AN EXPOSITION ON THE DEFINITION OF FISHING EFFORT[1]

BRIAN J. ROTHSCHILD[2]

ABSTRACT

The term "fishing effort" is well defined in population dynamics literature. The term as defined in the population dynamics literature is, however, difficult to reconcile with broader definitions of fishing effort, particularly those having economic implications. The present paper discusses the distinction between the definitions and gives some examples in the context of allocating inputs, the capacities of fishing boats, and several stocks to the catch in a manner which maximizes profits. Managerial behavior is also an important input to the fishing process; this is discussed in a decision theory format where decision quality can be measured relative to entropy in the decision environment affording a comparison among decision environments in terms of information and an imputed valuation of a bit of information under various circumstances. The conventional measures of the quality of the decision environment are often based upon expected catch. Alternate measures are discussed which include the expected loss or the risk involved in the decision process.

The deployment of fishing effort is one of the fundamental components of fishery management. While fishing effort has been rather precisely defined in the population dynamics literature, effort has not been well defined in its broadest context. This paper considers the definition of fishing effort with special reference to the development of techniques which are useful not only for the definition of effort in the usual strategic sense, but for the definition of effort in the tactical and operational sense as well. This definition is requisite for considering fishing as a total system (see Rothschild, 1971).

The transformation of wild stocks of fish into the "catch" is generally considered to be mediated by the quantity of fishing effort expended in the process of harvesting the catch. The measurement of the magnitude of fishing effort is of central importance to the theory of the dynamics of exploited fish populations because the various "optimal" catches which are developed in this theory must ultimately be related to optimal quantities of fishing effort. On one hand it seems quite obvious that fishing effort should be related to quantities that can be thought of as "inputs" to the fishing process, quantities such as hours fished, fuel consumed, number of fishermen, etc. Therefore, it is at least to some extent somewhat paradoxical that the basic definition of fishing effort which is used in population dynamics, and commonly used in most fishery management applications, does not necessarily refer to any of these usual "inputs." Fishing effort is defined in terms of the catch; that is, one unit of real or nonnominal effort is simply the numerical fraction of the average population that is caught. In order to emphasize this point, consider two fishing fleets. Each fleet fishes on separate populations which are in every respect identical. The fleets make identical catches and, therefore, each removes identical fractions of the average populations from each population. By definition, then, these two fleets both exert the same amount of fishing effort. The fact that "inputs" are not implicit in the theory can be seen by identifying the first fleet as consisting of 100 modern trawlers and the second as, perhaps, 10 pleasure yachts that have been modified just enough to enable them to catch fish. Even though both fleets exert equivalent amounts of fishing effort, their inputs—indexed by, say,

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[2] National Marine Fisheries Service, Northwest Fisheries Center, 2725 Montlake Boulevard East, Seattle, WA 98112.

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the costs of their operations—must differ considerably. This, of course, in no way invalidates the population dynamics theory and there are, in fact, methods for converting fishing effort, defined in terms of the magnitude of the catch, into numbers of fishing boats, etc. There is an extensive literature on this subject and, because of this, there is no need to prolong the discussion of this particular aspect of the fishing-effort problem. Rather, we shall concentrate on aspects of the problem of identifying and measuring inputs to the fishing process as well as discussing the methodology of relating the set of inputs to the outputs (the catch), which can, as we will see by the ensuing discussion, be treated in terms of several species and even, if necessary, in terms of strata (such as, for example, size classes) within several species. These aspects of the problem simply relate to the theory of production functions. Production functions have seldom been treated in fisheries, but when they have, they have been approached primarily from a regression analysis point of view. It is not clear, even given that we meet the assumptions of the estimation procedures and thus obtain credible statements on the "good properties" of the estimation procedure, that the curve fitting technique can do much more than describe, in an artificial way, the status quo; there is no inherently good advice in the curve fitting procedure on optimality; optimality must be implicitly assumed. What is needed are techniques of finding those combinations of inputs that produce extrema in the outputs, as well as to determine the sensitivity of this input-output system to changes in the magnitude of the inputs, and a reevaluation of the input-output system which will acknowledge the stochastic aspects of the decision process.

Our analysis of the fishing effort problem is divided into several parts. First, the fishing-effort problem is recast as a production function problem whereby valuable inputs to the fishing process are allocated among the outputs of the process in a manner which maximizes profit. In the particular example chosen the inputs are the capacities of three sizes of fishing boats in a fleet and the "catchable stocks" of two species of fish, yellowfin and skipjack tuna, whereas the outputs are the catches of the various species in the different boats. The components of the yellowfin and skipjack tuna catchable stocks are allocated among the various size vessels in the fleet to maximize profits. The technique used to explore the maximization of profits is linear programming. The technique enables the simultaneous exploration of fleet technological constraints, the interaction of multiple species as inputs to the decision process, and the range within which catches can be set without changing the nature of the profit maximization equation. Easy algebraic extensions of the model can be seen to have rather important implications. For example, instead of allocating two species of fish among three boat classes, the stocks of i species can be allocated among j classes of boats and k fishing nations. The ease of such an extension may, however, be somewhat deluding, particularly because of the difficulty in defining appropriate coefficients and constraints respecting the allocation among the k nations. Nevertheless the difficulty does not preclude solution and furthermore placing the problem in this context enables a much needed formulation of the problem of allocation of fish stocks among countries.

Most input-output analyses involve physical inputs and outputs. This was true in the example cited above. A classic example in fisheries is that of fishing power which is frequently related to fishing vessel horsepower. There are many instances, however, where the physical inputs (horsepower, fleet capacity, etc.) are less important than those related to the skill utilized by the fisherman in making managerial decisions such as where to fish, when to fish, when to stop fishing, etc. So, in the second part of this paper we consider the development of a decision theory model for adjudging fisherman skill in a "real world" probabilistic environment and show how the quality of the fisherman's skill in decision making relates to the entropy of his decision environment. Many important applications of this theory beyond the examples utilized in the text, such as the decision of whether to fish species a or species b when both species are available or whether to fish on one ground such as the eastern tropical Pacific tuna grounds or to move to another ground such as the tuna grounds off the west coast of Africa.

The third part of the paper considers, given the possibility that inputs and outputs can be related and that decision skill can be judged, that different fishermen apply different criteria to the signals that they obtain from their decision environment. This question is discussed in terms of maximizing catch versus minimizing risk in attaining the catch. One of the main conclusions that can be derived from the following discussion is that advances toward the management of fisheries as a total system which considers the strategic, tactical, and operational hierarchies and the flow of information and material among these are not limited by analytic techniques. The limitation arises from a lack of explicit formulation of the kinds of data needed for the development of a total management system.

INPUT-OUTPUT ANALYSIS

Let us contrive a simple production function problem in a linear-programming context. This approach is treated in some detail by Dorfman, Samuelson, and Solow (1958). We should mention that the linear-programming technique is, of course, not without assumptions, and these are discussed in any operations research text (for another application of linear programming in salmon management see Rothschild and Balsiger, 1971). Violations of the assumptions required for the linear-programming model are usually handled by other techniques in mathematical programming theory, but these are, in general, computationally more difficult. In order to provide a semblance of realism to the problem, we use some now somewhat outdated data provided in Table 7 of Green and Broadhead (1965). We begin by assuming we have a fleet of 300-, 400-, and 500-ton seiners. The capacity of the fleet is calculated in Table 1.

The capacity for each size class of boat is an input in the production function. We also need to supply as inputs to the production function some raw material in the form of fish. Let us say that we are limited to 90,000 tons of yellowfin tuna and 120,000 tons of skipjack tuna. Then the objective of production is to maximize profits

TABLE 1.—The capacity in tons of a hypothetical tuna fleet in terms of various size classes of fishing boats.

Size of boat (tons)	Size of fleet (No. of vessels)	Capacity of each boat (tons)	Annual capacity of each boat (tons)	Total capacity for fleet (tons)
300	20	273	1,173	23,460
400	60	364	1,419	85,140
500	20	455	1,592	31,840

by maximizing the objective function: $Z = 8.65H_{11} + 7.32H_{12} + 10.66H_{21} + 9.01H_{22} + 7.75H_{31} + 6.53H_{32}$ where the H_{ij}'s correspond to the ith boat size ($i = 1, 2, 3$; where the integers refer to 300-, 400-, and 500-ton boats, respectively) and the jth species ($j = 1$ is yellowfin tuna and $j = 2$ is skipjack tuna). The coefficients in the objective function correspond to the weighted average profit per ton for the jth species caught by the ith boat as deduced from Green and Broadhead. Now with respect to the allocation of two scarce inputs—the capacity of various size vessels in the fleet and the catchable stock of the two species—to the production process, the capacity of the fleet generates the following set of constraint equations:

$H_{11} + H_{12} \leqslant 23{,}460$ tons (capacity of small boats)

$H_{21} + H_{22} \leqslant 85{,}140$ tons (capacity of medium boats)

$H_{31} + H_{32} \leqslant 31{,}840$ tons (capacity of large boats)

whereas the stock inputs (viz. the catch quotas) generate the following set of constraints:

$H_{11} + H_{21} + H_{31} \leqslant 90{,}000$ tons ("quota" of yellowfin tuna)

$H_{12} + H_{22} + H_{32} \leqslant 120{,}000$ tons ("quota" of skipjack tuna).

Because different size boats catch different proportions of yellowfin and skipjack, the ratio of these species in the catch of each size class of boat is essentially a function of the configuration of the boat and its equipment. We can thus consider the ratio of skipjack to yellowfin as a technological characteristic of the boat's size class and in order to maintain the character of the technology, we use the percentages of yellowfin in the catch as given by Green and Broadhead (300-ton boats, 57%; 400-ton boats, 48%; and

TABLE 2.—Optimal allocation of skipjack and yellowfin tuna in tons of fish to various size classes of fishing boats.

Species of tuna	Size class of boat			Total
	1 (300 ton)	2 (400 ton)	3 (500 ton)	
Skipjack	10,112	43,886	18,511	72,509
Yellowfin	13,347	41,253	13,328	67,928
Total	23,459	85,139	31,839	140,437

500-ton boats, 42%) to obtain the yellowfin: skipjack ratios of 1.32, 0.94, and 0.72, respectively, thus yielding the technological constraints:

$$H_{11} - 1.32H_{12} = 0$$
$$H_{21} - 0.94H_{22} = 0$$
$$H_{31} - 0.72H_{32} = 0$$

Table 2 gives the maximization of the objective function which yielded \$1,248,835 in tons of fish. The optimal solution then indicates that in the process of production, the entire capacity of the vessels was utilized. Because the catchable portion of the stocks was greater than this capacity, 22,070 tons of yellowfin and 47,489 tons of skipjack were unused by the fishery (slack variables). Note also that the catch of skipjack is greater than that of the more valuable species, yellowfin, because of the technological constraints enforcing the lower yellowfin: skipjack ratios in the more numerous larger boats. The imputed marginal values, the so-called shadow prices of a ton of yellowfin and skipjack are, of course, zero because the capacity of the stock to produce these quantities of fish was not reached; but, however, the capacity of the vessels was reached and, therefore, the marginal value of an extra ton capacity on the 300-, 400-, and 500-ton boats is imputed to be \$8.08, \$9.81, and \$7.04, respectively. These shadow prices are simply the weighted average profits for each size class, e.g.:

$$\$8.08 = \frac{10{,}112}{23{,}459}\,7.32 + \frac{13{,}347}{23{,}459}\,8.65$$

Perhaps of even greater interest is the way in which the various production inputs interact with one another. For example, in this particular problem, we could increase the yellowfin and skipjack catchable population constraints *ad infinitum* without changing the nature of the optimal solution. But if we were to reduce the catchable population of yellowfin tuna from 90,000 tons to 67,930 tons or skipjack from 120,000 tons to 72,510 tons, we would eliminate the yellowfin and skipjack slack variables, respectively, and these would no longer be in the optimal solution. Putting it another way, insofar as this particular problem is concerned, the nature of the solution, in terms of, for example, those variables to which some monetary value greater than 0 would be imputed, would not change until the catchable population of yellowfin dropped below 67,929 tons or skipjack to below 72,510 tons. The point of this is that (again insofar as this particular problem is concerned) we are not going to change the nature of our optimal solution for any catchable populations of yellowfin $>67{,}929$ tons or of skipjack $>72{,}510$ tons. This means that it may not be necessary to be concerned with precise estimates of the catchable population if the catchable population is, as in this case, much larger than the lower bounds for changing the solution. This reflects, within the scope of the model, the bounds within which changes in the catchable population will have no effects upon the components of the objective function. This demonstrates, in an analytical way, that population dynamics theory may offer solutions that are, in some instances, apparently more precise than that which is needed. In other words, we frequently postpone resource decisions to obtain a certitude in our estimate, which would not change the optimal solution of the input-output process. This postponement is almost never without social costs which may be substantial.

Now with respect to modifying the fleet capacity, we can, given the stock constraints, increase the capacity of the small boats to 62,250 tons or decrease it to 0 tons. If we exceed the upper bound then this means that we need to catch at least 38,790 additional tons of fish and, of these, 57% must be yellowfin amounting to an additional catch of 22,110 tons of yellowfin. But if we catch this additional quantity of yellowfin, we will use up our 90,000 tons of yellowfin, dropping the yellowfin slack variable from our solution. At the lower bound, it is obvious that if we constrain the catch of small boats to be 0, we eliminate the variables corresponding to the catch of small boats from our optimal solution. The interpretations of the sensitivity of the 85,140-ton constraint upon the maximum catch of the 400-ton boats and the 31,840-ton constraint upon the maximum catch of the 500-ton boats are identical.

It is perhaps more subtle that the *full* utilization of the excess yellowfin tuna capacity is impossible because the 85,140 tons of fish that would be caught by the 400-ton boats consists of $85{,}140 \times 0.48 = 40{,}867$ tons of yellowfin tuna (the 0.48 is the appropriate technological constraint). To use up the yellowfin tuna surplus we would need to catch roughly an additional 50,000 tons of yellowfin tuna, but if we did this we would need, by virtue of our technological constraint, to catch a total of $90{,}000\ (0.48)^{-1}$ tons of fish which clearly exceeds the fleet capacity. With respect to the technological constraints, we could in the 300-ton boats, for example, increase the right-hand side of the equality to 23,460, which would modify the solution by eliminating any catch of skipjack by the small boats (in other words, H_{12} would be eliminated from the optimal solution). On the other hand, we could reduce the equality to —30,967, and if we did this, the catch of yellowfin by small boats would be eliminated from the solution $[(30{,}967)(1.32)^{-1}] = 23{,}460$. The negative right-hand constraint reflects more upon the nature of the solution than reflecting any physical meaning.

It is clear that since we used all the capacity of our hypothetical fleet that any increase in profits will not induce us to catch more fish. On the other hand, by inducing a negative profit we can show that in these instances some of the boat-species combinations should not be filled to capacity (Table 3). Thus we would have to lose

TABLE 3.—The lower bound of profit and "sensitivity" for yellowfin and skipjack tuna caught by various size classes of fishing boats. The results are reported in dollars.

Species of tuna	Boat class	Profit per ton in problem	Lower bound of profit	"Sensitivity"
	1	8.65	—5.54	14.19
Yellowfin	2	10.66	—9.58	20.24
	3	7.75	—9.07	16.82
	1	7.32	—11.41	18.73
Skipjack	2	9.01	—10.02	19.03
	3	6.53	—5.58	12.01

$5.54 per ton of yellowfin to generate empty capacity space in class 1 vessels. The difference between the lower bound profit and the profit used in the problem is a measure of sensitivity. We note for example that the behavior of the fleet is most sensitive in class 3 boats where a $12.00 decline in profits would generate excess fleet capacity, or a $16.82 decline in yellowfin profit would also generate excess fleet capacity.

Now let us make an apparently slight but important modification in our problem. We will keep everything the same, but we will increase the capacity of the small boats from 23,460 tons to 65,000 tons. In the first example we were interested, primarily, in the sensitivities of our model to changes in the constraints. Now, however, it is of interest to compare the optimal solutions in the two examples (Table 4). Thus by adding an extra 42,000 tons of capacity to the small boats, we increase the skipjack catch by only 16,000 tons and the yellowfin catch by 22,000 tons. We have not, owing to the constraints, caught an additional 42,000 tons of fish. We have caught proportionately more yellowfin than skipjack, increasing the optimal solution from $1,248,835 to $1,562,133. In the second example, in contrast to the first, we have used

TABLE 4.—A comparison of optimal solutions in Example I where the capacity of the small boats is 23,460 tons and in Example II where the capacity of the small boats is 65,000 tons. The comparison shows the optimal allocation in tons of fish for each example.

	Example I				Example II			
	Boat class				Boat class			
Species	1	2	3	Total	1	2	3	Total
Skipjack	10,112	43,886	18,511	72,509	26,831	43,886	18,511	89,228
Yellowfin	13,347	41,253	13,328	67,928	35,418	41,253	13,328	89,999
Totals	23,459	85,139	31,839	140,437	62,249	85,139	31,839	179,227

up our yellowfin tuna resource and have reduced the unused portion of the skipjack resource from 47,489 to 30,769 tons. In addition, we have 2,749 tons of empty capacity in the small boats. This excess capacity is enforced, to a large extent, by the technological constraints, and we can see that these modifications would enable utilization of the empty space with skipjack tuna. Thus we can formulate, in a programming context, the relation between the inputs and outputs of the fishing process. If we agree that the management process requires the kinds of information that are required in the programming problem, then we can see that we have been collecting the wrong kinds of information on our fisheries.

To sum up, then, we have discussed the production function from a linear-programming point of view. We have picked two possible examples out of an infinitude of possible examples. The particular examples we have chosen may be criticized from the point of view of their immediate applicability to real situations. This criticism is correct and indeed it is quite an important criticism which simply reflects that in these tuna fisheries and most of the other fisheries in the world, we simply neither have nor collect the kinds of data that we need to enter into an analytic evaluation of what is perhaps the most critical of fishery management problems, the allocation of fishery resources among various user groups throughout the time stream. This is not because these data do not exist; it is because, in general, explicit attempts have not been made to gather these sorts of data. It is a contradiction to deny the usefulness of utilizing the physical metric for managing fisheries and to not provide mechanisms for obtaining the kinds of data that are required to manage the fisheries in the appropriate way, in the value metric.

The point, then, of demonstrating the linear-programming technique is to (1) call attention to a powerful allocation tool which can be used for guidance in, for example, a serious contemporary tuna problem, the allocation of the tuna catch among the nations; (2) highlight the important difference between the inputs of the fishing process and the fishing effort used in population dynamics; (3) point out the nature of sensitivity in a programming context which can show, for example, that when we examine the entire productive process that, given the right kinds of economic data, we can think of managing stocks in terms of, say, an upper and lower bound on catch which could free research effort, for example, to other productive endeavors; and (4) finally, because of recent confusion on the subject, suggest that the term fishing effort be utilized only in the context in which it is defined in the population dynamics literature and that the term fishing inputs be reserved for the more general connotation of "fishing effort."

INTERPRETATION OF FISHING SKILL

Now let us look at the input process in a little more detail. When we do this we have to admit that we can, having established the definitions of fishing effort and fishing inputs, especially if we restrict our consideration of management to manipulating physical quantities of the catch, relate at least some but, in general, not all of the fishing inputs to fishing effort through the appropriate catchability coefficient. This enables the dynamicist to have comparable measures of the abundance of fish from time-space point to time-space point. Again the adjustment of estimates of abundance to common units through the computation of fishing power is well treated in the literature, and we will not belabor it here, except to note that fishing power is almost always calculated on the basis of some usually single physical feature of the fishing vessel such as engine horsepower, etc., or simply on empirical differences in the catch-per-nominal-effort that is obtained by the fleet. Differences in fishing power are certainly more complicated than comparisons among the physical attributes of the fishing vessels would indicate. A considerable portion of the variability in fishing power among fishing units can be attributed to variability in the skill of the fishing skipper. This assertion is subsumed in Figure 1.

Figure 1 is hypothetical and shows that the quality of fishing skippers could be a more important determinant of the "quality" of a fishing operation than the physical characteristics of the boats. We might guess that boats that are phy-

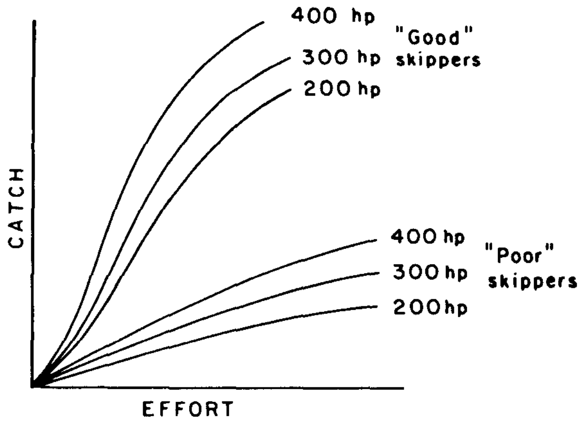

FIGURE 1.—Hypothetical relation between catch and effort for boats of varying horsepower and for "good" and "poor" skippers.

sically different in some important index in a ratio of say 2:1 may exhibit a range in catch-per-input where the best boat is, say, 10 or more times better than the poorest boat. The greater effectiveness of some boats over other boats can in large part be attributed to the skill of the skipper. This is ignored in many analyses primarily because this question of skill has never been appropriately formulated. In this section, we begin to develop some examples which contribute to the rudiments of analysis of the behavior of the skipper as an input to the production function—in terms of how a skipper perceives the fishing environment—and then mention the problem of the utility that the skipper places on the various signals that he obtains from the environment. We make a point of stressing that the relation of the input vector to the output vector in the fishing process is usually considered to be deterministic by students of the fishing process. Another approach is to use an average vector for inputs and assume an average vector for outputs. Unfortunately, it is unlikely that fishermen perceive the decision environment as either deterministic or average and we make use of this observation in our additional considerations.

In order to demonstrate these points we will construct a branch of a very simple decision tree which can serve as a framework for future analysis. The branch of the tree is shown in Figure 2. This is the skipper's decision environment. Nature deals the skipper good fishing, θ_1 or poor fishing, θ_2. The skipper has an opportunity to take a glimpse at the environment. This interpretation of the glimpse is denoted by $P(\hat{\theta}_i | \theta_j)$ where $\hat{\theta}_i$ is his guess of θ_i (j does not necessarily have to equal i). If the skipper guesses $\hat{\theta}_1$, then he commits himself to a fishing operation, but if he guesses $\hat{\theta}_2$, he moves to a less risky area and fishes. In this less risky area, nature deals new fishing conditions θ_1' and θ_2'. The reward for any particular fishing action is specified in Figure 2. We wish to use this model to show how chance enters the decision process.

We set

$$P(\theta_1) = 0.2$$
$$P(\theta_2) = 0.8$$
$$P(\theta_1') = 0.8$$
$$P(\theta_2') = 0.2$$

and examine three conditions:

Condition I

The skipper is perfectly skilled and thus $P(\hat{\theta}_1 | \theta_1) = P(\hat{\theta}_2 | \theta_2) = 1$ and $P(\hat{\theta}_1 | \theta_2) = P(\hat{\theta}_2 | \theta_1) = 0$. The expected value of the branch

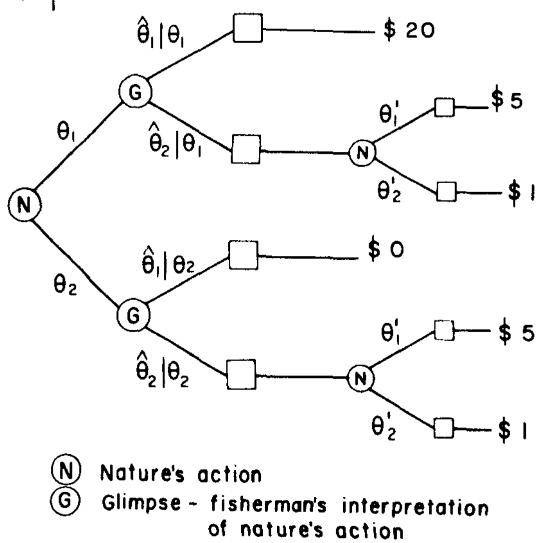

FIGURE 2.—Branch of decision tree showing various events and payoffs. (For a discussion of decision analysis see Raiffa, 1968.)

is $7.36 with a measure of entropy of 130 centibits. (Entropy is defined in the usual way, but measured in centibits rather than in bits owing to the relatively low degree of "randomness" in these hypothetical examples.)

Condition II

The skipper is quite skilled and thus $P(\hat{o}_1 | o_1) = 0.9$, $P(\hat{o}_2 | o_1) = 0.1$, $P(\hat{o}_2 | o_2) = 0.9$, $P(\hat{o}_1 | o_2) = 0.1$ (say). The expected value of the branch under this condition is $6.71, and a measure of its entropy is 172 centibits.

Condition III

The skipper is unskilled and thus $P(\hat{o}_i | o_j) = 0.5$ for $i = 1,2$ and $j = 1,2$. The expected value of the branch under this condition is $4.10, and a measure of its entropy is 209 centibits.

It is important to observe, in respect to the first example, that if nature dealt the o_i's with probability of 1 or 0 then entropy would be 0. Nature has not, in our example, chosen to deal the o's deterministically and, therefore, 130 centibits is the lower threshold of entropy, given that probabilistic behavior of nature remains the same.

Now, we note several interesting features of this analysis which are capable of many simple extensions. First, we have distinguished between the contribution to entropy made by the behavior of nature and the behavior of the fishermen. Second, we have quantified the randomness in the decision problem by measuring the randomness in bits and thus have the opportunity to quantify the required skill of the skipper; because when nature deals a low-entropy probability structure, relatively less skill is required to achieve equivalent results. Third, we can valuate the skipper's decision process as an input to the production function. For example, under Condition III an unskilled skipper can produce, on the average, $4.10 worth of fish in a 209-centibit environment, but a quite skilled skipper [skill being measured by $P(o_i | o_j)$] can *by his skill* reduce the entropy 37 centibits. The 37 centibits being a difference between entropies is thus a measure of information, and in this example 37 centibits of information are worth $2.61 or roughly 7 cents per centibit. A perfectly skilled skipper reduces entropy an additional 42 centibits, the additional information yielding 65 additional cents, or about 1.5 cents per centibit. In other words, in this example, the information accrued in moving from unskilled to quite skilled is about the same as that accrued in moving from quite skilled to perfectly skilled, but the value of a unit of information is 4 times greater in moving from unskilled to quite skilled than a unit of information acquired when moving from quite skilled to perfectly skilled.

DECISION CRITERIA

Thus, we have considered a model of the way in which the skipper "processes" signals from the fishing environment where the quality of his processing ability is measured relative to nature-generated entropy in the decision environment. We must now consider how the skipper valuates the signal and the criteria that he places upon these signals. First, consider what might be a traditional approach of where to fish. In this approach we have a field of expected catches and upon examining this field we advise the skipper to fish at the location where the expected catch is highest. A second approach is to examine the field of space-time points and consider the distribution of catches at each space-time point. Let us consider a simple aspect of this problem; two space-time points A and B, at which the fisherman's perception of the catch is that it has an approximately normal distribution. Figure 3 shows these two distributions. The figure also indicates the point on each distribution below which the fishing operation will lose money. If we look at only the expected catch, we would advise fishing at A. But if we examine the risk (that is, $\int xf(x)\,dx$, evaluated from $-\infty$ to the break-even point) we note that fishing at B will minimize risk, and if this were our criterion we would fish at B. We should note further that the fish-

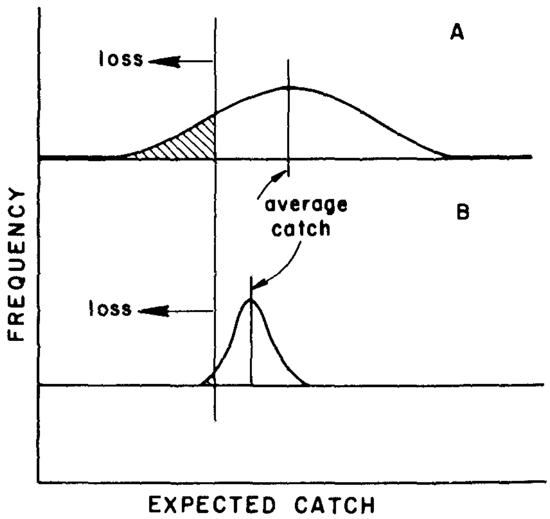

FIGURE 3.—The distribution of catch at two locations showing the average catch and the loss region.

erman samples the distribution dealt by nature and his sample can be biased and vary in precision. His perception of the correct action depends upon his view of how many times he can sample these distributions. This is clear because if the fisherman has only one chance to go fishing, he should choose B to minimize his risk, but if he has many chances to go fishing, he should choose A to maximize his gain since the sampling risk will be decreasing inversely proportional to the square root of the number of chances that the fisherman has.

A reasonable criterion for choosing a fishing location might be the expected gain less the expected loss; e.g.,

$$\int_a^b xf(x)\,dx - \int_a^B xf(x)\,dx$$

where $f(x)$ is the distribution function of the fisheries earnings, a is the minimum value of this function, b is the maximum value, and B is the break-even point. Note that this general form can be written in several alternative ways. But even the establishment of such a criterion is not sufficient to measure the skipper's behavior. We need to know the utility that the skipper places in any value of the criterion.

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ADDENDUM

The reader interested in applications of decision theory should examine "Marine decisions under uncertainty," by John W. Devanney III, Cornell Maritime Press, 1971, which was discovered while the present paper was in proof.

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