

# A multi-objective optimisation approach to water management

E. Xevi \*, S. Khan

*CSIRO Land and Water Griffith PMB 3 Griffith, NSW, Australia*

Received 6 May 2004; revised 25 May 2005; accepted 9 June 2005

---

## Abstract:

The management of river basins is complex especially when decisions about environmental flows are considered in addition to those concerning urban and agricultural water demand. The solution to these complex decision problems requires the use of mathematical techniques that are formulated to take into account conflicting objectives. Many optimization models exist for water management systems but there is a knowledge gap in linking bio-economic objectives with the optimum use of all water resources under conflicting demands. The efficient operation and management of a network of nodes comprising storages, canals, river reaches and irrigation districts under environmental flow constraints is challenging. Minimization of risks associated with agricultural production requires accounting for uncertainty involved with climate, environmental policy and markets. Markets and economic criteria determine what crops farmers would like to grow with subsequent effect on water resources and the environment. Due to conflicts between multiple goal requirements and the competing water demands of different sectors, a multi-criteria decision-making (MCDM) framework was developed to analyze production targets under physical, biological, economic and environmental constraints. This approach is described by analyzing the conflicts that may arise between profitability, variable costs of production and pumping of groundwater for a hypothetical irrigation area.

© 2005 Elsevier Ltd. All rights reserved.

**Keywords:** Optimization; Minimization; Multi-criteria decision-making; Water resource management

---

## 1. Introduction

Water is required for different purposes and users demand water for diverse needs and compete in terms of quantity, quality and timing. Uncertainty in water allocations, environmental flow requirements and intensive cropping systems requires a better seasonal distribution of water to satisfy consumptive and in-stream environmental demands. Water demand management that considers system constraints on water conveyance and losses in addition to environment requirements will result in optimum productivity of irrigation areas and better management of river flows. Many decision support systems in agricultural enterprises use a conventional linear programming approach to optimize a single objective function such as total gross margin. However, as agricultural systems become more complex, multiple objectives that are in conflict with each other need to be addressed. Competition for scarce resources by different enterprises is a major concern in many agricultural production systems. Competition occurs at

farm level e.g. between different crops as well as regional level, where utilization of scarce water resources for agricultural purposes often comes into conflict with the requirement for in stream ecosystem services. For example, in bio-economic systems conflict may arise from maximizing economic returns (i.e. net revenue) as opposed to minimizing the use of resources such as water, fertilizer applications. On the other hand, minimizing costs rather than maximizing net revenue may also be important in some water management systems. Under these conditions, multiple criteria decision-making techniques (MCDM) are useful tools to explore different management options. These techniques are used widely to solve multi-objective and multi-resource decision making problems where conflicts exist among different objectives (Teclé et al., 1998). MCDM techniques permit optimization of several objectives in many different logical formulations (Piech and Reyman, 1993). A multi-criteria approach has been used extensively to solve diverse decision problems including risk assessment in agricultural systems (Berbel, 1993).

Mendoza et al. (1993) used Fuzzy Multiple Objective Linear Programming techniques in forest planning where imprecise objective function coefficients are involved. Furthermore, Teclé et al. (1998) used Compromise Programming (CP) to develop a multi-objective decision support system for analyzing a multi-resource forest management problem. The use of these

---

\* Corresponding author. Tel.: +66 2 69601581; fax: +66 2 69601600.

E-mail address: [emmanuel.xevi@csiro.au](mailto:emmanuel.xevi@csiro.au) (E. Xevi).

Table 1  
Rainfall (ML/Ha or  $\times 100$  mm) for dry, average and wet seasons

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Dry	0.15	0.03	0.14	0.11	0.3	0.21	0.14	0.39	0.17	0.26	0.11	0.13
Average	0.22	0.12	0.28	0.27	0.27	0.29	0.4	0.3	0.35	0.37	0.26	0.28
Wet	0.49	0.18	0.33	0.32	0.73	0.49	0.42	0.42	0.45	0.48	0.32	0.36

Table 2  
Reference evapo-transpiration (ET, ML/Ha) for dry, average and wet seasons

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Dry	2.92	2.41	1.94	1.22	0.69	0.47	0.54	0.83	1.27	1.91	2.49	2.94
Average	2.72	2.24	1.87	1.12	0.67	0.46	0.52	0.74	1.11	1.72	2.24	2.63
Wet	2.65	2.16	1.84	1.08	0.59	0.41	0.43	0.7	1.02	1.67	2.16	2.58

techniques enables the decision maker (Irrigation Companies, River catchment's management authorities etc) to study the trade-offs and conflicts between, for example, profitability (measured by economic returns) and risk (measured by Partial Absolute Deviation (PAD)). Romero et al. (1987) applied CP techniques in agricultural planning and concluded that the method provides useful information about efficient sets and trade-offs among objectives without introducing more computational difficulties. Some basic concepts of MCMD can be found in Rehman et al. (1993). This paper demonstrates the application of a MCDM technique called Goal Programming (GP) to water resource allocation problems with conflicts between irrigation water demand and in stream environmental flow requirements. First, a solution is sought for the single objective function formulation and compared to a solution of three objective functions (Net Revenue (NR), Variable Costs (VC) and Total Groundwater Pumping from the irrigation areas (TP)) using Goal Programming. This approach has been applied to the hypothetical Irrigation Area using real data at Berembled weir on the Murrumbidgee River (Australia).

## 2. Methods

### 2.1. The irrigation area

For the purpose of this paper, the irrigated area is divided into eight regions with a total irrigable land of 121,808 ha and a potential for growing 14 crops (rice, wheat, oats, barley, maize,

canola, soybean, winter pasture, summer pasture, lucerne, vines, summer vegetables, winter vegetables, citrus and stone fruit). In the current analysis, groundwater pumping from the irrigable area is permitted to satisfy crop water demand if surface water supplies are not sufficient. Licensed bores are located within the sub-catchment that use water for stock, domestic use and irrigation. The evaporative water use of each of these crops is characterized by reference evapo-transpiration, crop coefficients and growing period within the year. Reference evapo-transpiration (ET) and rainfall data used in the analysis are shown in Tables 1 and 2.

The growing period for each crop is illustrated in Fig. 1.

Dry, medium and wet monthly inflows and outflows into the irrigation were obtained by taking the 10, 50 and 90 percentiles of ten years of historical flow measurements in the HYDSYS database (Pinnena version 7, Department of Land and Water Conservation, 1995) at Berembled Weir (on Murrumbidgee River, Australia). Environmental requirements are more difficult to determine due to the many complex issues involved and in this case was assumed simply as the measured flow downstream of Berembled weir. Irrigation water supply, demand and environmental requirement used in the analysis are shown in Figs. 2–4.

### 2.2. Schematic of irrigation area

The irrigation area is modeled using a schematic representation shown in Fig. 5. The network consists of a supply node,

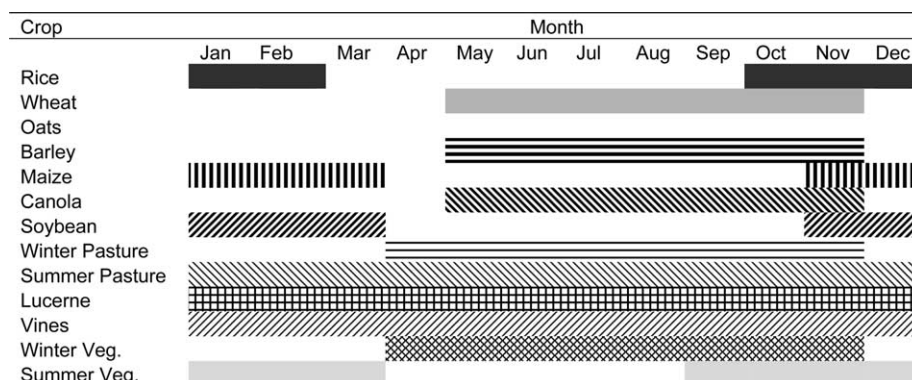


Fig. 1. Crop growing periods.

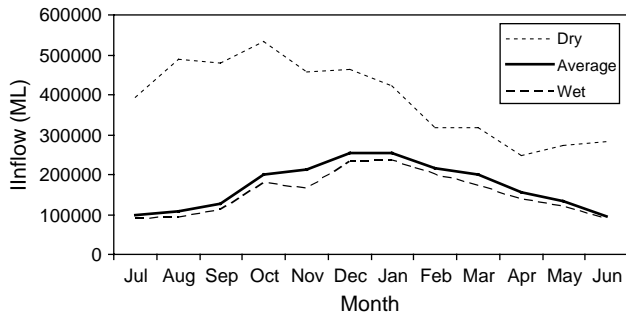


Fig. 2. Monthly inflow hydrograph at weir for dry, average and wet seasons.

demand nodes (irrigation areas), distribution nodes and an environmental flow link. The supply schedule and environmental flow targets are usually stipulated by water sharing plans and flow rules of a river system. These flows may be dependent on climate, aesthetics, social, economic and environmental factors. For the purposes of this study it is assumed that all the inflows into the network are used at demand nodes for irrigation (Table 3).

### 3. Model formulation

#### 3.1. Objective functions, decision variables and constraints

The multi-objective problem described in this paper consists of three objective functions: maximizing net returns (NR), minimizing variable cost (VC) and minimizing total supplementary groundwater pumping requirements (TP) to meet crop demand from the irrigated areas. Conceptually, NR and VC may represent the view of the agriculturalist while minimizing total pumping may be the desired goal to avoid groundwater mining and pollution of aquifers in situations where vertical segregation of aquifer salinity occurs. The management options to achieve the above objectives consist of selection of an appropriate mix of crops, optimum level of groundwater pumping and appropriate allocation of water for irrigation and environment. Constraints imposed on the system include seasonal environmental flows targets. In addition, water allocation rules and pumping targets for each month are constraints imposed on the system.

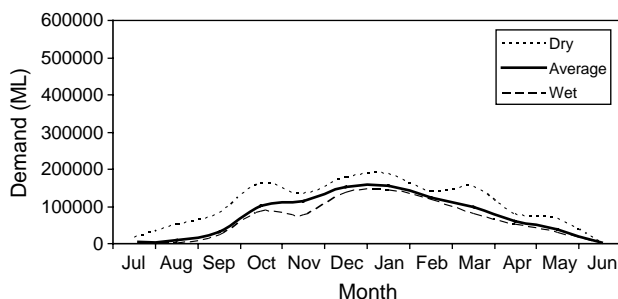


Fig. 3. Monthly demand curves in irrigation areas.

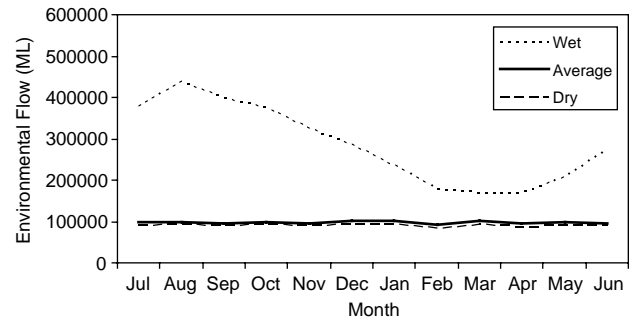


Fig. 4. Monthly environmental flow curves.

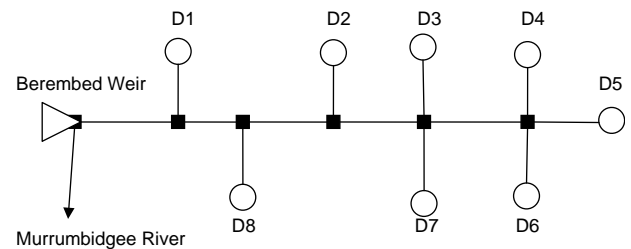


Fig. 5. Schematic of nodal network (D1–D8 are irrigation demand nodes).

The three objective functions were formulated as follows:

$$\text{Max NR} = \sum_c \text{CGM}(c)X(c) - \sum_c \sum_m \{ \text{WREQ}(c,m)X(c) \times C_w \} - C_p \sum_c \sum_m P(c,m) \quad (1)$$

$$\text{Min VC} = \sum_c \sum_m (X(c)\text{WREQ}(c,m)C_w) + \sum_c X(c)V \text{ cost}(c) \quad (2)$$

$$\text{Min TP} = \sum_c \sum_m P(c,m) \quad (3)$$

where  $X(c)$  = area of crop  $c$  (Ha),  $\text{CGM}(c)$  = gross margin for crop  $c$  (\$),  $\text{WREQ}(c,m)$  = water requirement for crop  $c$  in

Table 3

Economic data for crops (NSW DPI Farm Budget Report (2003/04))

	Yield (T/Ha)	Price (\$AUS)	Variable cost (\$AUS)
Rice	10	251	665
Wheat	5	237	363
Oats	3.5	276	277
Barley	4	206	339
Maize	10	221	860
Canola	2.7	537	487
Soybean	3	391	803
Winter pasture	12	35	167
Summer pasture	30	35	436
Lucerne	26	35	385
Vines <sup>a</sup>	12	100	700
Summer vegetables <sup>b</sup>	85	100	4485
Winter vegetables	85	220	4485
Citrus	35	220	3750
Stone fruit <sup>a</sup>	20	120	600

<sup>a</sup> Conservative estimates.

<sup>b</sup> Refers to tomatoes.

month  $m$  (ML),  $C_w$ =total cost of water per unit volume (\$/ML),  $C_p$ =cost of groundwater pumping and delivery (\$/ML),  $V_{cost}$ =variable cost (such as fertilizer and pesticides applications) per hectare other than water cost for crop  $c$  and  $P(c,m)$ =volume of ground water pumped from irrigation areas for crop  $c$  in month  $m$  (ML).

The model consists of a network of nodes that connect supply nodes to irrigation or urban areas (demand nodes). The links connecting the nodes include river reaches that may carry environmental flows as well as irrigation canals.

**Continuity equation.** For each node ( $i$ ), assuming no storage at the node, the continuity equation is given by the following:

$$\sum_j Q(i,j) = \sum_k Q(k,i) \quad (4)$$

where  $Q(i,j)$ =flow of water from node  $i$  to node  $j$ ,  $Q(k,i)$ =flow of water from node  $k$  to node  $i$ . The physical and environmental constraints imposed on the model are given by the following:

**Total water use.** Crop water use in the irrigation areas should not exceed total allocation in a given month:

$$\sum_c (X(c)WREQ(c,m)) \leq \text{Allocation}(m) \quad m = 1, \dots, 12 \quad (5)$$

Crop water requirements per month  $WREQ(c,m)$  may be estimated as a function of crop coefficient, crop growth duration, evapo-transpiration and rainfall using climatic data or based on water balance techniques. The water requirements in this paper are assumed to be the excess of evapo-transpiration over rainfall. Requirements for leaching of salts or pre-irrigation are not considered. The fraction of growth period in a given month for a given crop ( $d\_ratio(c,m)$ ) is given by:

$$d\_ratio(c,m) = G\_duration(c,m)/days(m) \quad (6)$$

where  $G\_duration(c,m)$  is the growth duration of a crop  $c$  in month  $m$  as depicted in Fig. 2, and  $days(m)$  is the number of days in month  $m$ . The crop water requirements are evaluated as follows:

$$WREQ(c,m) = k_a(c,m)d\_ratio \times ET(m) - d\_ratio(c,m)Rain(m) \quad (7)$$

where  $k_a(c,m)$  is the crop coefficient of crop  $c$  in month  $m$  and  $ET(m)$  and  $Rain(m)$  are evapo-transpiration and rainfall in month  $m$  as shown in Tables 1 and 2. where  $\text{Allocation}(m)$ =monthly water allocation for irrigation areas (ML).

**Total crop area.** The sum of all crop areas is equal to the total node area:

$$\sum_c X(c) = T \quad (8)$$

where  $T_{Area}$ =total irrigable farm area (Ha).

**Environmental requirements.** Environmental flows in each month should equal or exceed target flows:

$$Env\_f(m) \geq \text{Environmental flow}(m) \quad m = 1, \dots, 12 \quad (9)$$

where  $Env\_f(m)$ =environmental flow (ML) in month  $m$ ,  $\text{Environmental flow}(m)$ =target environmental flow in month  $m$ .

**Pumping requirements.** Total pumping (TP) from the irrigation area in any month should be less than or equal to allowable pumping.

$$\sum_c P(c,m) \leq \text{Pump}(m) \quad m = 1, \dots, 12 \quad (10)$$

where  $\text{Pump}(m)$ =allowable pumping in the irrigated areas for month  $m$ .

Two auxiliary equations were used to restrict the minimum cropped area to a given value when the crop area becomes a basic variable in the solution vector:

$$-X(c) + m_{Area} \leq T_{Area}Y(c), \quad X(c) \leq T_{Area}(1 - Y(c)) \quad (11)$$

where  $m_{Area}$ =minimum crop area (Ha) and  $Y(c)$ =binary variable for crop  $c$ . For the illustration problem given in the next section the minimum crop area was assigned a value of 1000 Ha for all calculations.

### 3.2. The goal programming model (GP)

GP solves the multiple objective problem by introducing the objectives into the problem as constraints and setting targets to be achieved. The objectives are included in the problem by adding positive ( $p_i$ ) and negative ( $n_i$ ) deviation variables that describe over-achievement and under-achievement of each goal.

The weighted version of goal programming model (WGP) was used in this example. The model is defined to minimize only the undesirable deviations from defined targets. The deviations were normalized by corresponding target values to account for differences in units:

$$\text{Min } Z = \beta_1 \frac{n_1}{T\_rev} + \beta_2 \frac{p_2}{T\_cost} + \beta_3 \frac{p_3}{T\_pump} \quad (12)$$

subject to:

$$\sum_c X(c)CGM(c) - \sum_c \sum_m WREQ(c,m)X(c)C_w - C_p \sum_c \sum_m P(c,m) + n_1 - p_1 = T\_rev \quad (13)$$

$$\sum_c \sum_m WREQ(c,m)X(c)C_w + \sum_c (V\_cost(c)X(c)) + n_2 - p_2 = T\_cost \quad (14)$$

$$\sum_c \sum_m P(c,m) + n_3 - p_3 = T\_pump \quad (15)$$

and constraints (5)–(12). The weights  $\beta_i$  are defined as:

$$\beta_i = \frac{\alpha_i}{\sum_{i=1}^3 \alpha_i} \quad i = 1, \dots, 3 \quad (16)$$

where  $T\_rev$ =target revenue,  $T\_cost$ =target cost,  $T\_pump$ =target pumping and  $\alpha_i$ =relative weights assigned to individual goals by the decision maker.

Table 4  
Pay-off matrix and crop mix for dry season

Pay-off matrix				Crop-mix (Ha)														
Optimiz- ation goal	Net rev- enue (\$)	Total cost (\$)	Total pumping (Ml)	Rice	Wheat	Canola	Vines	Citrus	Stone fruit	Summer veg	Winter veg	Oats	Barley	Maize	Soybean	Summer pasture	Winter pasture	Lucerne
Net rev- enue	152.3	100.5	482,605	48,819	22,382	13,594	5012	16,000	8000	8000								
Total cost	98.5	67.04	279,169	30,936	22,382		6000					52,090					10,400	
Total pumping	122.5	137.3	124,372	30,936	22,382		6000			46,530				15,959				

#### 4. Results

The multiple decision problems were solved using the General Algebraic Modeling System (GAMS) framework (Brooke et al., 1998). The pay-off matrix and the corresponding crop mix was determined using the three objective functions given by (1)–(3) and constraint equations (5)–(12) for the dry, average and wet seasons and shown in Tables 4–6.

The elements of the pay-off matrix were obtained by optimizing each of the objectives in equations (1)–(3) individually and then calculating the values of the remaining objectives using the solution vector of the decision variables. For example, the first row of Table 4 shows results from maximizing NR. When net revenue is maximized, its maximum value is \$152.28 million and the cost associated with it is \$100.5 million and total groundwater pumping from the irrigated area was 482,605 ML. The crop mix obtained by maximizing net revenue is Rice (48,819 Ha), Wheat (22,382), Canola (13,594 Ha), Vines (5012 Ha), Citrus (16,000 Ha), Stone fruit (8000) and Summer Vegetables (8000). This matrix contains valuable information pertaining to the existence or otherwise of conflicts between the objectives. The existence of conflicts enables us to use multiple decision criteria methods that combine all the objectives into a compromised model. The diagonal elements of the pay-off matrix in Table 4, 5 and 6 are the optimum values for each individual goal and the corresponding off-diagonal elements are the values of the other objectives evaluated using the basic elements of the optimized solution vector. The results clearly indicate the degree of conflict between the three objectives. There are some marked differences between the net revenue, cost and pumping as differentiated by the different objectives for all the seasons. However, the pay-off matrix in Table 6 indicates that for the wet season there is not much difference between minimizing total cost and minimizing total pumping in relation to pumping. Both objectives return the value for pumping as zero. Table 6 shows that minimization of total pumping under wet season results in many crops entering the solution vector than when net revenues were maximized. Nevertheless, the net revenue that was obtained under minimization of pumping was less than that obtained by maximizing net revenue. Using results from the maximization of net revenues, the total amount of water allocated to all irrigation areas together with supplementary pumping is shown in Fig. 6.

Supplementary water pumping was necessary to fulfill crop water requirements in the dry season in contrast with no pumping in the wet season. The actual and targeted environmental flow for the net revenue maximization case is shown Fig. 7 for dry, average and wet seasons.

The actual environmental flow exceeded their targets from the beginning of March to end of June and equaled the target in the summer months when irrigation water demand was high. However, in the wet season, the actual flow also exceeded the target in the months of July to November. Obviously, a decision maker is likely to be interested in an optimum combination of maximum NR, minimum cost and minimum total pumping that best reflects their priorities. However,

Table 5  
Pay-off matrix and crop mix for average season

Pay-off matrix				Crop-mix (Ha)														
Optimization goal	Net revenue (\$)	Total cost (\$)	Total pumping (MI)	Rice	Wheat	Canola	Vines	Citrus	Stone fruit	Summer veg	Winter veg	Oats	Barley	Maize	Soybean	Summer pasture	Winter pasture	Lucerne
Net revenue	168.1	98.0	308,955	61,426	22,382		6000	16,000	8000	8000								
Total cost	105.3	62.2	90,272	30,936	22,382		6000					52,090					10,400	
Total pumping	128.4	119.1	3593	30,936	22,382		17,981			1000	29,751			19,757				

Table 6  
Pay-off matrix and crop mix for wet season

Pay-off matrix				Crop-mix (Ha)														
Optimization goal	Net revenue (\$)	Total cost (\$)	Total pumping (MI)	Rice	Wheat	Canola	Vines	Citrus	Stone fruit	Summer veg	Winter veg	Oats	Barley	Maize	Soybean	Summer pasture	Winter pasture	Lucerne
Net revenue	174.3	91.8	112,573	61,426	22,382		6000	16,000	8000	8000								
Total cost	109.1	59.3	0	30,936	22,382		5012				1000	52,078					10,400	
Total pumping	119.3	78.3	0	31,658	22,382	7000	5715	6000	4000	1000	2000	6000	7000	4000	5000	7000	7000	6053



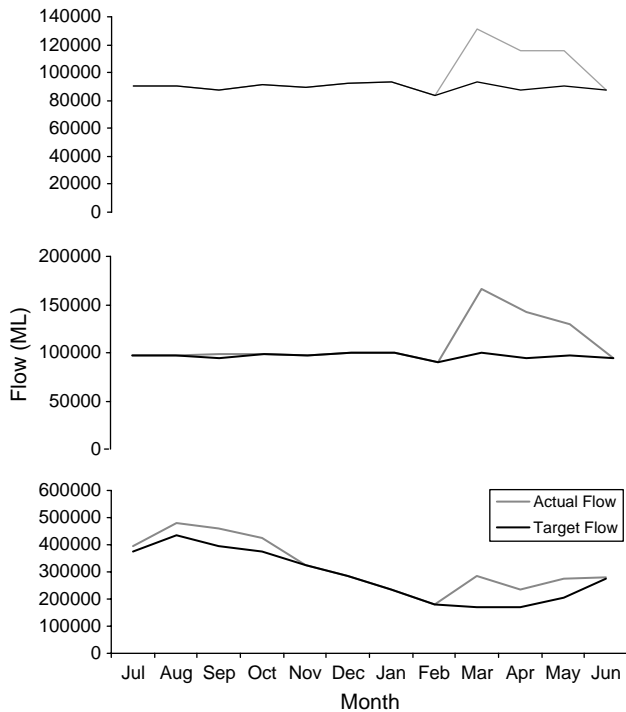


Fig. 6. Water allocations to irrigated areas for dry, average and wet seasons.

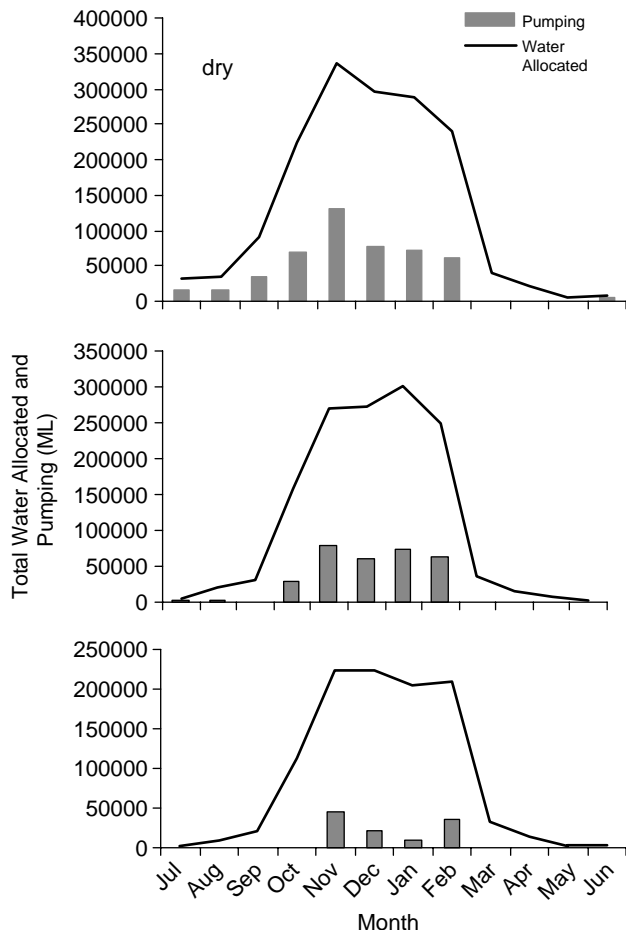


Fig. 7. Actual and targeted environmental flows for dry, average and wet seasons.

Table 7

Crop areas (Ha) for dry, average and wet seasons

Crop	Dry	Average	Wet
Rice	30,936	30,936	30,936
Wheat	22,382	22,382	22,382
Maize	15,959	19,758	
Vines	6000	17,981	5012
Winter veg.	46,530	29,751	
Summer veg.		1000	1000
Oats			62,478

because the objectives are in conflict, some sort of compromise solution must be found. Several MCDM methods are used to obtain solutions including Multi-Objective Programming (MOP), Compromise Programming (CP) and Goal Programming (GP). MOP methods generate a set of efficient solutions sometimes called Pareto optimal solutions and can be very difficult to implement when the number of objectives is large. On the other hand, CP looks for a solution as close as possible to the 'Ideal Point'. This point is normally taken as the individual optimal solutions.

Assuming that all goals are of equal importance i.e.  $\alpha_1 = \alpha_2 = \alpha_3$ , and setting the target values of the goals to values on the diagonal of the pay-off matrix of Table 6 for the wet season (i.e. net revenue = \$174.27 million, total cost = \$59.34 million and total pumping = 0), the following solution was obtained: crop areas for the three different seasons are shown in Table 7 and the corresponding deviational variables are shown in Table 8. The indices (1, 2 and 3) indicate the target net revenue, target total cost, and target pumping objectives respectively. The  $n$  and  $p$  variables refer to under- and over-achieved values of the targeted objectives. From Table 8, the revenue target in the dry season was under-achieved by \$51.79 million while the cost and pumping targets were over-achieved by \$77.95 million and 124,371 ML respectively. In the wet season the under-achievement of revenues increased while the cost target was over-achieved by only \$0.34 million and the pumping target was matched. The increased under-achievement of net revenue can be explained in part by the predominance of low value crop such as oats compared to maize and winter vegetables. Fig. 8 shows the actual and targeted environmental flow for dry, average and wet seasons. The actual flow equaled or exceeded the target flow for most of the months during the average and wet seasons and in the months of February to June during the dry season. Fig. 9 shows the actual water allocated to the irrigation areas for dry average and wet seasons as computed by the model.

Table 8

Positive ( $p$ ) and negative ( $n$ ) deviational variables for dry, average

Index	Dry		Average		Wet	
	$n$	$p$	$n$	$p$	$n$	$P$
1	51.79	0	45.83	0	59.8	0
2	0	77.94	0	59.76	0	0.34
3	0	124,371	0	3592	0	0

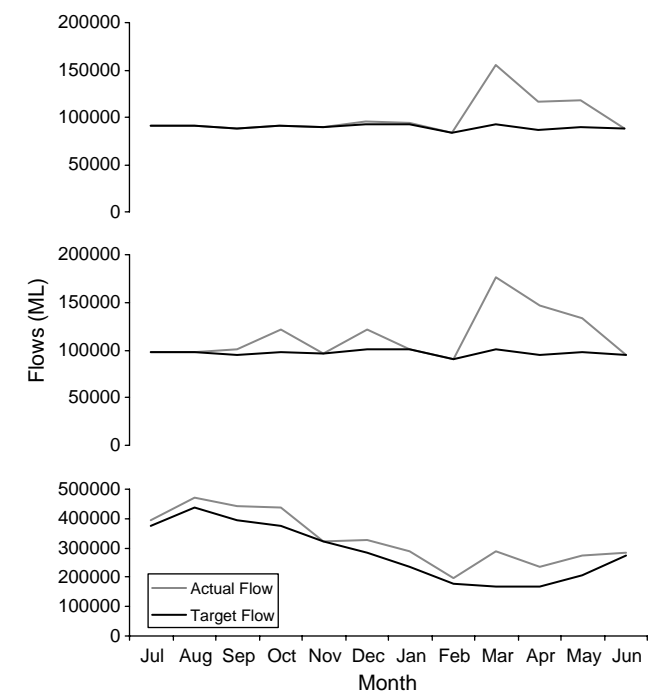


Fig. 8. Water allocations to irrigated areas for dry, average and wet seasons.

Decision makers often apply priorities to objectives when they are faced with multiple alternatives. The effect of this ranking behavior is incorporated in MCDM analysis by applying weights to each objective. The sensitivity analysis

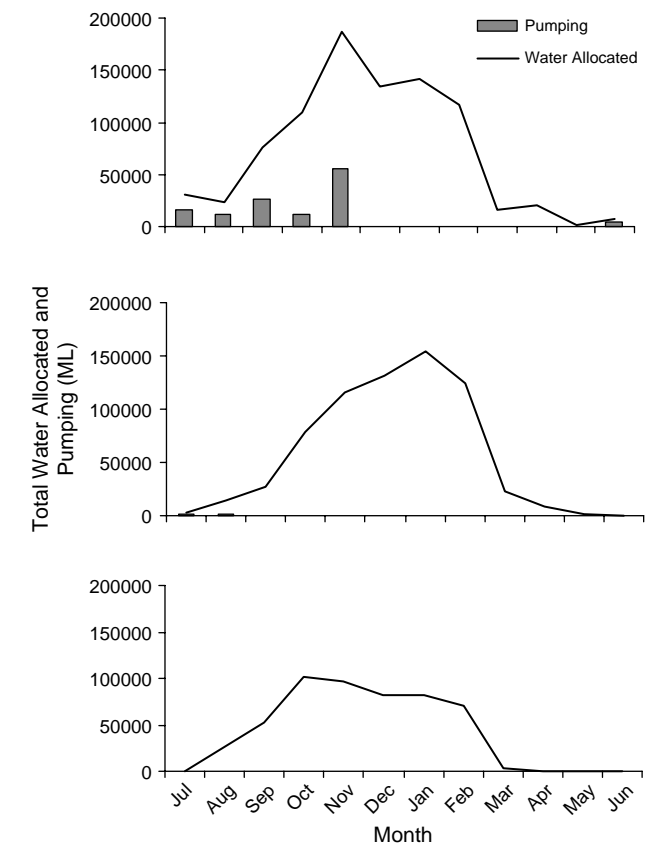


Fig. 9. Actual and targeted environmental flows for dry, average and wet seasons.

Table 9  
Crop areas (Ha) for dry, average and wet seasons

Crop	Dry	Average	Wet
Rice	30,936	30,936	36,382
Wheat	22,382	22,382	22,382
Maize	15,959	19,541	
Vines	6000	19,592	6000
Winter veg.	46,531	29,357	
Summer veg.			8000
Oats			25,044
Citrus			16,000
Stone fruit			8000

Table 10  
Positive (*p*) and negative (*n*) deviational variables for dry, average and wet seasons (\$ for indices 1 and 2 and ML for index 3)

Index	Dry		Average		Wet	
	<i>n</i>	<i>p</i>	<i>n</i>	<i>p</i>	<i>N</i>	<i>p</i>
1	51.79	0	47.07	0	22.8	0
2	0	77.94	0	59.48	0	16.67
3	0	124,371	0	3565	0	0

of applying different weights is demonstrated below. If we apply twice as much weight to the NR goal (i.e.  $\alpha_1=2$ ,  $\alpha_2=\alpha_3=1$ ) and the target values of the objectives are again set to values on the diagonal of the pay-off matrix of Table 6 for the wet season (i.e. net revenue=\$174.27 million, total cost=\$59.34 million and total pumping=0), the following results were obtained: crop areas for the three different seasons are shown in Table 9 and the corresponding deviational variables are shown in Table 10. The indices (1, 2 and 3) indicate the target net revenue, target total cost, and target pumping objectives respectively. The *n* and *p* variables refer to

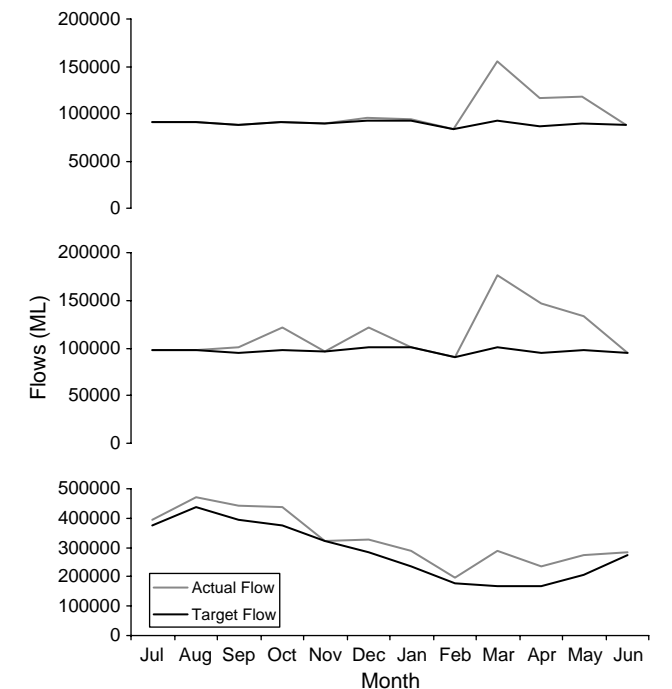


Fig. 10. Water allocations to irrigated areas for dry, average and wet seasons.



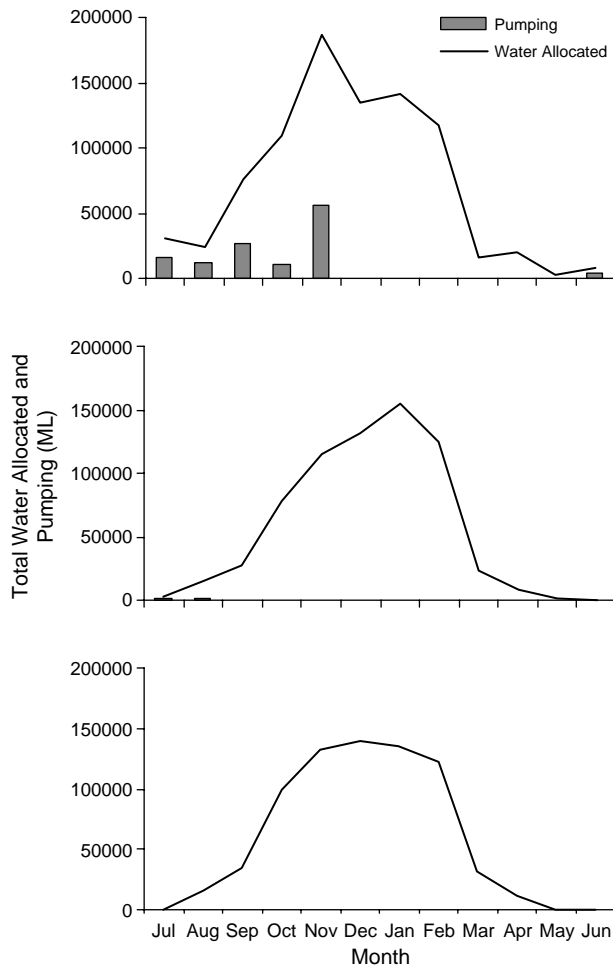


Fig. 11. Actual and targeted environmental flows for dry, average and wet seasons.

under- and over-achieved values of the targeted objectives. From Table 9, the under-achieved revenue target decreased from \$51.79 million in the dry season to \$22.8 million in the wet season, while the over-achieved cost and pumping targets decreased from \$77.94 million to \$16.67 million and from 124,371 to 0 ML respectively. Fig. 10 shows the actual and targeted environmental flow for dry, average and wet seasons. The actual flow equaled or exceeded the target flow for most of the months during the average and wet seasons and in the months of February to June during the dry season. Fig. 11 shows the actual water allocated to the irrigation areas for dry average and wet seasons as computed by the model.

The crop areas in Table 9 are remarkably different from those in Table 7. Comparing the values in Tables 7–9, it can be seen that weighting of the net revenue objective higher than the other two objectives reduced the under-achievement for net revenues by almost 62% (\$59.8 million to \$22.8 million) while increasing over-achieved cost from \$0.34 million to \$16.67 million in the wet season.

## 5. Conclusions

Most water management systems are concerned with satisfying conflicting demands of various groups and MCDM techniques provide a potential mechanism for resolving these conflicts. They provide better results than simple linear programming (LP) solutions because they integrate the effect of all the objectives simultaneously. There are an increasing number of highly sophisticated LP solvers that could easily be adapted to solve MCDM problems using Goal Programming (GP) or Weighted Goal Programming (WGP) as illustrated with the example problem. The application of MCDM techniques to the simple nodal-network example problem demonstrates its ability to provide solutions that integrate different goals and trade-offs. The pay-off matrix for the three goals illustrates the degree of conflict between the different goals and trade-offs. The effect of different ET and rainfall (dry, average and wet) on NR, crop areas, environmental flows and water allocated to the irrigation areas was clearly demonstrated. Furthermore, the sensitivity of the weights assigned to the different goals was shown to have marked impact on optimal crop areas and the degree of under- and over-achievement of the selected targets for all the three goals. Attaching different weights to goals, sets of decision variables (crop area, water allocations) could be formulated for different seasons that could aid in policy formulations and decision-making. Although goal programming is a useful tool to analyze MCDM problems, there is a difficulty of selecting the target values and weights for the different goals. Further work is required to incorporate market constraints that take account of price and demand fluctuations for the different crops.

## References

- Berbel, J., 1993. Risk programming in agricultural systems: a multiple criteria analysis. *Agricultural Systems* 41, 275–288.
- Brooke, A., Kendrick, D., Meeraus, A., Raman, R., 1998. *GAMS A User's Guide*. GAMS Development Cooperation, Washington DC 20007 USA 1998.
- Department of Land and Water Conservation, 1995. *State of the Rivers Report*, vol. 1 Murrumbidgee Catchment, Paramatta, NSW, Australia 1995 47pp..
- Mendoza, G.A., Bare, B.B., Zhou, Z., 1993. A fuzzy multiple objective linear programming approach to forest planning under uncertainty. *Agricultural Systems* 41, 257–274.
- NSW DPI Farm Budget Report 2003/4. <http://www.agric.nsw.gov.au/reader/Sumcropbud>.
- Piech, B., Rehman, T., 1993. Application of multiple criteria decision making methods to farm planning: a case study. *Agricultural Systems* 41, 305–319.
- Rehman, T., Romero, C., 1993. The application of the MCDM paradigm to the management of agricultural systems: some basic considerations. *Agricultural Systems* 41, 239–255.
- Romero, C., Amador, F., Barco, A., 1987. Multiple objectives in agricultural planning: a compromise programming application. *American Journal of Agricultural Economics*, 69, 78–86.
- Teclé, A., Shrestha, B., Duckstein, L., 1998. A multiobjective decision support system for multiresource forest management. *Group Decision and Negotiation* 7, 23–40.