
North American Journal of Fisheries Management
Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/ujfm20

# A Decision Support Model for Fisheries Management in Hawaii: A Multilevel and Multiobjective Programming Approach

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Available online: 08 Jan 2011

*North American Journal of Fisheries Management* 21:293–309, 2001


# A Decision Support Model for Fisheries Management in Hawaii: A Multilevel and Multiobjective Programming Approach

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*Abstract.*—Management of Hawaii's fisheries faces great challenges due to rapid growth that has intensified competition among fisheries and users with different interests. This study develops and applies a multilevel and multiobjective programming model to assist decision making in Hawaii's fisheries. The multilevel aspect of the model incorporates objectives of both policy makers and fishermen. The use of a multiobjective model is essential in fisheries management because the typical fishery policy problem is characterized by more than one objective or goal that decision makers want to optimize. The model covers 9 fleet categories, 5 fishing areas, 4 seasons, and 14 species, of which 10 are targeted species. Catch per unit of effort (CPUE) includes targeted and incidental catch species. A nonlinear relationship between CPUE and effort is incorporated into the model. By use of the various objectives or policy options of fisheries management, the current model provides optimum solutions in fishing effort and its spatial and temporal distribution, as well as the optimal harvest level. The current model has been applied to evaluate several management issues facing Hawaii's fisheries. Application of the model indicates that the trade-offs between recreational and commercial fishing vary by effort level. At the current fishing effort level, an increase of one recreational trip reduces commercial profit by US$12.14. Moreover, the study concludes that the area closure regime designed to reduce conflict between commercial and recreational fishing can cause profit loss to the commercial fisheries in the range of $0.44 million to $0.70 million.



Marine fisheries have a long history in Hawaii, and they have both economic and cultural importance to the state. Hawaii's commercial fisheries industry generated US$63 million exvessel revenue from 32 million pounds of commercial landings in 1996 (NMFS 1997). In addition, there are three other components of Hawaii's marine fisheries that also contribute substantially to the state in terms of their economic and cultural values: (1) recreational fishing, (2) subsistence fishing, and (3) charter fishing (Pooley 1993).

During the last two decades, Hawaii's commercial marine fisheries have experienced rapid growth and structural change. The dramatic development of the longline fishery contributed most to the growth. The rapid development of Hawaii's fisheries brought with it important biological, economic, and social impacts. Competition among fisheries and/or user groups with different interests for the limited resources has intensified, and consequently fisheries management faces great challenges in trying to balance the needs and interests of different groups while protecting the fisheries resources at the same time. In general, the central political issue facing Hawaii's fisheries management is how to balance all of these interests and to allocate the uncertain quantities of fish between segments of the fishery (Pooley 1993). However, research regarding distributive issues in Hawaii's fisheries is inadequate to support fisheries management (Skillman et al. 1993). Lack of quantitative measurement and analysis tools for the relative benefits and costs related to the various human components of the fisheries increases the difficulty of the decision-making process; thus, each regulation is undertaken with a high degree of uncertainty concerning its effect on the participants in the fisheries (Pooley 1993). Therefore, to improve fisheries management, an analytic tool is needed to evaluate the impacts of management actions from the perspective of the entire fishery as well as those of its various sectors. Research methodologies used to reveal trade-offs in terms of costs and benefits to the entire fishery, as well as to each individual segment under different management objectives or policy options, can be useful

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Received June 9, 1999; accepted August 15, 2000

in determining the optimal policy for Hawaii's fisheries management.

Mathematical programming is capable of solving a problem that has many decision variables within a multiobjective and multilevel environment. Therefore, it is an attractive approach for quantitative analyses in a complex fishery system (Meuriot and Gates 1983; Drynan and Sandiford 1985; Diaz-De-Leon and Seijo 1992; Önal 1996). Optimal control theory and simulation techniques are frequently used in quantitative research for fisheries management as well. However, computational difficulties hinder the use of optimal control theory in empirical research with a very large number of decision variables, and simulation techniques are unable to provide an endogenously determined solution of decision variables. In contrast, the mathematical programming technique operates at a highly disaggregated level. Moreover, it provides a particularly useful methodology to study distributive and operational issues facing fisheries management (Gunn et al. 1991). The mathematical programming technique has been applied to fisheries modeling and has addressed such issues as effort allocation, fishery industry structure, regulation scheme and impact, and harvest strategy for decades (Rothschild and Balsiger 1971; Anderson et al. 1981; Shepherd and Garrod 1981; Ahmed 1992; Sylvia 1994; Herrick et al. 1997).

In one application of the mathematical programming technique, a linear programming model was developed for the Northwestern Hawaiian Islands fisheries (E. R. G. Pacific, Inc., 1986; Kasaoka 1989). The initial intent of that model (hereafter referred to as the National Marine Fisheries Service linear programming [NMFS LP] model) was to analyze the potential impact of a limited-entry program on various fisheries in Hawaii and on the economic performance of various fishing fleets. However, this effort was not particularly successful, because the results of a baseline run of the model did not realistically depict the actual fisheries situation in Hawaii (E. R. G. Pacific, Inc., 1986; Pooley 1993). Further, Miklius and Leung (1990), in an evaluation of the NMFS LP model, concluded that the omission of microlevel decision making by the fishermen and the omission of decision makers' objectives other than simply profit maximization contributed to unrealistic solutions from the model.

Therefore, an appropriate modeling technique that includes multiobjective and multilevel analysis is needed to model Hawaii's fisheries to assist the decision-making process (Leung et al. 1999). In previous studies, however, the applications of mathematical programming models for multispecies fisheries were limited to linear programming models in which the stock–effort–catch per unit of effort (CPUE) relationship was constant and the species component of CPUE was fixed (Siegel et al. 1979; Shepherd and Garrod 1981; Overholtz 1985; Murawski and Finn 1986; Gunn et al. 1991). Moreover, the applications of multiobjective programming models in fisheries economics and management were limited to single-level modeling (Drynan and Sandiford 1985; Sylvia 1994), and the applications of multilevel programming models were limited to single-objective modeling (Meuriot and Gates 1983; Önal 1996). The objective of this study is to develop a multilevel and multiobjective programming model for Hawaii's fisheries to provide a decision support tool for fisheries management. This model is the first to incorporate both multiobjective and multilevel analyses, as well as the possible nonlinear catch–effort relationship of the multispecies fisheries for fisheries management.

The two-level multiobjective nonlinear programming model developed in this study allows fisheries management to consider the behavior of individual fishermen as well as fishery managers. The multiobjective formulation considers the importance of other management objectives, such as recreational fishing and employment opportunities, in addition to the profit-seeking commercial-fishing activities. By use of the various objectives (goals) and/or policy options facing Hawaii's fisheries, the current model not only provides optimal solutions for effort and catch and their spatial and temporal distributions but also can be used to evaluate the trade-offs between policy goals. This method can be positivist in the sense of identifying economic impacts of particular regulation or exogenous events and can be illustrative in the sense of simply comparing different regulatory states.

To illustrate the use of the current model as a decision support tool for fisheries management, this study applied it to several issues that are associated with the management of Hawaii's fisheries. Specifically, the model has been used for the following purposes: (1) to estimate the impact of change in the total available stock, (2) to assess the impact of declining CPUE, (3) to evaluate the trade-offs between recreational and commercial fishing, and (4) to estimate impacts of the longline area closures.

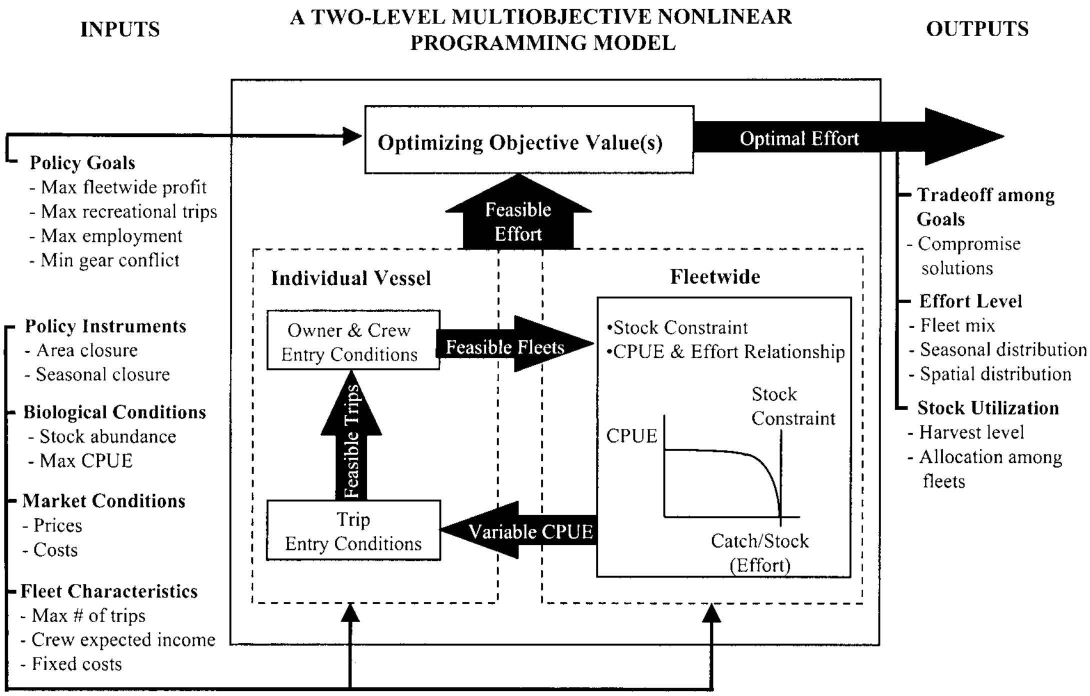


FIGURE 1.—Model structure and outline of the two-level and multiobjective nonlinear programming model.

## Model Description and Structure

A simple representation of the model and of its related inputs and outputs is given in Figure 1. Optimal solutions from solving the model can be viewed as the outputs of the model, whereas policy goals and instruments, as well as the parameters that represent biological, technological, and economic conditions of the fisheries, can be viewed as inputs to the model.

The mathematical formulations of the nonlinear two-level and two-objective model are illustrated in Table 1. The three components of the mathematical programming model, namely, decision variables, constraints, and objective functions, are further elaborated below. The present model is solved on a personal computer aided by the mathematical programming software General Algebraic Modeling System (GAMS Development Corporation 1996).

### *Decision Variables*

Fishing effort is an important decision variable in fisheries management. In the United States, effort control—such as limited entry, seasonal closures, area closures, and effort quotas—is a common practice in fisheries management. Therefore, fishing effort constitutes the decision variables in the current model. Because Hawaii's fishery is composed of heterogeneous fleets with respect to vessel sizes, gears, targets, fishing grounds, fishing seasons, and motivations, a comprehensive measure of effort is needed to capture the variations of the fishing activities in the fishery. Therefore, fishing effort (the decision variables) is expressed not only in terms of the number of vessels in various fleets (fleet mix) but also in terms of fishing strategies to capture the variations in fishing activities. In other words, the model will not only select the number of vessels from different fleets but also select fishing strategies, such as targeted species in different fishing grounds during various seasons, to achieve fleetwide optimal objectives. Thus, fishing effort can be represented by the use of a set of four-dimensional decision variables. The four dimensions are fleet categories, targeted species, fishing areas, and fishing seasons (Pan 1998).

The classification of the nine fleets is illustrated in Figure 2, and the delineation of the five areas is illustrated in Figures 3 and 4. The 10 target species are shown in Table 2. The four seasons are specified as November–January, February–May, June–August, and September–October. In all, there are 508 decision variables depicting the fishing

TABLE 1.—The mathematical formulation for the multilevel and multiobjective programming model.

**Objective functions**

(1a) $$\text{Max} \sum_i \sum_j \sum_k \sum_l \sum_s N_{ijkl}E_{ijkl} - \sum_i \sum_j \sum_k \sum_l \omega_i(d^f_{ijkl} + d^t_{ik})E_{ijkl} - \sum_i fc_iV_i \quad \text{for } i = 2 \text{ and } 4\text{–}9$$

(1b) $$\text{Max} \sum_i \sum_j \sum_k \sum_l E_{ijkl} \quad \text{for } i = 1 \text{ and } 3$$

**Constraints**

(2) $$E_{ijkl} - \epsilon_{ijkl}V_{ijkl} \le 0 \quad \forall\, i, j, k, l$$

(3) $$V_{il} - \sum_j \sum_k V_{ijkl} = 0 \quad \forall\, i, l$$

(4) $$V_i - V_{il} \ge 0 \quad \forall\, i, l$$

(5) $$\sum_i \sum_j d^f_{ijkl}R_{ijkls}E_{ijkl} \le s_{kls} \quad \forall\, k, l, s$$

(6) $$A_{kls} = 1 - \left(\frac{Q_{kls}}{s_{kls}}\right)^n = 1 - \left(\frac{\sum_i \sum_j d^f_{ijkl}R_{ijkls}E_{ijkl}}{s_{kls}}\right)^n, \quad n = 10 \quad \forall\, k, l, s$$

(7) $$R_{ijkls} = r_{ijkls}A_{kls} \quad \forall\, i, j, k, l, s$$

(8) $$N_{ijkl}E_{ijkl} \ge 0 \quad \text{for } i = 2, 4\text{–}9 \quad \text{and} \quad \forall\, j, k, l$$

(9) $$(A_{kls} - 0.9)E_{ijkl} \ge 0 \quad \text{for } i = 1 \quad \text{and} \quad \forall\, j, k, l$$

(10) $$\left[0.51 \sum_s (p_{ils}d^f_{ijkl}R_{ijkls}) - 0.3c_{ijkl}\right]E_{ijkl} \ge 0 \quad \text{for } i = 3 \quad \text{and } \forall\, j, k, l$$

(11) $$\left(\sum_j \sum_k \sum_l (1 - \alpha_i)N_{ijkl}E_{ijkl} - fc_iV_i\right)V_i \ge 0 \quad \text{for } i = 2 \text{ and } 4\text{–}9$$

(12) $$\left(\sum_j \sum_k \sum_l \alpha_iN_{ijkl}E_{ijkl} - \omega_i(d^f_{ijkl} + d^t_{ik})E_{ijkl}\right)V_i \ge 0 \quad \text{for } i = 2 \text{ and } 4\text{–}9$$

**Indices, variables, and parameters**

Indices of variables

$i$: fleet; $i = 1, \ldots, 9$

$j$: target species; $j = 1, \ldots, 10$

$k$: area; $k = 1, \ldots, 5$

$l$: season; $l = 1, \ldots, 4$

$s$: species; $s = 1, \ldots, 14$

Variables

$N_{ijkl}$: trip net revenue (\$/trip); $N_{ijkl} = \sum_s (p_{ils}d^f_{ijkl}R_{ijkls}) - c_{ijkl}$

$E_{ijkl}$: number of trips of fleet $i$ targeting species $j$ in area $k$ during season $l$

$V_i$: annual fleet size (number of vessels) of fleet $i$

$R_{ijkls}$: variable catch rate of species $s$ for effort (trip type) $E_{ijkl}$ (pounds/day)

$V_{ijkl}$: number of vessels of fleet $i$ targeting species $j$ in area $k$ during season $l$

$V_{il}$: number of vessels of fleet $i$ during season $l$

$A_{kls}$: catch per unit of effort (CPUE; daily catch rate) coefficient (value ranges from 1 to 0)

$Q_{ksl}$: total catch of species $s$ in area $k$ during season $l$ (pounds)

TABLE 1.—Continued.

| | |
|---|---|
| Parameters | |
| $\omega_i$: | expected wage per working day of entire crew in a vessel of fleet $i$ (\$/day) |
| $d^f_{ijkl}$: | trip fishing days for effort $E_{ijkl}$ (days/trip) |
| $d^t_{ik}$: | trip travel days for effort $E_{ijkl}$ (days/trip) |
| $d^f_{ijkl} + d^t_{ik}$: | trip length (days at sea) for trip $E_{ijkl}$ (days/trip) |
| $fc_i$: | fixed costs for a vessel in fleet $i$, including opportunity costs of investment, depreciation, maintenance, and insurance (\$/year) |
| $p_{ils}$: | fish price for species $s$ caught by fleet $i$ during season $l$ (\$/pound) |
| $c_{ijkl}$: | variable costs (travel costs, fishing costs, and turnaround costs) for $E_{ijkl}$ (\$/trip) |
| $\epsilon_{ijkl}$: | maximum number of trips for vessel $V_{ijkl}$ |
| $s_{kls}$: | total available catch of species $s$ in area $k$ during season $l$ (pounds) |
| $r_{ijkls}$: | maximum catch of species $s$ per fishing day for $E_{ijkl}$ (pounds/day) |
| $\alpha_i$: | crew share of net revenue for fleet $i$ (value ranges from 1 to 0) |
| $(1 - \alpha_i)$: | owner share of net revenue for fleet $i$ (value ranges from 1 to 0) |

effort for all possible combinations of fleets, targeted species, areas, and seasons.

*The Definition of CPUE*

The CPUE is an essential element in a bioeconomic model. In this study, CPUE is defined as a composite of targeted catch and incidental catch, and it is measured as the pounds of actual catch by species per fishing day. In agreement with the definition of the four-dimensional variables of fishing effort in the model, CPUE (including quantity and species components) varies by fleet, targeted species, area, and season.

The definition of CPUE adheres to the assumptions of production technology, jointness-in-input, and input–output separability in the model. Jointness-in-input implies a nonseparate harvesting process for multispecies product, and decisions about production of a species are dependent on decisions about other species (Squires 1987; Kirkley and Strand 1988). Separability between inputs and outputs implies that there is no specific interaction between any one species and any one input; then, it is possible to specify the technology in terms of a single composite output and a single composite input (Kirkley and Strand 1988). Hawaii's fisheries (pelagic fishery, bottomfish fishery, and lobster fishery) are all multispecies fisheries, and the harvest of one species can lead to the harvest, intentional or not, of another species. Also,

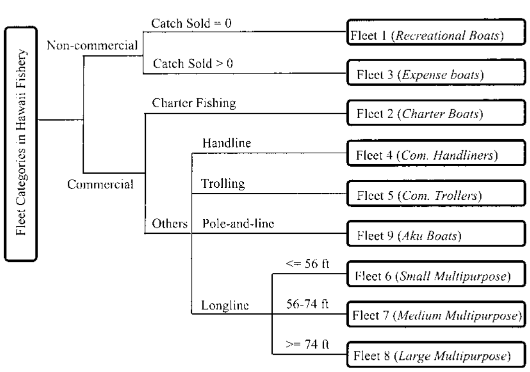


FIGURE 2.—The nine fleet categories and definitions of Hawaii's fisheries.

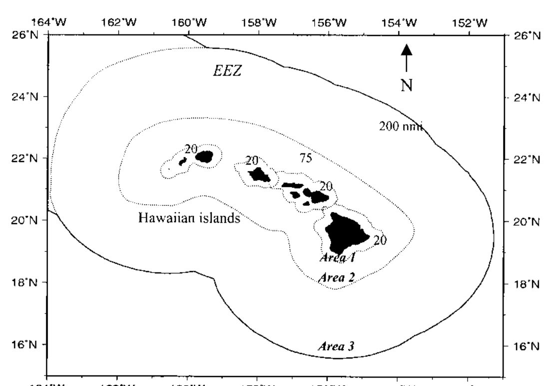


FIGURE 3.—The fishing areas of Hawaii's fisheries: areas 1–3 (adapted from the maps provided by D. R. Kobayashi of the NMFS, Honolulu Laboratory). Abbreviations are as follows: EEZ, exclusive economic zone (200-mile limit); and nmi, nautical miles.

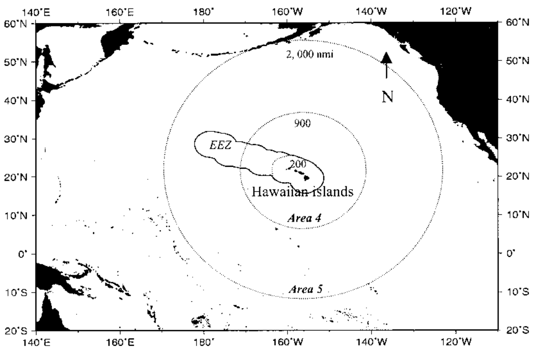


FIGURE 4.—The fishing areas of Hawaii's fisheries: areas 4 and 5 (adapted from the maps provided by D. R. Kobayashi of the NMFS, Honolulu Laboratory). Abbreviations are defined in Table 3.

a species that is an incidental catch for one fishery can be the targeted catch of another fishery. Such technologically interdependent fisheries may result in conflict between different fishing activities. Therefore, the definition of CPUE in this study allows the model not only to account for the total catch from all the fishing activities but also to consider the incidental catch. However, the formulation of CPUE in the current model considers only the nature of technical interaction and does not include the possible economic interaction of multispecies production.

The model includes 14 species or species groups that cover all the species caught and landed by Hawaii-based vessels (Table 2). Among these 14 species or groups, 10 are commonly targeted by different groups of fishermen in Hawaii's fisheries. Because the targeted species is usually the dominant component of CPUE, a species is defined as a targeted species if it is the majority of the landings of a fishing trip. In Hawaii, a species that is a target of one type of fishing effort could be an incidental catch of another type of fishing effort. For instance, blue marlin *M. mazara* is a target species for the recreational and ''expense'' fishermen (fleets 1 and 2), but it is an incidental catch of the longline fishery (fleets 6−8), which targets bigeye tuna *T. obesus* or swordfish *X. gladius.* Therefore, the incidental catch can be any possible combination of the other 13 species, whereas a targeted species is the dominant composition of CPUE. Fishermen may switch targets seasonally according to changes in fish abundance. However, most fishermen do not switch targets during a trip, due to the restrictions of technology and bait. To simplify the model, this study assumes that a single species is targeted during each trip and that fishermen do not switch their target during a trip.

There are two different formulations of the CPUE in the current model that are based on various assumptions of the effort and catch relationship. Many studies suggest that intensive local fishing pressure can reduce CPUE in a local area, without affecting abundance of the stock as a whole (Gulland 1968; Sathiendrakumar and Tisdell 1987; Boggs 1992). It is useful to consider such relationships and to evaluate the impact of the possible decline in CPUE on the fisheries. Therefore, the present study assumes two possible relationships between CPUE and effort, a constant catch rate (CCR) and a variable catch rate (VCR), as shown in Figure 5. Total catch can be linearly or nonlinearly related to total effort, depending on

TABLE 2.—Species or species groups included in the model.

| Species ($s$) | Common name | Scientific name | Species group | Targeted species ($j$) |
|---|---|---|---|---|
| 1 | Yellowfin tuna | *Thunnus albacares* | Pelagic | Yes |
| 2 | Bigeye tuna | *T. obesus* | Pelagic | Yes |
| 3 | Albacore | *T. alalunga* | Pelagic | No[a] |
| 4 | Skipjack tuna | *Katsuwonus pelamis* | Pelagic | Yes |
| 5 | Swordfish | *Xiphias gladius* | Pelagic | Yes |
| 6 | Blue marlin | *Makaira mazara* | Pelagic | Yes |
| 7 | Striped marlin | *Tetrapturus audax* | Pelagic | No |
| 8 | Dolphin | *Coryphaena hippurus* | Pelagic | Yes |
| 9 | Wahoo | *Acanthocybium solandri* | Pelagic | Yes |
| 10 | Sharks (mainly blue sharks) | *Prionace glauca* | Pelagic | No |
| 11 | Other pelagic fish | | Pelagic | No |
| 12 | Bottomfish (mainly snappers, sea basses, and jacks) | Lutjanidae, Serranidae, and Carangidae | Bottomfish | Yes |
| 13 | Lobster (spiny and slipper) | Palinuridae and Scyllaridae | Lobster | Yes |
| 14 | All others | | Miscellaneous | No |

[a] A few vessels (longline and handline) occasionally target albacore.

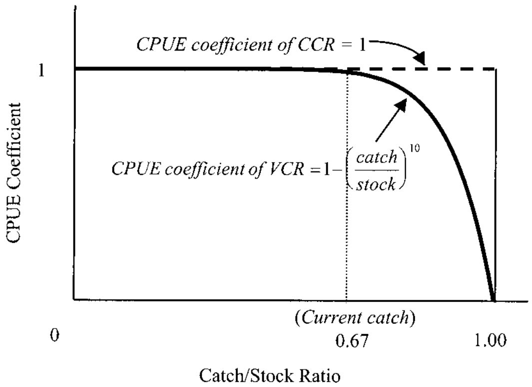


FIGURE 5.—The assumed relationships between catch per unit of effort (CPUE) and effort. Abbreviations are as follows: CCR, constant catch rate; and VCR, variable catch rate.

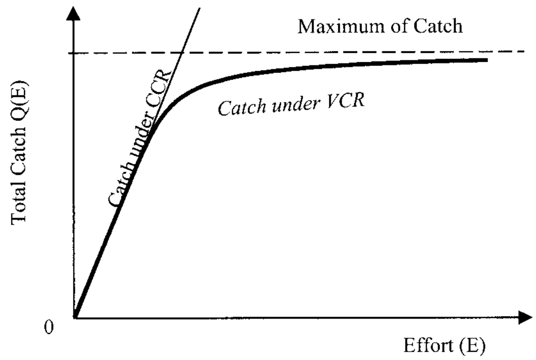


FIGURE 6.—The relationships between catch and effort based on the different assumptions of catch per unit of effort and effort relationships. Abbreviations are as follows: CCR, constant catch rate; and VCR, variable catch rate.

the two different assumptions regarding the CPUE and effort relationship (Figure 6).

If a nonlinear relationship between catch and effort is included in the model, the CPUE is a set of variables, in addition to the variables of fishing effort, of the current model. Otherwise, CPUE is a set of parameters of the current model. Although there are a total of 508 decision variables in the CCR formulation, approximately 7,000 decision variables are employed in the VCR formulation.

### *Objective Functions*

The number of objective functions incorporated into a multiobjective programming model depends on the problem at hand and the availability of information on it. Conservation is an essential goal of fisheries management in Hawaii (WPFMC 1998). The conservation goal (to protect fishery resources) is incorporated into the model by specifying total available catch constraints. To evaluate the trade-offs between commercial and noncommercial (including recreational and traditional subsistence) fishing, this study constructs a two-objective model. The two objectives considered in this study are (1) maximizing fleetwide profit and (2) maximizing recreational (or noncommercial) trips. These two objective functions are represented as equations (1a) and (1b) in Table 1.

Profit maximization is a behavioral assumption underlying any commercial activity based on positivist economic theory. Fleetwide profit can be derived by subtracting trip variable costs, expected crew income (representing the shadow price of labor), and fixed charges from the gross annual fleet revenue. Thus, fleetwide profit represents precisely the economic rents of the entire fishery if all inputs are priced at their shadow costs and outputs are valued at the margin.

Placing a value on noncommercial fishing involves complicated theoretical and philosophical concerns. In this study, the value of noncommercial fishing is measured by the total amount of participation, that is, the number of fishing trips taken by the recreational and traditional subsistence fishermen. Obviously, there are problems with the use of recreational fishing trips as a proxy for recreational fishing value. However, it is also clear that recreational fishing includes a variety of objectives, some of which are related to the availability of fish and some of which are not. The few economic studies on recreational fishing in Hawaii indicate clearly that the option to go fishing is probably as important if not more important than the catch itself. However, the optimal number of recreational fishing trips that resulted from this model increases if the availability (catch rate and local stock) of target species increases.

### *Trip and Vessel Constraints*

Equations (2)–(4) illustrate the relationship between the number of trips and the annual fleet size. Equation (2) represents the limitation of the maximum number of trips a vessel takes in a season $(_{ijkl})$. Equation (3) indicates that the seasonal fleet size ($V_{il}$) is defined as the aggregate number of vessels targeting various species ($j$) in various areas ($k$) in a season ($l$). This equation is included in the model to depict the seasonal variation of fishing activities of each individual fleet. Equation (4) indicates that the annual fleet size for a specific fleet ($V_i$) is defined as the largest fleet size among the four seasons of the fleet. This formulation accounts for annual fixed costs as long as the vessel is active in any one season.

### Stock Constraints

In this study, the total available catches in the areas exploited by Hawaii-based vessels represent the stock constraints or resource abundance for the fisheries. Equation (5) indicates that the aggregate catch of a given species, area, and season is less than or equal to the estimated available catch for that species and area during the same season. The dynamic aspects of a stock are often of most concern in fishery management research. Because the main catches of Hawaii's fisheries are highly migratory pelagic species and they comprise only a small fraction (about 8%) of Pacific-wide fisheries, catches from Hawaii's fisheries are unlikely to cause a stock effect and the consequential reduction of the overall abundance of the stock. Therefore, the dynamic impacts of fish mortality are not considered in this model; thus it is a static model. The stock constraint in the model represents local fish abundance that is associated with the rate of fish immigration and recruitment in a limited area. For Hawaii's pelagic fisheries, the current formulation may represent the long-run stock condition. However, for bottomfish and lobster fisheries, stocks are related to the reproduction and growth of resident fish; our specification of stock constraints represents only the short-run status of those stocks.

### The Effort and CPUE Relationship

The relationship between CPUE and catch is expressed mathematically in equations (6) and (7). It is assumed that each type of effort is associated with a specific initial (or maximum) value of CPUE ($r_{ijkls}$), which is determined by the stockwide abundance condition. A coefficient ($A_{kls}$), with a value that ranges from 1 to 0, is used to represent the degree of decline of CPUE that is associated with effort level. In the CCR formulation, the coefficient equals 1 for any effort level and CPUE is constant; in the VCR formulation, by contrast, the higher the effort the lower the value of the coefficient, and thus the lower the value of CPUE. Thus, the catch by one type of effort has an impact on the catch of another type of effort if they catch the same species, as defined by the VCR formulation. The VCR formulation is based on the assumption of previous studies that CPUE may decline as effort increases and total catch may increase toward an asymptote (Gulland 1968; Sathiendrakumar and Tisdell 1987; Boggs 1992).

The rate at which CPUE diminishes is dependent on the value of $n$ in equation (6), given the fixed amount of total available catch (exploitable stock) $s$ and total catch $Q$. We assume that the exploitable stock for Hawaii's fisheries is about 50% more than the current catch because there are no available empirical estimates of the exploitable stock. Thus, the maximum ratio of catch ($Q$) to total available catch is 0.667 within the current level of fishing effort. A time series study of Hawaii's pelagic fisheries from 1962 to 1992 indicated that no statistically valid relationship between catch rates and expanded fishing effort exists (He and Boggs 1996). We assume that the CPUE curve declines very moderately if fishing effort is limited to the current level in which the crowding effect is too small to result in a notable decline of CPUE. However, when fishing effort exceeds the current level, CPUE is assumed to decline at an increasing rate. The desired shape of the CPUE curve can be represented adequately with a value of $n$ equal to 10, in which CPUE does not substantially decline until the point at which the catch-to-stock ratio equals 0.667.

Because the CCR formulation assumes that CPUE remains at the same level for any effort level, the total catch increases proportionally to the effort increase (Figure 6). On the other hand, the VCR formulation presumes a nonlinear relationship between effort and total catch. As a result, fleetwide profit is nonlinear with respect to effort level, and it increases when effort level is low but eventually declines.

### Microlevel Entry Conditions

As discussed previously, the NMFS LP model omitted microlevel decision making by fishermen and consequently resulted in an unrealistic solution. Ideally, the two-level problem should be solved via optimization at the fishermen's level nested within optimization at the fishery managers' level. However, there is no practical solution algorithm for such a nested hierarchy model, particularly given the nonlinear nature of the current model (Önal 1996). To keep the model manageable and solvable, the optimization at the fishermen's level is approximated by a set of entry conditions in this study. In other words, it was assumed that fishermen would make their decisions to enter and continue fishing depending on certain conditions or expectations. These entry conditions include the trip-entry condition, the crew-entry condition, and owner-entry conditions. Under such a formulation, this model does not capture any dynamic adjustment of an individual fisherman's behavior, such as an increase of trip length or a lowering of the fisherman's expectations of entering the fishery, in response to the selection of policy instruments by the public sector. However, this model may predict some potential fleetwide behavior changes such as fleet size, targeting strategies, and the associated catch components by incorporating various policy options into the model.

*Trip-entry conditions*.—Fishermen decide whether or not to fish each production period. The appropriate time span for the short-run production process of the fishing vessel is the length of a fishing trip (Doll 1988). For commercial fleets, a trip is feasible if the revenue gained at least covers the operating costs, stated as equation (8). The noncommercial fishermen of fleets 1 and 3, who are not seeking income or profit from fishing activities, may have to meet certain conditions to continue their fishing practices. Recreational fishermen (fleet 1) may expect a certain percentage of successful fishing trips or expect a certain level of CPUE. The entry condition of this fleet, stated as equation (9), is the lower bound of the coefficient of CPUE, arbitrarily defined as 90%. Expense fishermen may expect a certain amount of revenue from fish sold to cover a portion of their fishing expenses. The entry condition of the expense fleet [equation (10)] was based on the actual practices reported in a recent study by Hamilton and Huffman (1997), in which expense fishermen sold about 51% of their catch and the revenue from fish sales covers at least 30% of the trip expenses.

*Owner-entry condition*.—The owner-entry condition is specified only for commercial fleets (fleets 2 and 4–9). It ensures that an owner's return adequately covers their investment in the long run [equation (11)]. Because most of the owner's expenses are fixed on an annual basis, the owner-entry condition specifies that the owner's annual net income be greater than or equal to fixed costs. Expected owner returns are built into the fixed costs, which include the opportunity costs of investment, depreciation, maintenance, and insurance. Therefore, a fleet ($V_i$) is feasible only if the annual income to the owner is greater than or equal to annual fixed costs.

*Crew-entry condition*.—The crew-entry condition [equation (12)] is included in the model to ensure that crew income is sufficient to attract crew members to engage in the fishery. For commercial fleets, the crew (including the captain) expects certain income from fishing; otherwise, they can be expected to switch to other types of employment. Therefore, the crew-entry condition specifies that the crew's annual income be greater than or equal to their expected income from other sources. Like the owner-entry condition, the crew-entry condition is specified for commercial fleets only. Moreover, due to the variations in labor intensity and the crew's motivation within the commercial fleets, the crew-entry condition is specified on the basis of the actual crew size and the expected returns of the crew for each individual fleet.

To account for the total rent associated with the fisheries, the present study measures labor cost by analyzing the crew's expected income instead of the returns that actually go to the crew, a fixed share of net revenue, or the gross catch. This approach was taken because the actual returns to the crew contain part of the rent, as the crew obtains a share of the gross or net returns. In addition, the traditional methods used in fisheries economic research that have assumed that all costs are directly proportional to effort would result in management schemes that overtax vessel owners (Griffin et al. 1976). To avoid this distortion and account for the rent accruing to crew, the fleetwide profit defined in this study accounts for the rent shared by the use of fixed labor costs.

The crew's satisfaction with their income does not imply that the owner breaks even in the fishing operations and vice versa. For instance, low-quality crews may enter fisheries with low expected incomes. The specification of the crew-entry condition in the model does not explicitly block the entry of low-quality crews. However, if low-quality crews enter the fisheries, the annual costs (other than labor costs) may increase and catch may decline, eventually resulting in reduction of the net returns to both owner and crew. Even though the crew may be willing to continue in the fisheries, the owner-entry condition may not be satisfied. Therefore, a commercial fleet is economically feasible on an annual basis only if both crew- and owner-entry conditions are satisfied.

In some fisheries, income from fishing fluctuates over years, and fishermen (crew and owner) may be willing to operate below their expected income in a year if they expect a higher income in the next year. However, the current model only covers a 1-year period. For the model to represent a long-run equilibrium, the parameters of expected return to the crew should be generated from a normal year or an average over a certain time period.

TABLE 3.—Optimal fleet structure under different stock conditions.

| Conditions and fleet structure | 1993 catch | 150% of 1993 catch | Difference (ratio) | 1995 catch | Difference (ratio) |
|---|---|---|---|---|---|
| Stock conditions | | | | | |
| Total available catch (million pounds) | 35.1 | 52.7 | 1.5 | 37.9 | 1.1 |
| Optimal solutions | | | | | |
| Recreational trips (1,000 trips) | 87 | 131 | 1.5 | 97 | 1.1 |
| Commercial vessels (number) | 358 | 537 | 1.5 | 325 | 0.9 |
| Charter boats | 45 | 68 | 1.5 | 20 | 0.4 |
| Commercial handliners | 163 | 245 | 1.5 | 147 | 0.9 |
| Commercial trollers | 64 | 96 | 1.5 | 89 | 1.4 |
| Small multipurpose boats | 14 | 21 | 1.5 | 28 | 2.0 |
| Medium multipurpose boats | 6 | 9 | 1.5 | 17 | 2.8 |
| Large multipurpose boats | 52 | 78 | 1.5 | 18 | 0.3 |
| Aku boats | 14 | 21 | 1.5 | 6 | 0.4 |
| Fleetwide profit ($ million) | 30.3 | 45.4 | 1.5 | 28.6 | 0.9 |



## Data

This section provides a brief summary of the sources and procedures used in generating parameters for model validation and applications. Only 1-year data (mostly in 1993) are used. Model parameters were calibrated such that for each fleet, total catch = CPUE per trip × number of trips per vessel × fleet size. Although there is no guarantee that such a process provides ''real'' parameters and constants for the model, it provides for internal consistency among all the parameters and constants. In addition, consistency checks for all parameters of the model are necessary because data came from three independent sources: the Hawaii Division of Aquatic Resources (1993) catch reports, the NMFS (1993) longline logbook, and the Joint Institute for Marine and Atmospheric Research (JIMAR) cost-earning surveys (Hamilton et al. 1996; Hamilton and Huffman 1997).

The baseline model, a single-objective model of profit maximizing with a fixed number of recreational trips and the constant CPUE (CCR) model, is constructed to test the current model. In general, the optimal result from the baseline model seems plausible, although there are differences between the outcome of the baseline model and the actual situation of Hawaii's fisheries. As expected, the optimal total catch is less than the actual catch, whereas total economic rents are higher because the model is supposed to provide the optimal allocation of efforts seasonally and spatially (Pan 1998).

## Applications

The applications of the model as a quantitative tool in the decision-making process rely on scenario or sensitivity analysis and the various algorithms provided by the mathematical programming approach. Policy options can be analyzed as different scenarios. By comparing the optimal solutions that resulted from different scenarios, decision makers may estimate regulatory impacts and determine important choice variables. Sensitivity analysis of an additional objective allows decision makers to evaluate the trade-offs between various management objectives. Moreover, sensitivity analysis of changes in the coefficient matrix provides information on how sensitive is the optimal solution response to changes in the uncertain natural and economic elements embedded in the parameters, such as stock, CPUE, and the prices of inputs and outputs. However, this decision model is quite restricted because it is static and does not model the decision–response process. This section illustrates the applications of the current model in analyzing several issues associated with Hawaii's fisheries management as a quantitative tool in assisting the decision-making process.

### *The Impacts of Total Available Catch*

The first application is to evaluate the impact of stock conditions (total available catch) on the optimal solution. The application indicates that a proportional change in fish stock for every species results in the same optimal fleet mix, whereas the optimal fleet mix will change if the relative abundance of different species changes.

If 150% of the 1993 actual catch is used as the total available catch constraint of the CCR formulation, the optimal fleetwide profit increases by exactly 50%, and total catch increases also by 50%, compared with the optimal solution determined with 100% of the 1993 actual catch as the total available catch constraints (Table 3). The op-

TABLE 4.—The optimal fleet mix and rent distribution (variable-catch-rate [VCR] versus constant-catch-rate [CCR] formulation).

| | Number of vessels | | | Profit ($1,000) | | |
|---|---|---|---|---|---|---|
| Fleet | VCR | CCR | Ratio | VCR | CCR | Ratio |
| Recreational | | | | | | |
| Recreational boats | 2,490 | 2,490 | 1.00 | | | |
| Expense boats | 952 | 952 | 1.00 | | | |
| Commercial | | | | | | |
| Charter boats | 43 | 68 | 0.64 | 617 | 962 | 0.64 |
| Commercial handliners | 169 | 245 | 0.69 | 2,530 | 4,884 | 0.52 |
| Commercial trollers | 77 | 96 | 0.80 | 1,398 | 1,622 | 0.86 |
| Small multipurpose boats | 7 | 21 | 0.33 | 805 | 1,910 | 0.42 |
| Medium multipurpose boats | 11 | 9 | 1.22 | 1,386 | 1,284 | 1.08 |
| Large multipurpose boats | 60 | 78 | 0.77 | 14,560 | 14,205 | 1.02 |
| Aku boats | 15 | 21 | 0.71 | 1,562 | 2,070 | 0.75 |
| Total recreational | 3,442 | 3,442 | 1.00 | | | |
| Total commercial | 382 | 537 | 0.71 | 22,858 | 26,936 | 0.85 |

timal number of vessels of each fleet increases proportionally as the total available catch for each species increases proportionally; thus, the structure of the fleets (fleet mix) does not change.

However, when the actual catch in different years is applied to the CCR formulation as stock constraints, the total available catch for each species is not proportional to the total available catch in 1993. In this case, the optimal fleet structure changes, as does the optimal profit. The optimal fleet structure resulting from the run in which the 1995 actual catch was used as the total available catch in the model is presented in Table 3. The optimal fleet structure (fleet mix) changes under these different stock conditions. For example, the optimal size of the large multipurpose fleet in the 1993 scenario is 52 vessels, and it is a dominant fleet for the three longline fleets. However, in the 1995 scenario, the optimal size of the large multipurpose fleet is reduced to 18 vessels, whereas the other two multipurpose fleets more than double their optimal fleet sizes compared with the 1993 scenario. The results suggest that multipurpose vessels of the longline fishery should comprise the principal fleet during the years with higher swordfish stock. However, if bigeye tuna and yellowfin tuna *T. albacares* are relatively abundant, small and medium multipurpose vessels are more profitable for Hawaii's longline fishery. Therefore, such a short-run mathematical optimum is not necessarily a management optimum. To determine an appropriate (or management optimum) fleet structure for Hawaii's longline fishery would require an evaluation based on the long-run conditions of the fish.

### *The Impacts of Declining CPUE (VCR Formulation)*

If CPUE declines as effort increases, the nonlinear relationship between catch and effort is modeled by equations (5) and (6). These two equations indicate that the CPUE of a specific species is associated with the aggregate catch, including direct catch and indirect catch. Determined with 150% of the actual catch as stock constraints, the optimal fleet structure yielded by the VCR formulation is summarized in Table 4. The optimal solution of the CCR formulation is presented in the same table for comparison.

In terms of effort, the VCR formulation suggests that the optimal number of vessels for all of the commercial fleets is 382, whereas the optimal number resulting from the CCR formulation under the same stock constraints is 537. In other words, if CPUE declines as effort increases, optimal effort in terms of the number of vessels is only 71%, and total catch is about 74%, of what they are when the CPUE is constant. The results differ because the fleetwide profit is not linear with respect to effort if CPUE is not linear with respect to effort. At the beginning, fleetwide profit increases as effort increases, but it eventually declines as effort increases to a certain level. The optimal solutions show that the stock constraint is not binding in the VCR formulation, whereas it is binding in the CCR formulation. Furthermore, the impact of the two formulations (CCR versus VCR) is not uniform among fleets, and the changes of fleet size range from 33% to 122%. Thus, the optimal fleet structure resulting from these two models is different. Optimal fleetwide profit yielded from the VCR for-

TABLE 5.—Optimal harvest rates from variable-catch-rate (VCR) and constant-catch-rate (CCR) formulations.

| Species | 1993 actual catch | Stock constraints (ratio to 1993 catch) | Optimal catch/stock | |
|---|---|---|---|---|
| | | | CCR formulation | VCR formulation |
| Targeted species | 30,997 | 1.50 | 1.37 | 0.99 |
| Yellowfin tuna | 6,162 | 1.50 | 1.47 | 1.06 |
| Bigeye tuna | 5,110 | 1.50 | 1.38 | 1.03 |
| Swordfish | 9,697 | 1.50 | 1.44 | 1.00 |
| Skipjack tuna | 3,517 | 1.50 | 1.49 | 1.13 |
| Groundfish | 1,115 | 1.50 | 1.37 | 1.03 |
| Blue marlin | 2,689 | 1.50 | 1.14 | 0.79 |
| Dolphin | 1,679 | 1.50 | 1.00 | 0.68 |
| Wahoo | 1,028 | 1.50 | 0.90 | 0.66 |
| Nontargeted species | 4,111 | 1.50 | 0.92 | 0.70 |
| Albacore | 1,265 | 1.50 | 0.89 | 0.61 |
| Striped marlin | 1,758 | 1.50 | 1.10 | 0.85 |
| Shark | 154 | 1.50 | 0.80 | 0.68 |
| Other pelagic | 887 | 1.50 | 0.63 | 0.53 |
| All others | 47 | 1.50 | 1.39 | 0.97 |
| Total | 66,105 | 1.50 | 1.35 | 0.97 |

mulation is about $22.8 million, which is 85% of the CCR results, whereas the optimal number of vessels was only 71% of the CCR results.

The VCR formulation dictates that no single species can be fully utilized under an optimality scenario, unlike the CCR formulation that results in full utilization of the total available catch for many species. The optimal catch that resulted from the VCR formulation is 33.5 million pounds, which is about 71% of the CCR formulation.

The optimal harvest rates from the CCR and VCR formulations are presented in Table 5. The left column lists the actual catch for each species in 1993. If there are assumed to be 50% more fish than the actual catch, the total available catch used as the stock constraint is 150% of the 1993 catch. When CPUE is constant, the CCR formulation suggested that the optimal catch could increase to 37% more than the actual catch for the targeted species. For some species, such as yellowfin tuna, we could harvest 47% more than the actual catch, assuming that there are 50% more yellowfin tuna than the actual yellowfin tuna catch. However, if CPUE declines as effort increases, the optimal harvest level is much lower than that if CPUE remains constant as effort increases, given the same amount of total available catch. For example, we could only harvest 6% more yellowfin tuna, 3% more bigeye tuna, 13% more skipjack tuna *K. pelamis*, and 3% more groundfish (Lutjanidae and Serranidae), under the same assumption of the total available catch used in the CCR formulation. Swordfish is very sensitive to the CPUE decline. The optimal catch of swordfish under the VCR formulation is almost the same as the actual catch. This implies that the profit margin of swordfish fishing is very limited under the current CPUE level and that any decline in CPUE (as suggested by VCR formulation) precludes increases in fishing effort.

### *Trade-Offs between Recreational and Commercial Fishing*

Allocation of fish between recreational and commercial segments has become one of the central issues facing Hawaii's fisheries management. Therefore, this study examines the trade-offs between the management objectives of recreational and commercial fishing in Hawaii.

The recreational objective is evaluated by recreational-fishing participation as measured by the number of recreational trips, whereas the commercial objective is evaluated by the profit generated from the commercial fleets. The noninferior set estimation (NISE) method developed by Cohon et al. (1979) is used to map out the trade-offs of the two management goals. The NISE method is the most effective technique to solve two objective problems (Romero and Rehman 1989). The detailed procedures of mapping the trade-off curve were discussed in Pan (1998).

The trade-offs between recreational and commercial fishing are examined within the current effort level. Therefore, the current catch is used as the total available catch (stock constraint) of the model, and the CCR formulation is used to generate the trade-off frontier because we assumed that there was no appreciable decline in CPUE when fishing effort does not exceed the current

TABLE 6.—The payoff matrix of recreational and commercial fishing.

| Objective | Commercial objective ($Z_c$) ($ million) | Recreational objective ($Z_r$) (1,000 trips) |
|---|---|---|
| Maximize $Z_c$ (point A) | 18.54 | 43.61 |
| Maximize $Z_r$ (point B) | 14.47 | 161.99 |

level. The payoff matrix for recreational trips and commercial profit of Hawaii's fisheries is presented in Table 6. The payoff matrix displays the degree of conflict between the two objectives. Maximum commercial profit is $18.54 million when the number of recreational trips is limited by its lower bound of 43,610 trips, which represents 50% of the actual number of recreational trips in 1993. This is represented as point A in Figure 7. However, the maximum number of recreational trips can be as many as 161,990 trips, but with this many trips, commercial profit has to drop from $18.54 million to $14.47 million (point B). Thus, computed from the two extreme points, the average trade-off of one recreational trip to commercial profit are $34.25. In other words, increasing recreational trips by one may lead to a reduction of $34.25 in profit in commercial fishing.

However, the trade-off curve is not necessarily a straight (linear) line between the two extreme points (A and B) because the degree of conflict between the two objectives can vary in different parts of the trade-off curve. The NISE method employs a weighted objective function to generate the trade-off curve that represents the set of noninferior solutions, assuming that the feasible region in the decision space (and therefore the objective space) is a convex set. The trade-off curve between the number of recreational trips and fleetwide profit for Hawaii's fisheries generated by the NISE method can be seen in Figures 7a and 7b. Figure 7a illustrates the trade-off curve in terms of recreational trips to commercial profit, whereas Figure 7b illustrates the same trade-off curve in terms of commercial profit to recreational trips.

As illustrated in Figure 7a, the trade-off curve in the section between point A and point A1 is flatter than the average trade-offs represented by the segment AB, whereas another section of the trade-off curve, the segment between point A1 and point B, is steeper than the average trade-off. This implies that the trade-offs between recreational trips to commercial rent in the range from 43,610 trips (point A) to 152,300 trips (point A1) are lower than the average trade-off. In this range, an increase of one recreational trip will require a commercial profit reduction of $13.16, whereas the average reduction in profit per recreational trip for the entire trade-off curve is $34.25. On the other hand, further increases in recreational trips beyond point A1 can cause much higher marginal profit loss. The slope of points A1 and B is –$272.45 per trip, which means that, on the average, an increase of one recreational trip in the range from 152,300 to 161,990 causes $272.45 in profit reduction. The trade-offs can be evaluated in terms of the number of trips to one unit of profit (Figure 7b). For example, the trade-off values for the increase of commercial profit to the reduction in the number of trips are low in the range from point B to point A1, where commercial effort is low and recreational effort is high. An increase of $100 of commercial profit in the range from $14.5 million to $17.0 million will cause a reduction of less than one trip (0.37) of recreational fishing between

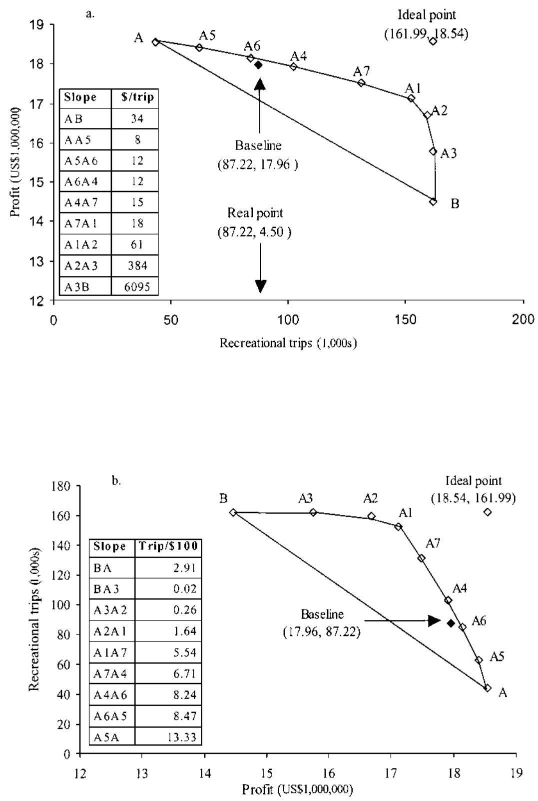


FIGURE 7.—**(a)** The trade-off curve of recreational trips to commercial profit for Hawaii's fisheries. **(b)** The trade-off curve of commercial profit to recreational trips for Hawaii's fisheries.

point B and point A1. However, an increase of $100 of commercial profit in the range from $17.0 million to $18.5 million will cost 7.6 recreational trips.

The technological interdependence (the interaction on stocks by different fishing operations) between recreational and commercial fishing leads to the various trade-off values along the trade-off curve as effort level changes. When recreational fishing effort is low, catch competition for the species caught by both recreational and commercial fishermen is less intense. The stock constraint for most species that are targeted by recreational fishermen and also caught by commercial fishermen as incidental catch is not binding. In this situation, an increase of one unit of recreational catch requires a trade-off value of less than one unit of commercial catch. However, as effort shifts to the recreational sector, the stock constraint for the species that are the target of recreational fishermen becomes increasingly binding, whereas the stock constraint for the species that are targeted by commercial fishing may become less binding. Then an increase of one unit of recreational catch requires reduction in a greater amount of commercial catch. According to the NISE analysis, when recreational participation falls in the range between 43,610 trips (point A) and 152,300 trips (point A1), it only needs to offset 27 pounds of commercial catch for every recreational trip, which yields 47 pounds of fish on average in Hawaii's fisheries. However, if the number of recreational trips exceeds 152,300 trips and approaches the maximum (point B), an increase of one recreational trip leads to a reduction of about 571 pounds of commercial catch. The average trade-off (point A to point B) of one recreational trip to commercial catch is 55 pounds.

Currently, the estimated recreational participation in Hawaii is about 87,220 trips annually. This point is located in the range between point A6 and point A4 of the trade-off curve. Within this range, the marginal trade-offs to commercial fishing of one recreational trip, which yields 47 pounds of fish on average, is $12.14 in terms of commercial-fishing profit, or 22 pounds in terms of commercial catch. This implies that, for the current effort level in Hawaii, the trade-offs to commercial fishing of one recreational trip is less than the average trade-off.

To date, fishery managers have tried to alleviate the conflict between recreational and commercial fishing through area restrictions on longline fishing. In terms of the reverse relationship, it would be fishing mortality by recreational fleets that would diminish the availability of fish for the commercial fleets. For example, if we increase the number of recreational fishing boats by 10% from the current recreational effort, then the trade-off from such a change is a $106,000 profit loss to the commercial fleets. On the other hand, if recreational fishing were dominated by catch-and-release ethics, then the model would not capture this effect, and the trade-offs would be one-sided. However, there is also the possibility, indeed the reality, of crowding between the weekend warriors (the mostly recreational and expense small-boat fishermen) and the full-time small-boat commercial fishermen (who tend to fish more during the week than on the weekend). We could not find a convenient method for dealing with congestion in this analysis without setting ad hoc standards.

TABLE 7.—The optimal profit and catch under different scenarios.

| Policy option | 1990 stock Profit ($ million) | 1990 stock Catch (million lbs) | 1993 stock Profit ($ million) | 1993 stock Catch (million lbs) |
|---|---|---|---|---|
| Open access | 7.69 | 12 | 18.4 | 26.42 |
| Area closure | 6.99 | 11 | 17.96 | 26.35 |
| Difference | −0.70 | −0.94 | −0.44 | −0.07 |

*The Impacts of Area Closure*

An area closure regulation was imposed on Hawaii's longliners in 1991 (WPFMC 1991). The purpose of the area closure is to eliminate the physical gear conflict between the longline fishery and the other fisheries. To investigate the costs of this policy (in terms of profit loss), this study applied the model under two scenarios (the open access and area closure scenarios). To estimate the possible range of the cost, the same analyses are conducted with the actual catch figures from 1990 (the year before the area closure regime was fully implemented) and 1993 (the year after the area closure regime was implemented) as the stock constraints.

The summary of these analyses is presented in Table 7. When the actual catch of 1990 was used as the stock constraint, the optimal commercial profit in the area closure scenario is $6.99 million, which is $0.70 million less than that in the open access scenario, and the total optimal catch in the area closure scenario is 0.94 million pounds less than that in the open access scenario. When the actual catch of 1993 was used as the stock constraint, the differences in catch and profit between these two scenarios are less than when the actual catch of 1990 was used as the stock constraint. The commercial profit in the area closure scenario is $0.44 million less than that in the open access scenario, and the total catch in the area closure scenario is 0.07 million pounds less than that in the open access scenario.

Because the actual catch in 1993 after the area closure is greater than the actual catch in 1990 before area closure and pelagic fish are highly migratory, it is unknown whether longline fishermen could have caught those fish before they moved into the closed areas or whether these fish could have simply passed by the islands when no one was able to catch them because of area closure. Therefore, the loss of $0.70 million in profit under area closure determined with the 1990 catch as a stock constraint can be viewed as the upper bound of commercial loss for reducing gear conflict, whereas the loss of $0.44 million in profit under the area closure determined with the 1993 catch as the stock constraint can be viewed as the lower bound of the cost for reducing gear conflict.

## Conclusions

Applications of this model suggest that it provides a useful quantitative tool with which fisheries managers can quantify the possible impacts of certain policy instruments, endogenous changes within the fisheries, or exogenous changes to Hawaii's fisheries. The predicted impacts that are fleetwide are given through scenario analysis, even though any endogenous change of individual fishermen's behavior is not included. The results obtained from the model applications are summarized as follows: First, the longline area closure apparently causes a decline of profit to the commercial fleets in a range of $0.70 million to $0.44 million if recreational fishing is fixed at the current effort level. Second, the trade-offs between recreational and commercial fishing vary by effort level. At the current level of effort, an increase of one recreational trip reduces commercial profit by $12 and commercial catch by 22 pounds. This study suggests that if total recreational trips exceed 152,300 trips (about double the current recreational participation), the cost of each additional recreational trip in terms of commercial profit loss would increase dramatically (from $13.16 per trip to $272.45 per trip). Third, the economic efficiency of Hawaii's commercial fisheries could improve if the number of handline vessels increased and longline vessels were more flexible in switching targets because the relative abundance of fish resources affects the choices of optimal fleet mix (fleet structure).

## Potential Uses of the Current Model

The model can be extended and applied to examine other issues of concern in Hawaii's fisheries management and to evaluate the impact of policy options associated with these issues. For example, the catch and sale of blue marlin caught by longline fishermen as incidental catch have lately been an issue facing the Western Pacific Fishery Management Council (WPFMC). The WPFMC would need to know the impact of this ban on the longline fishery to determine whether it should be considered as a regulatory policy. The current model, by setting the price of blue marlin at zero, may be applied to evaluate the economic impact of banning blue marlin sales on the longline fishery and the other fisheries in Hawaii.

Recently, another issue is the incidental mortality of protected species (e.g., green sea turtle *Chelonia mydas* and seabird albatrosses [Diomedeidae]) by longline vessels, which has been one of the major management problems facing fisheries managers in the WPFMC. A number of technical and operational measures, as well as other regulation regimes such as area closure, might be introduced within Hawaii's longline fishery to attempt to reduce or eliminate this incidental mortality of seabirds. However, these measures may cause the fisheries to assume different degrees of loss. Technical measures may result in an increase in operating costs, operational measures may actually reduce the catchability of targeted species, and regulatory regimes may reduce the total available catch. To assist the decision maker in choosing a suitable or acceptable policy option for the longline fishery, the current model can be used to evaluate the impacts of the various policy options.

## Model Limitations

Like other models, the current model is just a simplification of the real world. Thus, the generated results should be treated as indicative of reality rather than an exact representation of real effects. The results are only as good as the data and the assumptions used in constructing the model. Several potential areas for further development of the model include use of an alternative approach to model bilevel optimization, consideration of the dynamic aspects of stock, and incorporation of some constants in the form of stochastic elements. The present model offers a starting point for developing a more advanced dynamic model. With a more dynamic framework, many of the model's limitations would no longer exist. Also, entry conditions would become more realistic because expected returns can be adjusted over time. However, due to the complexity of the current model, incorporating dynamic aspects may lead to trade-offs between a tractable model and a computationally more difficult model.

## Acknowledgments

This research is funded by Cooperative Agreement NA37RJ0199 between JIMAR and the National Oceanic and Atmospheric Administration. We thank JIMAR for supporting this research and for making the data available. We also thank Fang Ji for assistance with the programming algorithm and Stuart T. Nakamoto for valuable comments toward the improvement of this research.



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