in the report however they are ranked in order in Table 3. It can be seen that first three ranking are same in ELECTRE-3, ELECTRE-4, CCR/w and RCCR/w, while CCR/w and RCCR/w rankings are exactly same. It is also observed that bottom rankings are in unison with MCDM and DEA model so *alternative 23* and *alternative 11* are the least preferred alternatives. The main finding from the analyses can be summarized as the MCDM approaches and weighted DEA models satisfy the DM(s) to determine the *best* and *worst* choice.

Table 3. Increasing rank order of alternatives

Rank	MCDM techniques					DEA models		
	EL.-3	EL.-4	CP (p=1)	CP (p=2)	CP (p=∞)	CCR/w	BCC/w	RCCR/w
1	26	26	26	26	28	26	26	26
2	28	28	28	28	26	28	30	28
3	2	2	14	14	14	2	28	2
4	4	30	30	2	2	14	32	14
5	14	32	2	16	16	30	34	30
6	16	14	25	25	27	16	36	16
7	25	34	16	27	25	32	2	32
8	30	4	32	30	32	4	6	4
9	32	36	34	32	13	34	14	34
10	27	10	4	13	1	25	18	25
11	34	16	27	18	15	27	10	27
12	36	18	18	4	4	18	16	18
13	3	12	36	1	30	36	20	36
14	8	25	13	6	18	6	22	6
15	18	27	6	34	6	20	8	20
16	33	6	29	15	20	8	4	8
17	1	8	20	20	36	1	29	1
18	13	20	1	36	34	29	25	29
19	6	22	22	22	22	22	31	22
20	29	29	15	3	31	13	27	13
21	15	24	8	29	3	10	33	10
22	20	31	31	31	8	15	24	15
23	22	33	10	8	10	31	12	31
24	10	1	33	10	24	3	35	3
25	24	35	3	24	29	24	5	24
26	31	3	24	17	5	12	1	12
27	12	13	17	5	19	33	17	33
28	35	15	12	19	17	35	13	35
29	17	5	35	33	35	17	9	17
30	5	17	5	12	12	5	7	5
31	7	19	19	35	33	19	3	19
32	21	21	21	7	7	7	15	7
33	19	7	7	21	21	9	19	9
34	9	9	9	9	9	21	21	21
35	11	11	23	23	23	23	11	23
36	23	23	11	11	11	11	23	11

The Spearman rank correlation coefficient (r), which is useful to determine the measure of association between ranks are used to understand how well the ranks of each of techniques correlated with each other. Spearman r values of 1, 0 and -1 represent perfect association, no association and perfect disagreement between the methods, respectively. The correlation results of the DEA models and the MCDM techniques are given in Table 4. Significant correlations exist among each of the MCDM techniques when compared to the various weighted DEA models. Thus, incorporating value judgments into DEA through the use of additional constraints seems to provide results that are correlated to some of the MCDM approaches. Results indicate that DEA models, especially RCCR model applied with weight restrictions obtained by reasonable lower and upper bounds, are suitable for the present irrigation policy making problem.

Table 4. Spearman r values for weighted DEA and MCDM techniques

	EL.-3	EL.-4	CP (p=1)	CP (p=2)	CP (p=∞)	CCR/w	BCC/w	RCCR/w
EL-3	1.000	0.862**	0.941**	0.910**	0.875**	0.945**	0.760**	0.945**
EL-4		1.000	0.885**	0.793**	0.750**	0.925**	0.934**	0.925**
CP (p=1)			1.000	0.965	0.925**	0.983**	0.834**	0.983**
CP (p=2)				1.000	0.984**	0.945**	0.719**	0.945**
CP (p=∞)					1.000	0.911**	0.661**	0.911**
CCR/w						1.000	0.873**	1.000
BCC/w							1.000	0.873**
RCCR/w								1.000

** Correlation is significant at the 0.01 level (2-tailed)

Considering all the scenarios along with some MCDM techniques and DEA models, it is concluded that *alternative 26* (combination of drip irrigation system with moderate change in the existing water pricing with existing cropping pattern and growing crop with green fertilizers) is selected as the best while *alternative 28* is given second position differentiated in the cropping pattern with less cotton and more fruits.

It is also shown that incorporating DM value judgments with tight bounds on DEA based techniques can provide a better comparison to discrete alternative MCDM approaches. The ranking pattern obtained by RCCR/w (10%) is correlated with EL-3, EL-4, CP (p=1), CP (p=2) and CP (p=∞) with an r value of 0.945, 0.925, 0.983, 0.945 and 0.911, respectively. Data Envelopment Analysis thus seems to perform well as an alternative or additive tool to MCDM.

6. CONCLUSION

The present study demonstrates the use of DEA as a tool for MCDM for ranking different policies to regulate water consumption for irrigation practices. With this aim, the results of the project report that use MCDM methods, ELECTRE-3, ELECTRE-4 and CP, are compared with the DEA models, CCR, BCC and RCCR. Since the traditional DEA models do not satisfy the DMs requirements with respect to ranking DMUs and incorporating their preference judgments to analysis, the DEA models are applied with additional weight constraints, and well correlated results with some MCDM methods are obtained. Although there is no generally accepted approach for making a comparison of DEA or any other MCDM tools among themselves, incorporating DM preferences does greatly enhance the correlation between the DEA and the outranking/distance-based approaches, so using both the methods together will increase the credibility of the decisions. Here, the conclusion base on the results obtained by DEA models with reasonable tight bounds of criteria weights (10%). Future studies can be driven by the use of tighter or looser bounds in DEA, or subject to the application of other types of MCDM methods.

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