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A Review of Applications of Multiple-Criteria Decision-Making Techniques to Fisheries

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Abstract *Management of public resources, such as fisheries, is a complex task. Society, in general, has a number of goals that it hopes to achieve from the use of public resources. These include conservation, economic, and social objectives. However, these objectives often conflict, due to the varying opinions of the many stakeholders. It would appear that the techniques available in the field of multiple-criteria decision-making (MCDM) are well suited to the analysis and determination of fisheries management regimes. However, to date, relatively few publications exist using such MCDM methods compared to other applicational fields, such as forestry, agriculture, and finance. This paper reviews MCDM applied to fishery management by providing an overview of the research published to date. Conclusions are drawn regarding the success and applicability of these techniques to analyzing fisheries management problems.*

Key words Fisheries, literature review, mathematical programming, multiple-criteria decision-making, multiple objectives.

Introduction

Fisheries management is concerned with the utilization of fisheries resources for the greatest benefit to society. Optimal use, however, depends on the objectives of society. From a purely economic viewpoint, optimal use of fisheries resources is to achieve the maximum level of producer and consumer surplus possible (Cunningham, Dunn, and Whitmarsh 1985). However, fisheries managers are also subject to pressure from groups with political, social, or conservation objectives. As a result, fisheries management is often characterized by multiple objectives, some of which may be conflicting (Crutchfield 1973).

Examination of fisheries management policies from around the world suggest that the most common objectives of fisheries management are: (*i*) resource conservation, (*ii*) food production, (*iii*) generation of economic wealth, (*iv*) generation of reasonable income for fishers, (*v*) maintaining employment for fishers, and (*vi*) maintaining the viability of fishing communities (Charles 1989). The U.S. Magnuson-Stevens Fishery Conservation and Management Act (Public Law 94-265) states that fisheries managers shall develop management plans that achieve the "optimum yield" from each fishery. These management measures must consider eco-

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nomic efficiency, but no measure has economic allocation as its sole purpose. Management measures must also ensure that overfishing is prevented to provide for sustained participation of fishing communities and minimize adverse economic impacts on such communities.

Similar multiple objectives are present in the management of European fisheries. Objectives of the Common Fisheries Policy (CFP), as embodied in Article 2 of Regulation No. 3760/92, are, "to protect and conserve available and accessible living marine aquatic resources and to provide for rational exploitation on a sustainable basis, in appropriate economic and social conditions for the sector, taking into account of its implications for the marine ecosystem, and in particular taking into account of the needs of both producers and consumers" (European Commission 1992, p. 1).

Considerable effort has been undertaken globally to develop biological and bioeconomic models of fisheries to assist in fisheries management. However, results from these models are largely ignored by fisheries managers because they focus on single objectives. Due to the increased importance of fisheries management and the associated requirements of conservation, plus social and economic factors, conflicts apparent in the fishery management process are increasing (Hanna and Smith 1993). Therefore, multi-objective evaluation of fishery management plans would appear the logical approach for both theoretical and practical reasons (Bishop, Bromley, and Langdon 1981).

The MCDM techniques, especially the subset of multi-objective programming (MOP) techniques, appear to be an ideal set of tools to aid in the task of fisheries management. The application of MCDM to fisheries problems is relatively small scale compared to other fields, such as forestry, water resource planning, agricultural planning, and finance. However, there are case studies reported for all major MCDM techniques for fisheries problems, although few in number (see appendix).

The purpose of this paper is to provide an overview of the types and applications of MCDM methods applied to fishery issues. Techniques are divided into three main sections: multi-objective programming, multi-criteria decision analysis, and other important concepts. An overview of how each of these techniques can be applied to fisheries and examples of applications are presented. In addition, the related area of multi-level programming is also examined. Finally, a discussion is presented regarding the potential future usefulness of MCDM techniques in assisting fisheries management decision-making.

Multi-objective Programming in Fisheries

The key feature of MOP is that it directly incorporates the tradeoffs between the modeled objectives in the analysis. Decision maker preferences are also incorporated into the analysis; *e.g.*, through a set of weights assigned to the multiple objectives. When several interest groups with diverse objectives are involved in the decision-making process, as is the case in many fisheries problems, different sets of weights can be applied, and a set of "optimal" solutions estimated. If several interest groups are active in the process, then a single "best" solution is unlikely. However, tradeoffs between objectives become explicit rather than implicit, as is often the case in fisheries management decision-making.

A key characteristic (typically a requirement) of multi-objective programming solutions is that of Pareto efficiency.[1] As with the economic concept of allocative efficiency, Pareto efficiency occurs when no objective or goal can be improved with-

[1] Pareto efficient solutions are also often termed noninferior or nondominated.

out degrading another. A Pareto efficient solution frontier, or discrete set of Pareto efficient points, exists for most problems. From there, a best-compromise solution can be identified given specific decision maker preferences. Incentive-compatible solutions (where Pareto efficiency may not be detectable) are defined as the solution state where no decision maker finds it advantageous to alter their behavior pattern in order to achieve a more satisfactory result. Thus, the solution(s) developed will ultimately best reflect the situation under investigation.

From the reviews of MOP applications, fisheries management appears to have been slow to adopt MOP planning process opportunities. In a recent bibliography of general MOP applications, White (1990) cites 504 publications, none of which coincide with the fisheries references in this paper. Romero (1991) cites 351 goal programming applications of which only three relate to fisheries. This lack of studies is predominantly an artifact of the journals in which applications to fisheries appear, as few fisheries journals are listed in operational research bibliographic databases. Therefore, unless a specific literature search for multi-objective fisheries applications in the fisheries and economics literature is performed, few will be found.

Generally, MOP techniques are applied to model a form of management plan in a similar approach to linear programming (LP) models. Some problems that have been considered in fisheries are policy management, fleet structure, stock planning, resource allocation, quota allocation, development planning, optimal harvest, and resource management. The following subsections describe the MOP techniques and fisheries applications using goal programming, generating methods, and nonlinear MOP.

Linear Goal Programming

Goal programming (GP) was first thoroughly introduced by Charnes and Cooper (1961), and is perhaps the oldest of the MCDM techniques. It has since been further developed by many researchers. Recent comprehensive discussions are given by Romero (1991) and Ignizio and Cavalier (1994). The most common paradigms of linear goal programming techniques are weighted (or Archimedian) GP (WGP) and lexicographic (or preemptive) GP (LGP) (Tamiz, Jones, and El-Darzi 1995). Others include MinMax (or Chebyshev), fuzzy, fractional, and nonlinear GP. Linear GP is a computationally efficient approach (*i.e.*, standard linear programming techniques are used for solution), generally only seeking one solution for a specified model (Cohon and Marks 1975; Willis and Perlack 1980).

The structure of a GP model minimizes the sum of absolute deviations from given target (goal) values using the Simonian philosophy of "satisficing." The typical mathematical representation of a WGP is,

$$\min z = \sum_{i=1}^{k} (u_i n_i + v_i p_i) \tag{1}$$

subject to

$$f_i(\mathbf{x}) + n_i - p_i = b_i \qquad i = 1, \dots k \tag{2}$$

$$\mathbf{x} \in \mathbf{X} \tag{3}$$

$$\mathbf{x}, \mathbf{n}, \mathbf{p} \geq 0 \tag{4}$$

where $f_i(\mathbf{x})$ defines a typical objective function or goal (often linear), b_i is the target value of goal i, $\mathbf{x} \in R^n$ is the set of decision variables, $\mathbf{n}$, $\mathbf{p} \in R^m$ are deviational variables, and $\mathbf{u}$, $\mathbf{v} \in R^m$ are the respective deviational variable predetermined weights. Equation 1 is termed the achievement function, equation 2 is the k goals (or objectives) to be satisficed, and equation 3 represents an optional set of hard constraints in the traditional LP style (*e.g.*, the sum of a given species' landings cannot exceed that species' total catch). The achievement function weights specify the relative degree of importance of each goal. From equation 2, if the target level, b_i, is exceeded, then the positive deviation variable, p_i, is nonzero, and the negative deviation variable, n_i, is zero. Conversely, for an underachieved target level, n_i is positive, and p_i is zero. For example, b_i may represent the target level of fishery profits, while $f_i(\mathbf{x})$ represents the actual levels of profits achieved in the model. In this case, n_i represents the shortfall in actual profits compared to target profits, whereas p_i represents the excess of actual profits over target profits.

The achievement function measures the total deviations (in absolute terms) from the target level of each goal, where the predetermined weights in the achievement function represent the relative importance of the goals. If it is acceptable to exceed a goal, but not to underachieve it, then the goal's positive deviational variable, p_i, will have zero weight, v_i, in the achievement function, while the negative deviation weight, u_i, will be nonzero.

The deviations from the specified goals are typically measured in different units, and, particularly, different magnitudes of units; *e.g.*, dollars and people employed. This may cause significant difficulty in setting up a representative achievement function with appropriate weights **u** and **v**. However, normalization of the deviations using a variety of techniques can help overcome such incommensurability.

Similarly, LGP can be represented in a mathematical form by altering the achievement function to a lexicographically ordered vector,

$$\min \mathbf{a} = [a_1, a_2, ..., a_l] \tag{5}$$

where $a_* = \sum_{i=1}^{m} (u_i^* n_i + v_i^* p_i)$ represents a typical priority level (PL_*), and u_i^*, v_i^* are predefined interpriority level weights. Equation 3 is not necessarily required in the case of the LGP definition, as these hard constraints can appear as goals in the first priority level. With LGP, each priority level is optimized in turn; therefore, this assumes that priority level one is infinitely more important than priority level two and so on. For example, the solution (0,1,10,50), in priority order $PL_1 - PL_4$, is preferable to (0,2,1,1), even though the latter is closer to the goals in more levels.

In a fishery model, this might represent an objective of minimizing catch beyond the quota as a priority over maximizing profitability or employment. In such a case, a solution that yields a lower level of over-quota catch is preferable to one which yields higher levels of other objectives, even if substantial improvement in achieving the other objectives can be obtained through alternative solutions.

The number of published applications in fisheries (table 1) that specifically use GP is very small compared to other fields such as forestry, water resource management, and agriculture (Romero 1991). These started receiving significant attention in the early 1980s, but there was (and has been subsequently) very little application of GP to fisheries. Cohon and Marks (1975) suggest that GP is less suited to public sector problems than to those in the private sector as a possible reason. This is primarily due to value judgments required for modeling, as no one has complete knowledge of the situation under investigation.

All of the fisheries studies using GP have noted the diverse number of "optimal" solutions which may be obtained when optimizing a model. This is achieved by simple redefinition of weights, GP method, and possible goal re-specification. A distinct advantage of the method is that it easily allows the analysis of a wide range of possible scenarios. However, several authors have questioned the effectiveness of the GP approach. The three main criticisms that have been leveled at GP are that: (*a*) value judgments are required to formulate an accurate model; (*b*) Pareto inefficient solutions can occur, particularly if low target values are set; and (*c*) incommensurability may cause incorrect modeling of decision maker's preferences. All of these points can be handled sufficiently with appropriate modeling techniques.

A case study of the English Channel fishery overcomes these deficiencies in GP by using a variety of modeling techniques (Pascoe, Tamiz, and Jones 1997). Three objectives were identified: maximize economic profit; maintain employment; and minimize discards of quota species. All of these are measured in significantly different units. To overcome this, a percentage normalization technique was incorporated into the achievement function for each objective; *i.e.*, sum of the penalized deviation variables divided by the target value. The economic profit target value was calculated by performing an initial optimization of the model, where the only objective was to maximize profit, thus giving an upper bound for the economic profit goal. The target values for employment were taken as current levels, and those for discards as zero. Therefore, underestimation of target values was not a factor in the development of this model. Different weighting schemes were attached to each objective in the achievement function and investigated. Furthermore, a full tradeoff analysis was performed between economic profit and employment, giving a graphical representation of the alternative scenarios for the two most important objectives.

The authors concluded that this approach was a useful way of incorporating economic, biological, and social objectives into a single framework for analysis. Such an approach is beneficial when trying to identify an "optimal" fleet configuration given a multi-objective context. The approach was not applied to the analysis of management options, and may not be appropriate for such analyses. The question, "how might fishers respond to management," is significantly different from the question, "how would an 'optimally' managed fishery look." However, in the latter case, identifying the management targets is as important as identifying means to achieve the targets.

The main difficulty with the technique in the case studies examined was the identification of the appropriate weights to attach to each objective and the appropriate levels of each goal. While the approaches adopted were well suited to the problem being addressed, elicitation of these goals and weights from managers would be required if such techniques are to be practically applied in fisheries management.

Generating Methods

The aim of generating methods is to provide all of the information that can be derived from a multi-objective model, without the need for explicit preferences (or value judgments). The most common of these techniques is the weighting and constraint methods (Cohon and Marks 1975).

The mathematical representation of the weighting method is:

$$\max \sum_{i=1}^{k} w_i z_i(\mathbf{x}) \tag{6}$$

subject to

Table 1
Fisheries Applications Using MCDM Techniques (by method, including multi-level programming)

Reference	Region	Species	Comment
(*a*) *Linear Goal Programming*			
1. Everitt *et al.* (1978)	Skeena River	Salmon	Policy management of the salmon fishery with the impact of a large hydroelectric development program—5 water management units and 3 salmon stocks over a 15-year time horizon.
2. Amble (1981)	Northern Norway	Multi-species	Fleet structure analysis (6 vessel types) of a local fishing fleet—WGP with 30 goals, including yearly catch, monthly fish deliveries, monthly employment, income, *etc.*
3. Weithman and Ebert (1981)	Lake Taneycomo	Trout	An introductory GP paper promoting the technique to those involved in fishery management—a simple WGP with 3 goals to define a stock management plan for a 3-species trout fishery.
4. Sandiford (1983)	Scotland	Multi-species	Resource allocation for the Scottish inshore fishery (see also Sandiford 1986; Drynan and Sandiford 1985)—WGP applied to model fisheries management and policy development (also MinMax GP in Drynan and Sandiford 1985). The size of the model was structured on 10 vessel groups in 4 areas with 6 specified goals.
5. Stewart (1988)	South Africa	Pilchard, anchovy etc.	Catch quota policies were formulated using an interactive decision support system (DSS) consisting of 3 methods: interactive multiple GP (IMGP), interactive sequential GP (ISGP), and STEP method (STEM). Thirteen attributes (or goals) for pilchard, anchovy, and other pelagic species were included for the examination of quota allocation using 3 interest groups.
6. Muthukude, Novak, and Jolly (1991)	Sri Lanka	n.a.	Fisheries development plans were investigated using a 4-year single time period WGP for 4 vessel types with 7 suggested goals, which include boat numbers, crew training, income, *etc.*
7. Weerasooriya, Hills, and Sen (1992)	Sri Lanka	Multi-species	The fleet requirements for 3 types of small vessel in Sri Lanka were optimized considering 3 goals: maximize catch, maximize internal rate of return, and maximize number of vessels.
8. Pascoe, Tamiz, and Jones (1997)	English Channel	Multi-species	Resource allocation and fleet composition with application to the UK fishery in the English Channel, using a large-scale WGP considering 35 goals (20,000 variables[1] and 1,700 constraints). Parametric programming was used to aid the evaluation of target values for the WGP.

[1] Separable programming is incorporated to estimate the nonlinear catch-effort curve.

Table 1. Continued

Reference	Region	Species	Comment
(*b*) *Generating Methods*			
1. Sylvia and Enríquez (1994)	Pacific, U.S.	Whiting	A hybrid of the weighting and constraint solution methods (see Chankong and Haimes 1983) to analyze policy management alternatives for the Pacific whiting fishery of the U.S.—3 objectives: maximizing the female spawning biomass, the present value of net revenues, and the output of the fishery. The generation of 16 solutions was done, modeling a 15-year time period.
2. Padilla and Copes (1994)	Philippines	Multi-species	The hybrid solution technique (see b.1. above) was used to solve a bi-criteria programming model analyzing and investigating management schemes for a small multi-species, multi-gear pelagic fishery. Catch allocation was considered for 7 major species fished by 9 fleets with 5 gear types, maximizing employment, and fishing profits. Two main policy scenarios are discussed.
(*c*) *Nonlinear Programming*			
1. Garrod and Shepherd (1981)	UK	Multi-species	An investigation of fishing effort input by the UK fleet—3 goals were considered: quota mismatch, fleet disruption, and economic efficiency. The conjugate gradient method was used to determine a solution. Shepherd (1980) and Shepherd and Garrod (1981) described this application of resource allocation as a "cautious" nonlinear optimization; *i.e.*, a weighted composite objective function.
2. Placenti, Rizzo, and Spagnolo (1992)	Italy	Multi-species	The analysis of optimal harvesting scenarios for Italian fisheries using the conjugate gradient method for solution—43 species and 4 gear types in 10 regions where economic, biological, inertia, and catch variables were optimized under 4 alternative scenarios.
3. Diaz de Leon and Seijo (1992)	Mexico	Octopus	Box's complex method was used to investigate resource management for the Yucatan (Mexico) octopus fishery under 3 scenarios with given decision maker goals for 8 objectives, including biomass, yield, employment, *etc*. Several scenarios were investigated, modeling external effects (Hurricane Gilbert) within the analysis. A simulation model was used to forecast the population dynamics of the fishery on a fortnightly basis. A nonlinear multivariate function subject to nonlinear constraints was developed.
4. Seijo, Defeo, and de Alava (1994)	Uruguay	Yellow clam	A MinMax approach using Box's complex optimization method was developed for the management of the yellow clam fishery of Uruguay—3 major objectives were analyzed: sustainability of the yield (and, therefore, net revenues), ensuring employment opportunities, and avoiding destruction of (other) resources.
5. Mardle *et al*. (1997)	North Sea	Multi-species	Resource allocation for the North Sea demersal fishery to the 7 main coastal states, for the 7 major species targeted for human consumption using 4 gear types. Predator/prey interactions and price flexibilities are included. Considered objectives are max. fishery rent, min. discarding, maintaining employment, and maintaining TAC distribution levels. Nonlinear WGP with 72 goals.

Table 1. Continued

Reference	Region	Species	Comment
(*d*) *Multi-attribute Utility Theory*			
1. Keeney (1977)	Skeena River	Salmon	Two experts asked to evaluate the developed additive and multiplicative utility functions in order to aid in policy decisions for salmon management—2 overall objectives were considered for 5 interest groups and 12 resulting attributes/objectives.
2. Hilborn and Walters (1977)	Skeena River	Salmon	Ten individuals' preferences were examined for the management of salmon. The 6 most important indicators were selected, and 4 enhancement policies were evaluated using multiplicative utility functions.
3. Bishop, Bromley, and Langdon (1981)	Alaska	Multi-species	Alaskan fisheries improvement—8 objectives including the equitable distribution of rents, maintaining stocks, improving the economy, enhancing family fishing, and economic efficiency. An optimal portfolio of the 14 attributes with respect to the objectives was determined.
4. Walker, Rettig, and Hilborn (1983)	Oregon	Salmon	An evaluation of the usefulness of MUA in order to assist fishery managers in developing Oregon coho salmon management policy—12 proposed policies were considered for 2 attributes; namely, average annual catch and wild escapement.
5. Healey (1984)	Skeena River, New England	Salmon	A comparison of management models of the Skeena salmon fishery (based on Keeney 1977), with 16 attributes and 6 management regimes, and the New England herring fishery, with 5 biological, 7 economic, and 8 social goals examining 9 management alternatives.
6. Healey (1985)	Gulf of Maine	Herring	An examination of the contradictory stance of fishermen who want stock rebuilding when catches are low, but a quick profit when recruitment is high, applied to policy management of the herring fishery in the Gulf of Maine. Short- and long-term returns were evaluated with other noneconomic factors in 5 simulations.
7. Bain (1987)	Michigan	Trout	The management of the Michigan trout fishery on the Au Sable River, where 13 forms of fisheries regulation and 4 attributes were included to analyze 3 management objectives.
8. Boutillier *et al*. (1988)	British Columbia	Multi-species	Twenty-six fisheries experts were asked to consider 76 of 192 invertebrate fisheries in British Columbia—13 invertebrate groups were analyzed based on 11 attributes in order to examine possible alternative commercial sampling schemes.
9. McDaniels (1995)	Pacific, N. America	Salmon	Alternative commercial fishery opening dates for salmon management are considered in the Chilko and Horsefly River tributaries of the Fraser River—6 objectives and 6 attributes are included in the analysis. An additive utility function is developed with a fishery manager.

Table 1. Continued

Reference	Region	Species	Comment
(*e*) *Analytic Hierarchy Process*			
1. DiNardo, Levy, and Golden (1989)	Maryland	Herring	Three main management policies were considered for the Maryland river herring fishery: close the fishery, restrict access, and allow open access. The model incorporates biological, political, economic, and social decision factors. Six levels with 57 nodes are modeled.
2. Merritt and Criddle (1993)	Kenai River, Alaska	Salmon	The model considered recreational fisheries management of chinook salmon in the Kenai River. The decision hierarchy contained 7 primary issues, with 182 issues and options in total.
3. Kangas (1995)	Eastern Finland	Multi-species	Six alternative fishing sites are considered for analysis, with 5 primary levels of the probability of catching 6 species of fish, suitability of 3 modes of fishing, accessibility, service facilities, and attractiveness measures of the environment.
4. Leung *et al*. (1998)	Hawaii	Multi-species	Four alternatives for limiting entry of longliners into the Hawaii pelagic fishery, where the bulk of the catch is tuna and swordfish. Determining the management goals and eliciting their weights was done using two questionnaires sent to members of four interest groups.
(*f*) *Multi-level Programming*			
1. Meuriot and Gates (1983)	U.S.	Multi-species	An evaluation of the value of foreign access to U.S. fisheries with respect to the imposition of fees. The two levels inherent in this application were the maximization of aggregate producers' surplus (outer) and maximization of decision maker (fleet/single vessel controller) profits (inner). Linear programming was used to model both stages, with a nonlinear catch-effort function modeled by piecewise linear segments.
2. Önal (1996)	Texas	Shrimp	A model of the Texas brown shrimp fishery was developed, allocating fishing effort to maximize harvest within economical and biological limits and to maximize the quality of harvest. The bi-level model consisted of the management authority and individual user groups. The computational difficulty was noted with respect to the solution, as a large, lower-level problem

$$\mathbf{x} \in \mathbf{X} \tag{7}$$

$$\mathbf{x} \geq 0 \tag{8}$$

where $\mathbf{x} \in R^n$ is the set of decision variables, $\mathbf{z}(\mathbf{x})$ is the set of k objective functions, and w_i are the weights associated with each objective, such that $w_i \geq 0,\ \forall i$ with $w_i > 0$ for at least one i. Thus, optimal solutions can be generated by parametric variation of w_i, initially set with arbitrary values.

Similarly, the mathematical representation of the constraint method is:

$$\max z_j(\mathbf{x}) \tag{9}$$

subject to

$$\mathbf{x} \in \mathbf{X} \tag{10}$$

$$z_i(\mathbf{x}) \geq b_i \quad (i \neq j) \tag{11}$$

$$\mathbf{x} \geq 0 \tag{12}$$

where $\mathbf{b}$ is a vector of lower bounds on $(k - 1)$ objectives $\mathbf{z}$, for all i except $i = j$.

The set of noninferior solutions can be produced by parameterization of w_i and b_i for each method, respectively. Hence, the methods generate (all) optimal solutions from which the decision maker can then adopt the solution that most closely represents their perception of the *best* scenario. Therefore, no *a priori* assessment of decision maker preferences is required. The constraint method has the advantage that Pareto efficient solutions will be determined, and it can also be argued that parameterization of objective lower bounds is more straightforward (Cohon and Marks 1975; Willis and Perlack 1980). However, in the constraint method, b_i must first be initiated (Cohon and Marks 1975).

Willis and Perlack (1980) compared these generating techniques with GP by investigating their effectiveness with four criteria. These included the three key criteria defined by Cohon and Marks (1975) for determining a MOP technique, combined with the validity of decision maker interaction. Generation of the noninferior set was found to be computationally explosive for large numbers of objectives ($k > 4$), but they fared well in the other criteria, offering maximum information to the decision maker, with possible graphical depiction of objective interaction for $k < 4$. Sylvia and Cai (1995) noted that methods such as these can be most consistently applied to fisheries policy problems based on a pluralistic (open) process. They also briefly discuss the usefulness of generating techniques for aid in fisheries policy decision-making.

In the two fisheries applications referenced in table 1, a hybrid of the weighting and constraint methods was used to analyze policy management scenarios. In both cases, only a portion of the objective space was investigated for analysis.

The main advantage of the technique raised by the authors was that the subjectivity of the modeling process was removed as weights and target values of the goals did not need to be preassigned. Instead, the decision maker is presented with a "menu" of potential solutions from which the desired allocation could be chosen (Padilla and Copes 1994). In addition, the technique makes explicit the tradeoffs between objectives that are not observed in a single objective model (Sylvia and Enríquez 1994). In both cases, a frontier of optimal outcomes was presented for a range of weights. The decision as to which combination is the most desirable can be made by the decision maker with full knowledge of the tradeoffs involved. For this reason, the approach was considered more appropriate as a means to identify potential management targets than goal programming, which generally aims to find a single "optimal" point that best satisfies the range of objectives.

The main disadvantages of the process noted by the authors, however, were that the models were complex and required considerable quantities of information and data. They also required the analyst to have an interdisciplinary knowledge of the system, and could be difficult to understand and evaluate by the decision makers (Sylvia and Enríquez 1994). As noted by Sylvia and Enríquez (1994), making the benefits of such multi-objective techniques outweigh the costs is the challenge that lies ahead.

Nonlinear, Multi-objective Programming

Most real-life problems exhibit some degree of nonlinearity. Multi-species bioeconomic fisheries models are a typical case, where the species' catch/effort relationships, catch prices, fishing costs (variable returns to scale), and biomass functions are nonlinear in nature. Such nonlinearities are often intrinsic to the real-life problem. However, due to solution limitations of (large-scale) nonlinear models, linear approximations may be necessary. Where appropriate, separable programming techniques can be used to transform a nonlinear curve into piecewise linear segments (Williams 1993).

The general definition of a nonlinear MOP follows the same form as that of the standard linear cases. However, the objective functions and/or constraint functions may take a nonlinear form. Therefore, any linear MOP model definition could feasibly take nonlinear status, although the optimization would become substantially more difficult, and the solution technique employed would typically differ considerably. Many mathematical programming modeling/solution packages currently available offer such nonlinear capabilities.

Nonlinear programming models with nonlinear equality and/or inequality constraints are considerably more complicated to solve than those with linear constraints (Gill, Murray, and Wright 1981). A variety of solution methods exist, and one should be selected which is appropriate to the model; *e.g.*, does the model include nonlinear equality and/or inequality constraints, and is feasibility a significant issue? Generally, a problem must be solved as a sequence of subproblems, due to ill-conditioned matrices (singularities) through the iterative procedure. Highly nonlinear models can lead to solution problems with derivative errors, very slow convergence, and/or tendency to a local optimum. Typically, unless specific known structures are used, the global optimum cannot be guaranteed by the optimizer. The most common approaches incorporated into nonlinear optimization solvers are typically variants of the gradient-type search methods.

Nonlinear, multi-objective programming fisheries models are given in table 1. These consider the investigation of fleet management, optimal harvesting strategies, resource management, and resource allocation. Although incorporating multi-objective properties, all of these examples use single objective nonlinear optimization methods for solution; *e.g.*, minimize the weighted sum of deviations. This is primarily due to the complexities involved in the models and solution process.

In the studies examined, the choice of nonlinear, multi-objective techniques over simple linear goal programming or linear generating methods was more a reflection of the underlying system being modeled rather than as an alternative multi-objective technique. In most cases, goal-programming techniques were used with a range of alternative weights. Nonlinearities were largely incorporated through either the underlying biological relationships or through endogenous prices. The key advantages, then, were that the models were better representatives of the fisheries than their linear counterparts. The main difficulties, however, were those facing nonlinear optimization. These include problems of local optima. For large, nonlinear models, additional constraints were required to ensure a feasible solution (see Mardle *et al*. 1997).

Multi-criteria Decision Analysis in Fisheries

The other distinct field of MCDM is multi-criteria decision analysis (MCDA). This is sometimes termed multi-criteria decision aid, multi-attribute decision analysis, or multi-objective decision analysis. Typically, MCDA is employed to analyze more general management issues than MOP; *e.g.*, which management policy is preferred, rather than how best to allocate resources given a set of objectives. Quantitative and qualitative aspects to the problem may be included in the model. In practice, there is usually only a small number of alternatives that are selected for investigation. The preferred option for implementation is determined using the MCDA technique. Management options are rated, scored, or ranked according to the preferences of the decision maker.

Two main types of MCDA have been applied to fisheries: multi-attribute utility theory and the analytic hierarchy process, both developed in the 1970s. The problems under consideration in fisheries are policy management, sampling strategies, resource management, fishery management, fishing site analysis, and recreational fishery management. These techniques tend to be general in terms of analysis, dealing with pure policy rather than specific quantitative plans.

Multi-attribute Utility Theory

Multi-attribute utility theory (MAUT) is based on the underlying idea that decision makers attempt to maximize their utility with respect to a number of criteria or independent attributes which often include implicitly present factors (Keeney and Raiffa 1976).

Applications of MAUT to fisheries problems are presented in table 1. The aims of the models are to provide management with supporting information for a number of proposed alternative scenarios. The majority consider the development of policy decisions for improved fishery management. However, other examples examine fishermen's behavior, sampling strategies, and fishery availability.

The additive model is the simplest and most common form, where the mathematical representation of the n-attribute additive utility function can be defined as,

$$u(\mathbf{x}) = \sum_{i=1}^{n} k_i u_i(x_i) \tag{13}$$

where $u_i(x_i)$ is essentially a scaled indicator of the desirability of the ith attribute $[0 \leq u_i(x_i) \leq 1]$, and k_i is the attribute utility weight[2] of the ith attribute ($\sum_{i=1}^{n} k_i = 1$). This additive form models an indifferent decision maker preference between any two attributes.

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[2] One method for calculating the k_i is to evaluate the utilities of two attributes subject to the best and worst consequences from an indifferent perspective (see Keeney 1977).

An alternative model consists of the *n*-attribute multiplicative utility function, which is often represented as,

$$ku(\mathbf{x}) + 1 = \prod_{i=1}^{n} [kk_i u_i(x_i) + 1] \tag{14}$$

where $0 \leq u_i(x_i) \leq 1$, and $\sum_{i=1}^{n} k_i \neq 1$. The scaling constant, k, is computationally dependent on the development of the attribute utility weights, k_i, where

$$1 + k = \prod_{i=1}^{n} (1 + kk_i) \tag{15}$$

Conversely to the additive utility function, the multiplicative model describes no indifference between attributes. These properties are generally intrinsic to the problem and should be investigated before analysis is undertaken.

In order to determine the level of utility associated with the level of each activity, it is common to hold workshops involving interested parties (often represented by an individual or small group). This is exhibited in the case study by Hilborn and Walters (1977), where after identification of the interest groups, individual preferences were modeled to develop the results and assess the alternatives in order to attain consensus. This feature of uncovering individual preferences so that quantitative and qualitative information can be incorporated into the model, is an important aspect of multi-attribute utility analysis (MUA). It, therefore, offers a focus for points of agreement and disagreement between interest groups (Hilborn and Walters 1977; Boutillier *et al*. 1988). McDaniels (1995) also discusses the development of technical and preference judgments by management team members in a workshop. The understanding and structuring of such judgments in a formal framework proved valuable for participants in developing difficult management choices.

A simpler form of model representation that has been used in the fisheries literature, termed by some as the simple multi-attribute rating technique, is given by,

$$U_i = \sum_{j=1}^{n} w_j S_{ij} \tag{16}$$

where u_i is a measure of the performance of the *i*th management regime, with $j = 1, \ldots, n$ attributes, and w_j is the weight associated with each attribute ($\sum_{j=1}^{n} w_j = 1$). The variable, S_{ij}, is a measure of the performance of the *i*th management regime against the *j*th attribute, typically $0 \leq S_{ij} \leq 100$, representing the range of possibilities from worst to best (Healey 1984, 1985; Bain 1987; Boutillier *et al*. 1988).

The applications all note the potential usefulness of this technique and the wide range of management options that can be easily considered. The key feature of MAUT is that it focuses on points of agreement and disagreement between the interest groups (Boutillier *et al*. 1988). Healey (1984) notes that the more sophisticated MAUT approaches have a disadvantage over simple MAUT, as they are more difficult to identify with. He also notes four main advantages of the simple MAUT technique. It provides a practical solution to multi-attribute decision problems, mimics the natural decision-making process, provides a structured analytic framework, and allows a broad range of information, both quantitative and qualitative. However, value judgments are a disadvantage. Simple MAUT is a practical and useful tool for fishery management decisions (Bain 1987). Walker, Rettig, and Hilborn (1983) comment that, generally, MAUT may offer a better perception of questions that need considering rather than a clear statement of answers.

Analytic Hierarchy Process

The analytic hierarchy process (AHP), developed by Saaty (1977, 1980), involves four main steps: (*i*) develop a hierarchy of interrelated decision elements describing the problem; (*ii*) perform pairwise comparisons on the decision elements, typically using a nine-point weighting scale, to generate the input data; (*iii*) compute the relative weights of the decision elements (*e.g.*, using the eigenvalue method); and (*iv*) aggregate the relative weights of the decision elements to calculate ratings for the alternative decision possibilities.

The AHP has been applied to a diverse range of applications (see Zahedi 1986). However, it is only in the last ten years that AHP has been applied to fisheries, and only to a small degree (table 1). Despite its simplicity, this decision analysis framework is remarkably powerful.

Most users of this technique have highlighted a number of weaknesses associated with each step of the method. There is no existing theoretical framework for establishing the hierarchy in step 1; *i.e.*, modeling a decision problem into a hierarchy. Instead, the specification of the hierarchy is subjective and can be influenced by the judgments of the modeler. An incomplete hierarchy can lead to counter-intuitive composite weights. The use of pairwise comparisons as the evaluator of the decision elements may lead to inconsistent rankings in step 2. Therefore, a consequence of this is that random errors may not be eliminated with consistency checks. Due to the many estimation methods that have been proposed and applied to compute the relative decision element weights in step 3, no single method appears to be more applicable than another for a given analysis. If more than one evaluator is present in the analysis (step 4), there is no preferred approach for the combination of judgments.

Leung *et al.* (1998) attempted to overcome these problems by sending a questionnaire to all individuals involved in the decision-making process (including fishermen and managers) to elicit the key objectives of concern. These included main criteria (*e.g.*, biological, social, economic, and political) as well as subcriteria (*e.g.*, employment and profit as part of the economic factors). Weights for each criteria were obtained by a subsequent survey using pairwise comparison of the identified goals. Geometric means were estimated to give an overall rank for each alternative. Results for the evaluation completed were found to be comparable to previous decisions made. It was felt that the mail surveys, although an acceptable method, lost vital interaction between the participants. However, the authors believe the AHP to be a valuable tool for many fishery decision management problems.

An advantage of the AHP is that it provides a complete decision-making framework for the analysis of appropriate fishery management problems (DiNardo, Levy, and Golden 1989). It allows managers to make use of their professional judgments and may include interest group preferences (Merritt and Criddle 1993). Similar to MAUT, value judgments are also incorporated in the process, giving decision makers the opportunity to explicitly state their preferences with respect to identified objectives.

Other (Multi-objective) Optimization Techniques in Fisheries

There are several other MCDM techniques that can be incorporated into the analysis and determination of natural resource management; *e.g.*, step method (Benayoun *et al.* 1971) and outranking methods such as ELECTRE and PROMETHEE (Vincke 1992). Other useful approaches include dynamic programming (Bellman 1957) and meta-heuristics (Osman 1996). The following applications are further indicators of the different approaches that consider multiple objectives in fisheries management.

Mathiesen (1981) considered the optimal size and structure of the Norwegian fishmeal industry with regard to four objectives: social profitability, private profitability, employment, and catching ability. Capelin, mackerel, and other species were of greatest significance to the industrial fishery. Parametric linear programming was used to analyze goal values for the multi-criteria model. The aim of this project was to allow decision-maker analysis of objectives in the industry, especially with respect to tradeoffs. However, with few results presented, definite conclusions were not made concerning the applicability of the method applied.

Kendall (1984) outlined an approach to investigate a typical problem inherent in fisheries management, that of multi-objective, multiple interest group, and interdisciplinary resource planning. The discussion outlined several approaches, including participation methods, multi-criteria decision-making, dynamic analysis, and adaptive implementation. The main purpose of this discussion was to consider a method which could potentially adapt to the multi-objective, participative, and dynamic demands of evolving fisheries management questions.

In an interactive decision support system, Stewart (1988) compared the step method (STEM)[4] (Benayoun *et al.* 1971) with two GP approaches for pelagic fish quota analysis (see the Linear Goal Programming section). The interactive multiple GP (IMGP) approach was deemed to be the most useful in this case and was reported to aid in reaching a consensus between the interest groups.

Charles (1989) described an optimal control theory procedure and used simulation for the analysis of four management objectives: total economic rent, fishermen's income, employment, and fishing community viability. A simulation of over thirty years was pursued that investigated two possible systems. The modeling framework was developed to assist in highlighting the data required to undertake such a detailed analysis.

Sylvia and Cai (1995) discussed an example illustrating their model as a nonlinear program in order to solve a policy problem that included the level of rent and biological impacts on nonmarket species to determine harvest rate. They concluded that multi-objective techniques, especially MOP, have significant potential in the development of fisheries policy issues.

Multi-level Programming

In structure, a multi-level program (which may also include multiple objectives) may be able to describe fisheries problems more "realistically" than other techniques. It is an approach that optimizes models in which the policy maker does not have complete control over all policy variables; therefore, it exhibits multiple levels to the problem structure. This contrasts with the multi-objective programming approach where the policy maker aims to optimize given objectives (Candler, Fortuny-Amat, and McCarl 1981). Some, or all, levels in the multi-level program may contain multiple objectives; however, the nested feature of multi-level programs may not, by default, be described as multi-objective. Therefore, while it may not be completely consistent with the MCDM philosophy in its general form, the pluralization nature of fisheries management models makes multi-level programming a potentially useful tool for policy analysis.

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[4] STEM progressively articulates decision-maker preferences by first setting up ideal (maximum) objective values on the k objectives, and subsequently seeking the decision maker to indicate at each stage of the solution process which objectives may be decreased to allow for possible improvements in others.

Multi-level programming is applicable to many planning and optimization problems which generally describe a hierarchical structure (see Candler, Fortuny-Amat, and McCarl 1981; Vicente and Calamai 1994). There are typically two or more decision makers involved with independent goals (some conflicting), where each decision maker has expertise over only part of the problem. The simplest and most commonly implemented case is the bi-level program, which can be extended into the multi-level case by subsequently making each level a further bi-level program.

The definition of the bi-level programming model is expressed as,

$$\max_x F(\mathbf{x}, \mathbf{y}) \tag{17}$$

subject to

$$f(\mathbf{x}, \mathbf{y}) \leq 0 \tag{18}$$

where for each value of x given, y is the solution of the lower-level problem,

$$\max_y G(\mathbf{x}, \mathbf{y}) \tag{19}$$

subject to

$$g(\mathbf{x}, \mathbf{y}) \leq 0 \tag{20}$$

For this bi-level case, F defines the upper-level objective function controlling the policy variables, $\mathbf{x}$. The lower level, G, then optimizes the response variables, y, given the decisions made by the upper level.

Multi-level programming provides a concept of nested optimization, where each level describes an optimization that relies on the outcome of the previous level. Although the natural structure of such a model includes an objective for optimization at each level, the underlying philosophy is not necessarily multi-objective. However, in order to model many "real" fisheries management problems, multiple objectives would need to be incorporated into the relevant level(s). Candler, Fortuny-Amat, and McCarl (1981) noted that multi-level programs are analytically difficult, and the recognition of such a problem is considerably easier than its solution. A recent and thorough bibliographic review of the topic is given by Vicente and Calamai (1994).

The solutions to such problems are not guaranteed to be Pareto optimal over all levels. However, it is argued that "incentive compatibility" provides a more accurate reflection of solution efficiency for problems of this kind (Meuriot and Gates 1983). That is, the position where no decision maker finds it advantageous to alter their behavior pattern if the others do not.

Even though many fisheries management regimes may follow a hierarchical structure, there have been few applications of multi-level programming for the investigation of fisheries management problems (table 1). Meuriot and Gates (1983) evaluated foreign access to U.S. fisheries with respect to the imposition of fees. While the authors generally agreed that multi-level programming provided a better representation of the system being modeled, the approach has computational difficulties. If more efficient solution algorithms were available, then many more interesting and needed applications would result (Meuriot and Gates 1983). Önal (1996) developed a model of the Texas brown shrimp fishery, although the complex multi-objective structure of the problem was not fully incorporated into the model.

Discussion and Conclusion

There is a significant level of diversity in fisheries management papers that specifically discuss the application of multiple-objective techniques. This implies that there is far greater importance attached to the subject matter than to the technique applied for analysis. Therefore, the passing reader will come across few MCDM fisheries publications discussing specific techniques, unless specifically searching. This gives a definite impression that there are far fewer publications in this area compared to other fields. Generally, the more publications that appear for a given topic, the more research is stimulated, and, thus, further publications are generated. The lack of published material does not necessarily imply that there is little or no work being undertaken in an area, but it inevitably appears as such. This leads to unfamiliarity of managers with the capability of certain techniques, and an unwillingness to trust the results obtained. If such an opinion is held by decision makers, then this is a crucial hurdle that such analysis must cross to prove its usefulness.

It appears from the publications cited that few of the applications of MCDM in fisheries management have actually been incorporated into the policy development process. However, it is difficult to confirm the extent to which such methods have been used in the decision-making processes due to the probable nonpublication of many of the models applied that ultimately determined fisheries policy. The applications discussed in this paper all report to be successful in developing the management aims under analysis, although many are presented as investigative studies. The MCDM techniques have generally been used to examine potential management policy measures, and have gained supporting evidence. Hence, the results of the analyses provide managers with an indication of the effects of possible management decisions. Correspondingly, such multi-objective methods may be having a greater impact on the direction and formulation of policy than is apparent.

The complex decision-making process that exists in the fisheries hierarchy (described as typically pluralistic [Sylvia 1992], and with an absence of structure [Bain 1987]) makes thorough problem definition and analysis considerably more difficult, especially when addressing the various interest groups in order to develop suitable fisheries policy. Moreover, not understanding the concepts of goals, objectives, and values in the fisheries management process leads to broadly defined goals without substantial justification (Barber and Taylor 1990). Such poorly defined goals increase the difficulty of applying and analyzing multi-objective models. However, the increased adoption of co-management and formalization of involvement of interest groups should help to reduce these problems. Further, to ensure that each group's interest is properly represented in the decision-making process, an objective and transparent decision-making system will be required. As a consequence, the role of MCDM in fisheries analysis is likely to increase.

Multi-level programming, although not strictly a multi-objective method, may model the fisheries management hierarchy to resemble the true structure of the problem more realistically. However, due to solution complexities, it is difficult to use this approach for large models, especially where multiple objectives are a necessary feature. Therefore, if a computationally efficient method for solution becomes available, then multi-level (multi-objective) programming may prove a significant approach for fisheries analysis. At present, it remains a potentially useful modeling technique.

Using the techniques with interactive procedures provides an extremely useful extension to investigating given scenarios. Such a facility offers decision makers a procedural process, and, therefore, greater flexibility in refining their utility towards stated objectives. This allows a more direct path to obtaining an "efficient" or "best compromise" or "incentive compatible" solution. Stephenson and Lane (1995) argue for "conceptual change" in fisheries management by proposing "a new discipline of Fisheries Management Science" in order to provide a framework for effective management (Lane and Stephenson 1995, p. 215). The MCDM techniques are highly significant in such a development.

There are many avenues for further research which could be investigated using MCDM in fisheries management. For example, existing techniques can be combined with others, such as Delphi (achieving consensus among experts), and the AHP with goal programming as in other applicational fields, to establish utility in terms of weights and quantities. Generally, the techniques can be applied to aid in analysis of a variety of scenarios in order to offer advice and direction for policy implementation. Scenario analysis is an important and effective part of determining strategy definition.

Undoubtedly, MCDM can play an important role in the development of fisheries management policy. It is clear that with pressure being exerted on fisheries to be well managed and sustainable, the capability to include multiple objectives for analysis in the modeling procedure is important. The question that Rettig (1987) asks, "are bioeconomic models really helpful?" is central to the development of MCDM within the management process. However, for economists to have an impact on fisheries management decisions, consideration needs to be given to the multiple objectives of fisheries management. While this may lead to a less-than-optimal outcome from a purely economic efficiency perspective, it is likely to result in a better outcome than if economic efficiency was not considered at all.

Fisheries managers, as in most fields of management, require advice, direction, and justification for possible action. Given the multi-objective nature of most fisheries policies and the growing involvement of multiple user groups in policy formulation, multi-criteria decision-making models are highly applicable to fisheries management.

This paper is not intended to discuss every work mentioning multi-objective techniques in fisheries, but rather to provide an overview of the type of applicational work that has been undertaken in recent years. Based on the applications cited, it can be concluded that multi-criteria decision-making can play a useful and significant role in fisheries management.

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Appendix

Distribution of Papers

There is a wide distribution of fisheries applications papers using MCDM. This is apparent in that there is an average of two publications cited per journal (1.9 per source, including proceedings, *etc*.). The content of journals in which such papers appear also varies considerably. The output rate is small over the twenty years of referenced papers, with thirty-eight applicational publications, averaging approximately 1.73 per year. This statistic is dramatically reduced if emphasis is placed only on a specific optimization approach. However, since 1977, publications concerning fisheries applications using MCDM have appeared consistently (figure 1), even though typically only one or two papers each year.

The distribution of papers that discuss the use of MCDM techniques for fisheries in the fifteen cited journals and proceedings, *etc*., is depicted in figure 2. Of these, *Marine Resource Economics* has published the most such papers with six since 1985.

A breakdown of publications by MCDM technique is given in table 1. (Note that Stewart (1988) is included twice; *i.e*., GP and other). The majority of work is spread over a variety of sources and not confined to one specific journal for cited publications. Goal programming and multi-attribute utility theory have been the most common forms of analysis used.

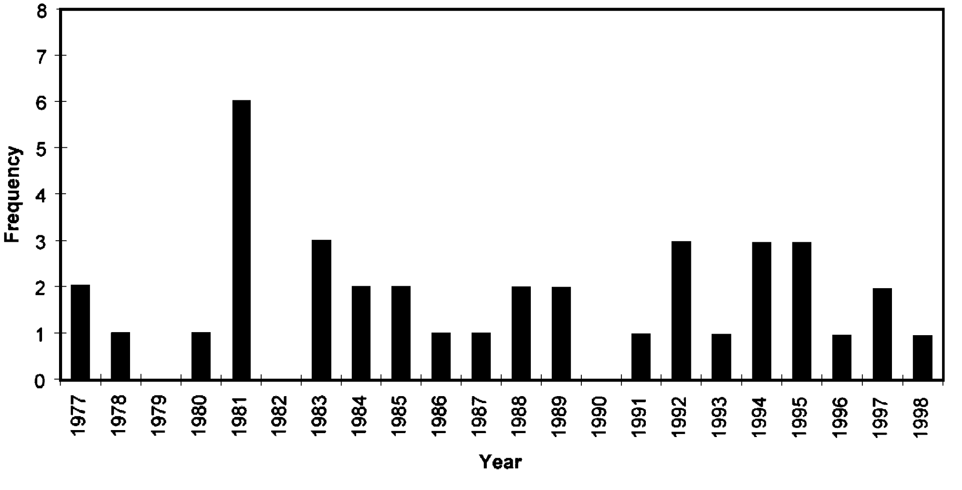

Figure 1. Number of MCDM Fisheries Application Publications Per Year

Note: Figure 1 includes all thirty-eight multi-objective application papers cited. However, table 1 does not contain the "other" multi-objective methods category. Further, where authors have published more than one paper on a particular topic, table 1 lists the first publication and then discusses the others in the "Comment" column.

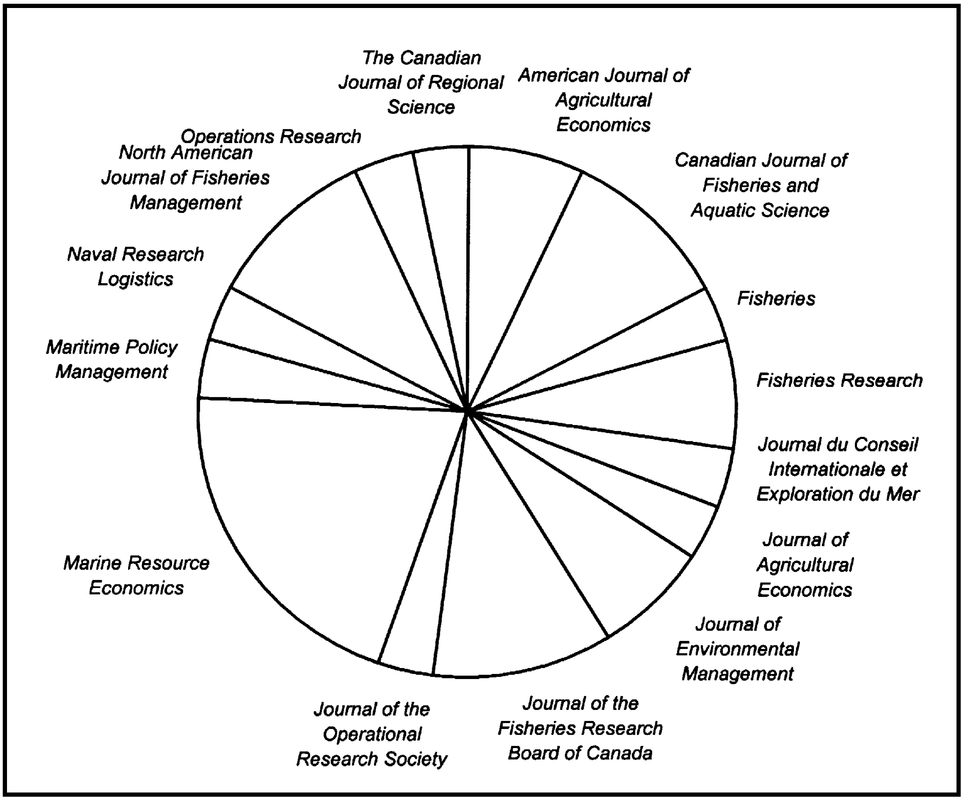

Figure 2. Proportion of MCDM Fisheries Application Publications by Journal