Journal of Environmental Management (1990) **31**, 237–246

#3 octo bly

Designing Forest Plans with Conflicting Objectives using *de Novo* Programming

B. Bruce Bare

College of Forest Resources and Center for Quantitative Science in Forestry, Fisheries and Wildlife, University of Washington, Seattle, WA 98195 U.S.A.

and Guillermo A. Mendoza

Department of Forestry, University of Illinois, Urbana, Illinois 61801 U.S.A.

Received 14 *March* 1989

Optimization techniques which incorporate multiple objectives and operate within a soft decision environment offer great promise for increasing the utility of forest planning models. Using *de novo* programming, we illustrate the potential use of designing optimal forest systems in the face of conflicting objectives. A multiple objective linear programming model is used to illustrate this approach. Both the generation and evaluation of compromise solutions under *de novo* conditions are discussed.

Keywords: linear programming, multiple criteria decision making, multiple objective programming, soft optimization.

1. Introduction

Forest planners were introduced to *de novo* programming by Bare and Mendoza (1988) who briefly described the approach and demonstrated its use on an illustrative forest planning example. In this paper, we wish to further describe this approach within a forest planning context by incorporating multiple design criteria, considering more than two objectives, examining the trade-offs between conflicting objectives, and discussing ways to generate and evaluate compromise solutions. We employ a modified version of the same problem used in our previous paper to facilitate comparison of the results.

Linear programming (LP) is the dominant quantitative tool used for forest land management planning in the United States. However, LP's inherent limitations (i.e., linearity, divisibility, and certainty) remain as barriers to more effective forest land management planning (Bare and Field, 1987; Iverson and Alston, 1986). Further, it is very difficult to incorporate the political, social and non-quantifiable dimensions of national forest planning into a traditional LP formulation. Although several attempts

0301–4797/90/070237 + 10 $03.00/0

have been made (e.g., Mendoza *et al.*, 1987; Mendoza and Bare, 1987; Mendoza and Sprouse, 1989), two key aspects of forest planning LP formulations remain of concern: (a) the use of a single objective function and (b) the common use of LP to optimize a given system rather than to design an optimal system. While other problems remain troublesome (i.e., spatial integrity, hierarchical structure and problem size), the objective of this paper is to illustrate how a *de novo* programming approach can be used to help resolve forest planning problems when faced with conflicting multiple objectives.

2. *De novo* programming

The literature on *de novo* programming is dominated by the work of Zeleny (1981, 1982, 1985, 1986*a*, 1986*b*). This approach addresses multiple (single) objective problems by determining the right hand side (RHS) of some, or all, constraints for given resource costs and limitations. Those constraints whose RHSs are fixed (given) are termed "hard" and those which are to be determined through analysis are labeled "soft". Soft constraints permit the analyst to design an optimal system (i.e., simultaneously determine the RHS along with the level of output).

A related technique known as generalized LP (Dantzig, 1963; Lasdon, 1970) allows the objective function and technical constraint coefficients to vary. However, the RHSs are fixed in such problems.

Zeleny's External Reconstruction Algorithm (ERA) is an example of a *de novo* algorithm which can be used to solve problems where some of the constraint levels are to be designed. This solution is accomplished by defining an aggregate constraint for each design criterion which initially consists of either: (a) fixed inequality constraints, (b) soft inequality constraints to be designed, or (c) any combination of the above. All equality constraints are viewed as hard (fixed) and are excluded from the aggregate constraint(s).

As described by Bare and Mendoza (1988) and Zeleny (1986*a*), an iterative procedure is used successively to decouple all fixed inequality constraints from the aggregate constraint(s) until all of the original fixed inequalities are satisfied. At this point, the optimal solution also shows the RHSs of the soft constraints being designed. For instance, consider the mathematical model shown below:

$$\text{Max } Z = \Sigma_j c_j x_j \tag{1}$$

s.t.

$$\Sigma_j a_{ij} x_j <= \text{or} = b_i \quad i = 1,2,\ldots,m \tag{2}$$

$$x_j >= 0 \qquad j = 1,2,\ldots,n \tag{3}$$

Suppose that s of the m constraints are soft while the remaining h ($h = m - s$) constraints (including any equalities) are hard. Given this situation, the mathematical model for *de novo* programming is:

$$\text{Max } Z = \Sigma_j c_j x_j$$

s.t.

$$\Sigma_j a_{ij} x_j <= \text{or} = b_i \text{ for all } i \epsilon h \text{ hard constraints} \tag{4}$$

$$\Sigma_j (\Sigma_i a_i p_{ik}) x_j = \Sigma_i p_{ik} b_i <= B_k \qquad k = 1,2,\ldots,p \qquad (5)$$
$$x_j >= 0 \quad \text{aggregate constraints}$$

where $p_{ik} > 0$ is the per unit cost of a given resource b_i which is to be designed, and B_k is the amount of the kth resource available for designing. Equation (5) is used to determine the amount of each resource to purchase to design the most efficient system. As constraints are decoupled from the aggregate constraint [equation (5)], they are treated as fixed [i.e., transferred to equation (4)]; the B_k are reduced; and another iteration is performed.

For previous applications to forestry, Bare and Mendoza (1988) discuss a soft optimization approach to forest planning and Mendoza and Bare (1988) investigate a log allocation problem common in forest industry.

3. Forest planning illustration

The sample problem used to illustrate *de novo* programming is extracted from Johnson (1986). However, as described by Bare and Mendoza (1988), it is modified to reflect multiple objectives and additional resource alternatives. Table 1 contains the coefficient matrix for this problem, showing four analysis areas, possible management alternatives for each area over a three decade planning horizon, constraints and the objective functions.

The land accounting and the bird habitat constraints are expressed in acres; the yield constraints sum the cubic foot harvest for each decade and insure a non-declining yield over time; the clearcutting constraints limit clearcutting to at most 30% of the two loblolly pine analysis areas in any one decade; and the picnic and hiking constraints limit output to at most 200 picnic sites and 50 miles of hiking trails over three decades. As depicted in Table 1, the problem involves four objective functions, 19 constraints and 27 decision variables.

3.1. CASE I

The first analysis consists of solving four LP problems derived from the information presented in Table 1. Each involves the optimization of one of the objective functions without consideration of the remaining three objectives. Standard LP solution procedures are used and all constraints are taken as fixed. Thus, the problem is viewed in the classical sense of optimizing within a previously specified decision environment. The resulting pay-off table shown in Table 2 contains the ideal solution on the diagonal.

The objective functions are defined in terms of maximizing net present value (NPV), minimizing sediment production (SED), maximizing timber yield (TBR), and maximizing forage production (FOR). As expected, the four optimal solutions derived when optimizing each objective function separately are quite different. The MAX NPV solution ($14 781·25) produces 145 000 ft^3 of harvest volume from analysis area 3 as well as 200 picnic sites and 10 miles of hiking trails. Units 1 and 2 are both assigned the minimum level of management and unit 4 is managed for high intensity forage, producing 30 000 AUMs of forage. Sediment production over the three planning periods totals 541·875 tons and no clearcut harvest alternatives are selected. Labor utilization over the three periods is 100, 62·5, and 100 man-days, respectively.

TABLE 1. Coefficient matrix for sample forest planning problem (after Johnson, 1986)

	Analysis area 1 Loblolly pine age 5					Analysis area 2 Mixed hardwood age 15						Analysis area 3 Loblolly pine age 35									Analysis area 4 Meadow			Accounting Variables					
	x_{1T1}	x_{1T2}	x_{1M1}	x_{1D1}	x_{1U1}	x_{2T1}	x_{2T2}	x_{2T3}	x_{2M1}	x_{2D1}	x_{2U1}	x_{3T1}	x_{3T2}	x_{3T3}	x_{3M1}	x_{3B1}	x_{3B2}	x_{3C1}	x_{3D1}	x_{3U1}	x_{4L1}	x_{4H1}	x_{4H2}	H_1	H_2	H_3	C		
Maximize	75	182		25	15	−56	−11	6		25	15	542	408	294		187	161		25	15	−18	−11	−18					NPV	
Minimize	3	3				6	6	4				3	3	3		1·4	·7				3	4·5	4					Sediment	
Maximize	1500	2300				835	1235	1050				3000	3300	3500		1900	1600											Timber	
Maximize																					200	300	300					Forage	
Subject to:																													
Land	1	1	1	1	1																							= 200 Ac.	1
						1	1	1	1	1	1																	= 300 Ac.	2
												1	1	1	1	1	1	1	1	1								= 700 Ac.	3
																					1	1	1					= 100 Ac.	4
Bird habitat																1	1	1										= 90 Ac.	5
Timber yield						490						3000				900								−1				= 0	6
	1500					345	805						3300				1600								−1			= 0	7
		2300					450	1050						3500		1000										−1		= 0	8
																								−1	1			⩾ 0	9
																									−1	1		⩾ 0	10
Clear cut	1	1										1	1	1													−1	= 0	11
												1															−0·3	⩽ 0	12
	1												1														−0·3	⩽ 0	13
		1												1													−0·3	⩽ 0	14
Labor						2						2				2												⩽ 100 man-days	15
	2					2	2						2				2											⩽ 100 man-days	16
		2					2	2						2		2												⩽ 100 man-days	17
Picnic site				10	2					10	2								10	2								⩽ 200 sites	18
Hiking trails				0·2	0·1					0·2	0·1								0·2	0·1								⩽ 50 Mi	19

Decision variables: x_{sik} = acres assigned to timing choice k of prescription i of analysis area s where i can be T (timber); M (minimum level); B (birds/timber); C (birds/minimum level); L (low intensity forage); H (high intensity forage); D (high intensity recreation); and U (low intensity recreation).
Accounting variables: H_j = total timber harvest volume in the $_j$ + h period (ft³); C = acres assigned to prescriptions that allow clearcutting.

TABLE 2. Case I: ideal solution for sample forest planning problem

Objective function	Functional value			
	Z_1 ($)	Z_2 (Tons)	Z_3 (CF)	Z_4 (AUMs)
Maximum Z_1 (NPV)	14 781·25	541·875	145·000	30 000
Minimum $\|Z_2$ (SED)	− 1800·00	300·000	0	20 000
Maximum Z_3 (TBR)	12 581·25	391·875	145 000	20 000
Maximum Z_4 (FOR)	− 1100.00	450·000	0	30 000

NPV = net present value ($); TBR = timber production (CF); SED = sediment yield (Tons); FOR = forage production (AUM).

The MIN SED solution (300 tons over the three decades), yields a net present value of − $1800 and no timber is scheduled for harvest. Instead, minimum level management is selected for planning units 1–3. Low intensity forage production for unit 4 produces 20 000 AUMs of forage. No picnic sites or hiking trails are constructed and 100 man-days of labor are unallocated each period.

The MAX TBR solution produces 145 000 ft^3 and a net present value of $12 581·25. The solution is similar to the MAX NPV solution with minimum management selected for units 1–2 but low intensity forage for unit 4. Thus, only 20 000 AUM of forage are produced. All timber harvested comes from unit 3, but no picnic sites or hiking trails are constructed. Sediment production is 391·875 tons and over the three periods 100, 62·5, and 100 man-days of labor are utilized.

Finally, the MAX FOR solution produces 30 000 AUMs of forage with a net present value of − $1100 and a sediment production of 450 tons. Timber production and recreational benefits are nonexistent as minimum management is selected for units 1–3 and high intensity forage production for unit 4. All labor remains unallocated.

3.3. CASE II

To this point, the analysis has proceeded in a classical fashion. Clearly, the decision maker is faced with a variety of conflicting objectives for the area in question. For example, trade-offs exist between higher NPVs and lower amounts of sediment production or higher levels of forage production with increased sediment yields. Ways of dealing with this have been examined in a variety of multiple objective analyses as cited earlier in this paper. Here, we wish to illustrate the use of *de novo* programming for designing an optimal system when faced with conflicting objectives. To begin this procedure, we assume that man-days of labor and dollars of budget allocated to the two recreational activities are soft resources. Thus, we identify two design criteria—labor and budget. The unit costs for picnic sites and hiking trails are $1000/site and $3000/mile, respectively. Thus, the total cost of including these two activities at the maximum levels shown in Table 1 is $350 000 (i.e., 200 × $1000 + 50 × $3000). The three decade labor resource is limited to 300 man-days which is the amount of available labor shown in Table 1.

Using Zeleny's ERA, the three labor constraints are converted into one aggregate labor constraint and the two recreational constraints into one aggregate budget constraint. This yields the following two soft constraints which are substituted for the original five constraints, respectively:

Labor

$$2x_{1T1}+2x_{1T2}+4x_{2T1}+4x_{2T2}+2x_{2T3}+2x_{3T1}+2x_{3T2}+2x_{3T3}+4x_{3B1}+2x_{3B2} \\ <=300 \text{ man-days}$$

Budget

$$10{\cdot}6x_{1D1}+2{\cdot}3x_{1U1}+10{\cdot}6x_{2D1}+2{\cdot}3x_{2U1}+10{\cdot}6x_{3D1}+2{\cdot}3x_{3U1}<=\$350$$

Maximizing NPV with these two design criteria yields a MAX NPV of \$17 184·61 and a three decade timber harvest of 163 800 ft^3. In addition, 562·92 tons of sediment, 304·34 picnic sites, 15·22 miles of hiking trails, and 30 000 AUMs are produced. In terms of NPV, this solution is superior to that obtained when resource levels are considered fixed (i.e., Case I). While more timber is generated, so too are more picnic sites, hiking trails, and sediment. Although the advantages of designing the optimal system in terms of NPV are clear, the conflict between competing objectives still exists. This solution also specifies that the requirements for labor over the three decades is 115·2, 64·8, and 120 man-days, respectively. Thus, all 300 man-days are allocated. Further, the total budget is allocated to the two recreational activities.

When minimizing sediment production, it is not possible to design a more efficient system than was shown for Case I. Thus, 300 tons is the minimum production over the three planning periods.

Designing the optimal system when maximizing TBR leads to a harvest volume of 190 189 ft^3 over the three periods. However, sediment production is increased to 803·868 tons and NPV is reduced to \$8312·26. Forage production is retained at its maximum value of 30 000 AUMs. No picnic sites or hiking trails are constructed (i.e., the budget remains unallocated), but all labor is allocated (i.e., 0, 118·86, and 181·14 man-days, respectively, for the three decades).

The maximum forage production remains at 30 000 AUMs when designing the optimal system. However, timber production is increased from zero (Case I) to 161 280 ft^3 and sediment yield rises to 503·32 tons. The net present value is \$14 187·60. No picnic sites or hiking trails are constructed (i.e., the budget remains unallocated) and only 295·2 man-days of labor are required (i.e., 115·2, 64·8, and 115·2, respectively, for the three decades).

These four solutions define the "system ideal"—that is, the optimal solution when the soft constraints are designed for each objective function. It differs from the ideal solution (Table 2) which is obtained by assuming that all constraints are "hard" and not subject to design. A summary of the system ideal is contained in Table 3.

3.3. CASE III

While Case II illustrates the use of *de novo* programming for designing an efficient system, it does not directly address the conflicts between the multiple objectives. However, it is clear from results shown for Case I that the ideal solution cannot be achieved. And, this remains true when we attempt to design a more efficient system as in Case II.

TABLE 3. Case II: system ideal solution for sample forest planning problem using *de novo* programming

Objective function	Functional value			
	Z_1 (\$)	Z_2 (Tons)	Z_3 (CF)	Z_4 (AUMs)
Maximum Z_1 (NPV)	17 184·61	562·920	163 800	30 000
Minimum Z_2 (SED)	− 1800·00	300·000	0	20 000
Maximum Z_3 (TBR)	8312·26	803·868	190·189	30 000
Maximum Z_4 (FOR)	14 187·60	503·320	161 280	30 000

NPV = net present value (\$); TBR = timber production (CF); SED = sediment yield (Tons); FOR = forage production (AUM).

Retaining the two soft aggregate constraints (associated with the two design criteria) in place of the three labor and the two recreational constraints, and recognizing that the system ideal solution is not possible to attain, we now analyse ways of producing satisfactory compromise solutions which get us as close to the system ideal as possible.

Two related issues now confront us. First, we need to generate a set of feasible compromise solutions and second we need to evaluate each solution to determine how well it performs across the entire set of objectives. Both aspects of the analysis are done under conditions of a soft decision environment.

Mendoza *et al.* (1987) discuss Modeling to Generate Alternatives as a way to generate maximally different solutions in decision space while producing satisfactory levels of performance in objective space. Another possibility is to use goal programming (or some other multiple objective programming technique) whereby the weights assigned to different objective functions are manipulated until a satisfactory compromise solution is derived (Rustagi and Bare, 1987). Lastly, Bare and Mendoza (1988*a*) illustrate use of the STEM method for identifying compromise solutions in an interactive decision environment. Below we employ both the STEM method and the use of a weighted objective function to demonstrate how compromise solutions can be identified in a *de novo* environment.

Once generated, the compromise solutions need to be assessed systematically. This can be done following a structured framework (e.g., the analytic heirarchy process) or a more heuristic approach. Because our primary purpose is to demonstrate the use of *de novo* programming and not to discuss techniques for generating and assessing alternative solutions (e.g., Mendoza and Sprouse, 1988), we adopt the less-structured heuristic approach.

First, we equally weight the four objectives (after scaling) and use the ERA to design the optimal levels of the two soft constraints. This compromise solution produces a NPV of \$17 170·21, a sediment load of 553·32 tons, 161 280 ft^3 of timber and 30 000 AUMs of forage over the three planning periods. This solution calls for minimum level management in units 1 and 2 and high intensity forage in unit 4. The total timber harvest of 161 280 ft^3 comes from unit 3 as do the 304·34 picnic sites and 15·22 miles of hiking trails. In comparison with the Case I ideal solution, this compromise solution produces more net present value and timber; an equal amount of forage; but higher sediment yields. In comparison with Case II, this solution produces less NPV, more sediment, less timber and equal amounts of forage and recreational opportunities. Labor utilization over the three periods is 115·2, 64·8 and 115·2 man-days, respectively, for a total allocation of 295·2 man-days. This compromise solution is summarized in Table 4 (row five) along with the system ideal in rows 1–4.

At this point, the decision maker must decide whether or not to accept the compromise solution obtained when using equal weights. Suppose the decision maker is satisfied with the level of attainment of the NPV and FOR objectives, but wishes to determine if lower levels of sediment and higher volumes of timber can be obtained. An examination of Table 1 shows that lower sediment yields only can be attained by lowering forage and/or timber production. Further, lower sediment yields and/or higher levels of timber output can only be achieved by allowing for reduced levels of net present value and forage. Thus, the conflicts between the various objectives must be resolved if a satisfactory compromise solution is to be realized.

To further explore other compromise solutions using *de novo* programming, several additional weighting schemes are examined. Results of these calculations, shown in Table 4, reveal the sensitivity of solutions to the weights. Compromise solution number two (row six) uses larger weights for the two objectives judged to be unsatisfactory in the first compromise solution (i.e., sediment and timber) and smaller weights for the remaining two objectives. A comparison of the first two compromise solutions shows the magnitude of the trade-offs which result. By assigning increased weight to the sediment objective, both the level of forage and timber production have decreased. And, this occurs even though a larger weight was assigned to the timber objective. Predictably, the net present value objective has also decreased. Assuming that the decision maker is satisfied with the NPV and TBR objectives as shown in compromise solution two, but not the forage or sediment production levels, an additional compromise solution is needed. Inspection of Table 1 reveals that increased forage production can only be realized at the expense of decreased timber production—if reduction of sediment yields is also required. A third compromise solution shown in Table 4 (row seven) attempts to do this by assigning a larger weight to the forage objective and a smaller weight to the timber objective. The resulting compromise solution produces satisfactory levels of output for the NPV, TBR and FOR objectives. However, the solution also leads to increased levels of sediment yield relative to the second compromise solution.

TABLE 4. Case III: compromise solutions for alternative weighting schemes using *de novo* programming

	Weights				Functional values			
Row	NPV	SED	TBR	FOR	NPV ($)	SED (Tons)	TBR (CF)	FOR (AUMs)
1	1·0	0·0	0·0	0·0	17 184·61	562·92	163·800	30 000
2	0·0	1·0	0·0	0·0	− 1800·00	300·00	0	20 000
3	0·0	0·0	1·0	0·0	8312.26	803·87	190 189	30 000
4	0·0	0·0	0·0	1·0	14 187·60	503·32	161 280	30 000
5	0·25	0·25	0·25	0·25	17 170·21	553·32	161 280	30 000
6	0·05	0·45	0·45	0·05	16 412·61	401·77	160 615	20 000
7	0·05	0·45	0·05	0·45	16 412·61	501·77	160 615	30 000
8	—	—	—	—	16 300·00	451·38	160 000	25 000
9	—	—	—	—	16 300·00	401·38	160 000	20 000

Rows 1–4 contain the system ideal solution. Rows 5–7 contain compromise solutions using the weighted objective approach. Rows 8–9 contain compromise solutions using the STEM method.
NPV = Net present value ($); TBR = Timber production (CF); SED = Sediment yield (Tons); FOR = Forage production (AUM).

These three compromise solutions illustrate the process one employs when using a weighted objective function approach for resolving conflicts among multiple objectives using *de novo* programming. Because all compromise solutions produced equivalent recreational outputs and used equal amounts of labor, there was no difference between solutions with regards to the two soft constraints. To determine if a more satisfactory compromise solution can be derived we now switch to an alternate approach which uses the STEM method.

Assuming that the decision maker wishes to find another compromise solution which yields less sediment without seriously reducing the output of the three remaining objectives, we can proceed by minimizing sediment subject to the additional constraints that NPV be at least \$16 300; TBR be at least 160 000 ft^3 and FOR be at least 25 000 AUMs. These minimum values represent the lowest values that the decision maker deems acceptable. Given these attainment levels, and using *de novo* programming, the fourth compromise solution (Table 4, row eight) produces a minimum of 451·38 tons of sediment while just satisfying the specified attainment levels for the three remaining objectives. This compromise solution clearly demonstrates that lower sediment yields only can be achieved by lowering the attainment level for forage.

For example, a fifth compromise solution shown in Table 4 (row nine) reduces the desired forage output to 20 000 AUMs while keeping the net present value and timber objectives unchanged. The compromise solution results in a sediment yield of 401·38 tons while just satisfying the specified attainment levels for the three remaining objectives.

The fourth and fifth compromise solutions—obtained using the STEM method—produce slightly different levels of recreational outputs and use different amounts of labor than the previous compromise solutions. For example, 305·28 picnic sites, 14·91 miles of trail and 289·6 man-days of labor are generated under *de novo* conditions for the last two compromise solutions. The allocation of acres to management treatments does not differ significantly between any of the compromise solutions, with the exception that the last two involve a small allocation of unit one to developed recreation.

4. Conclusions

Multiple objective LP is receiving increased attention as a viable forest planning technique. However, most analysts use this tool to optimize given systems and not to design optimal systems. In this paper, we demonstrate the value of *de novo* programming involving multiple objectives.

Soft optimization procedures allow the analyst to design an optimal system by treating the RHSs of constraints as soft, and not fixed as in traditional multiple objective LP. Using a forest planning example, we demonstrate how optimal plans can be derived using *de novo* programming when two design criteria are employed. Both a weighted objective and the STEM method are used to generate compromise solutions under a *de novo* environment. Although generated solutions are evaluated subjectively, a more structured approach could be used.

The examples illustrate the potential usefulness of *de novo* programming in generating efficient forest plans under conflicting objectives. However, in the final analysis, the decision maker must assume the responsibiltiy for making the ultimate choice of which compromise solution will be adopted.

References

Bare, B. B. and Field, R. C. (1987). An evaluation of FORPLAN from an operations research perspective. FORPLAN: an evaluation of a forest planning tool. *Proceedings of a Symposium.* (Denver, CO, Nov. 4–6, 1986). USDA Forest Service, General Technical Report RM-140, Rocky Mountain Forest and Range Experiment Station. Fort Collins, Colorado. pp. 133–144.

Bare, B. B. and Mendoza, G. A. (1988). A soft optimization approach to forest land management planning. *Canadian Journal of Forest Research* **18**, 545–552.

Bare, B. B. and Mendoza, G. A. (1988*a*). Multiple objective forest land management planning: an illustration. *European Journal of Operational Research* **34**, 44–55.

Dantzig, G. B. (1963). *Linear Programming and Extensions.* Princeton: Princeton University Press.

Iverson, D. C. and Alston, R. M. (1986). *The Genesis of FORPLAN: a Historical and Analytical Review of Forest Service Planning Models.* USDA Forest Service, General Technical Report INT-214, Intermountain Research Station, Odgen, Utah.

Johnson, K. N. (1986). *FORPLAN Version I: an Overview.* Land Management Planning Systems Section, USDA Forest Service, Washington, D.C.

Lasdon, L. S. (1970). *Optimization Theory for Large Systems.* New York: Macmillan.

Mendoza, G. A., Bare, B. B. and Campbell, G. E. (1987) Multiobjective programming for generating alternatives: a multiple-use planning example. *Forest Science* **33**, 458–468.

Mendoza, G. A. and Bare, B. B. (1987). Models for enhancing the planning capability of the national forest system. *Proceedings of the Annual Convention of the Society of American Foresters.* (Minneapolis, Minnesota. October 19–21). Bethesda, Maryland.

Mendoza, G. A. and Bare, B. B. (1988). Designing an optimal wood utilization system using a *de novo* programming approach. Systems analysis in forest resources management symposium. *Proceedings of a Symposium.* (Asilomar, CA, March 29–April 1, 1988). USDA Forest Service, General Technical Report RM-161, Rocky Mountain Forest and Range Experiment Station, Fort Collins, Colorado. pp. 81–86.

Mendoza, G. A. and Sprouse, W. (1989). Forest planning and decision making under fuzzy environments: an overview and illustration. *Forest Science* **35**, 481–502.

Rustagi, K. P. and Bare, B. B. (1987). Resolving multiple goal conflicts with interactive goal programming. *Canadian Journal of Forest Research* **17**, 1401–1407.

Zeleny, M. (1981). On the squandering of resources and profits via linear programming. *Interfaces* **11**(5), 101–107.

Zeleny, M. (1982). *Multiple Criteria Decision Making.* New York: McGraw-Hill.

Zeleny, M. (1985). Multicriterion design of high-productivity systems: extensions and applications. *Proceedings of the VI International Conference on Multiple Criteria Decision Making (MCDM).* New York: Springer-Verlag.

Zeleny, M. (1986*a*). An external reconstruction approach (ERA) to linear programming. *Computing and Operations Research* **13**, 95–100.

Zeleny, M. (1986*b*). Optimal system design with multiple criteria: *de novo* programming approach. *Engineering Costs and Production* **10**, 89–94.