Estimating Capacity and Efficiency in Fisheries with Undesirable Outputs

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VIMS Marine Resource Report No. 2007-6

August 2007

Executive Summary

Fishery managers throughout the world are concerned about finding ways to reduce undesirable and nonmarketable bycatch (i.e., bycatch discards) and excess harvesting capacity. Both of these issues are associated with economic waste in the form of unnecessarily high production costs, potential reductions in future harvest levels, or unnecessary utilization of factors of production to discard undesired catch. The Food and Agriculture Organization (FAO) of the United Nations, the National Marine Fisheries Service (NOAA Fisheries), and various member nations of the FAO adopted a voluntary code entitled The Code of Conduct for Responsible Fisheries in 1995, which promotes the reduction in bycatch discards and excess capacity in commercial fisheries.

Extensive progress has been made towards reducing bycatch of undesired species through new regulations and modifications to traditional fishing gear. Substantial progress has also been made towards assessing and reducing harvesting capacity in fisheries. Unfortunately, these efforts have been made in isolation. That is, efforts to reduce bycatch have not concurrently considered the ramifications of bycatch reduction on harvesting capacity, and efforts to assess capacity have not incorporated how capacity would vary with reductions in undesirable outputs. Without proper attention to the relationship between reducing undesirable outputs and the maximizing desirable outputs, it is quite likely that the estimates of capacity used to help develop capacity reduction programs may be subject to error.

We examine four approaches for estimating and assessing both capacity and technical efficiency of production activities that involve the production of both desirable and undesirable outputs. Although we primarily focus on estimating capacity while explicitly recognizing the need to allow desirable outputs to expand and undesirable outputs to contract, we also consider several other options for changing the direction (expansion and contraction) of desirable and undesirable outputs.

All four methods considered in the report are based on data envelopment analysis (DEA), which is a mathematical programming approach for estimating technical efficiency (TE) and capacity output. We first examine the more traditional DEA approach for estimating capacity; this is an output-oriented approach, which only takes desirable outputs into account and ignores undesirable outputs. We then introduce and summarize (2) a directional distance function approach, which permits desirable outputs to increase and undesirable outputs to decrease by the same proportion. Next, (3) a hyperbolic approach is then presented and discussed; this approach allows desirable outputs to expand by a scalar and undesirable outputs to contract by the inverse of the scalar. Last, we present (4)

the approach of Seiford and Zhu (2002), which is an output-oriented approach but allows desirable outputs to increase and undesirable outputs to decrease. We then apply the various models to a data sample from fishing vessels making trips to Georges Bank in the northwest Atlantic Ocean. Results show that it is difficult for fishing vessels to reduce undesirable outputs without reducing desirable outputs.

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1. INTRODUCTION

Unwanted bycatch (also known as "discards") is recognized as a major problem for the restoration and rebuilding of fish stocks, as well as maximizing benefits to society. As noted by Kellcher (2005), discards constitute a significant portion of global marine catches. Discarding fish represents substantial economic waste and results in suboptimal utilization of fishery resources. Unwanted bycatch is not restricted to the capture of finfish and shellfish; sea birds, turtles, and other marine mammals are also often caught in some fisheries. In all cases, such captures result in the loss of benefits to society.

The United Nations Food and Agriculture Organization (FAO), along with member nations, adopted the Code of Conduct for Responsible Fisheries in 1995 (FAO 1995). The Code is strictly voluntary and emphasizes a wide range of options for the conservation, management, and development of fisheries. One major concern identified in the Code is to promote options for all member states to reduce discards through appropriate regulatory strategies. The Code also recommends that member states develop guidelines and procedures to promote the efficient harvesting of fishery resources. In addition, the Code also calls for reducing excess capacity in fisheries. In 1998, the FAO, along with member nations, developed an International Plan of Action (IPOA) for the Management of Fishing Capacity (FAO 1999). An objective of the IPOA is to prevent and eliminate excess levels of fishing capacity.

Since the implementation of the Code of Conduct, the FAO and member nations have embarked on a wide range of programs to address discarding, inefficient operations, and the methods to eliminate and prevent excess harvesting capacity in fisheries. Unfortunately, these programs have been instituted separately from one another. For example, Alverson et al. (1994) provided a comprehensive assessment of the levels of discards and options for reducing discards in fisheries. FAO has an extensive listing of research reports, which focused on developing options for the more efficient harvesting of resources. Between 1997 and 2005, FAO and member nations facilitated a wide range of research to estimate, assess, and address capacity in commercial fisheries (e.g., Pascoe et al. 2004). Even so, there has been no effort to address the assessment and subsequent management of capacity, efficiency, and undesirable discards in a collaborative and comprehensive manner.

Recent research in efficiency analysis has identified various approaches for estimating efficiency and capacity and for adjusting such estimates to reflect the consequences of discards. Although numerous researchers have recognized that some production activities generate undesirable outputs (such as discards), only recently has research directly estimated efficiency for production technologies involving both desirable and undesirable outputs. Ethridge (1973) provided a basic framework for including undesirable outputs in the theory of the firm, and Pittman (1983) and Färe et al. (1989a) offered more formal quantitative methods for estimating economic and technical efficiency, respectively, in the presence of undesirable outputs. Färe et al. (2006) offer one of the first empirical analyses of technical efficiency in a fishery adjusted for undesirable outputs. Scott et al. (2006) provide a recent example of estimating capacity in a fishery with undesirable outputs, but the analysis was restricted to observations obtained from experimental trips.

Because discarding takes place on fishing trips, there is a need to estimate capacity in fisheries when there are undesirable outputs (i.e., discards). Many fishery management strategies and regulations focus on the rebuilding of stocks and give less attention to enhancing economic returns to the fishery. As such, regulations often initially reduce productivity, technical efficiency, allocative efficiency, undesirable outputs, and capacity utilization. If regulations are designed to reduce undesirable outputs and the level of capacity is also of concern to managers, capacity estimates must be adjusted to reflect reductions in undesirable outputs.

In this report, we present and illustrate several methods for estimating capacity when there are undesirable outputs. All the methods are based on data envelopment analysis (DEA), which is a mathematical programming approach. We initially consider the more standard approach for estimating capacity which ignores undesirable outputs. We next introduce several methods for estimating capacity which incorporate restrictions and formulations to estimate capacity with an explicit desire to reduce undesirable outputs (i.e., bycatch discards). We then test the algorithms by using a sample data set for the New England Georges Bank otter trawl fleet. The data were collected as part of the Northeast Fisheries Science Center observer program. The data set from 307 vessel trips analyzed information on catches of 12 desirable species and 17 undesirable species, crew size, days at sea, and vessel characteristics. Results indicated considerable similarities among the various approaches that allowed desirable outputs to expand and undesirable outputs to contract. Overall, the results suggest when producers are forced to reduce the undesirable outputs, the production of desirable outputs could be reduced by an average of 32% per trip, and a maximum of 46.0% per trip.

The remainder of this report is organized as follows. Section II reviews concepts of production, including technical efficiency and capacity, and highlights how undesirable outputs can be incorporated into an understanding of the production process. Section III presents approaches for estimating efficiency and capacity, and section IV presents an overview of several mathematical programming approaches for estimating efficiency and capacity while considering undesirable outputs. Section V provides an illustration of these approaches with an application to the New England multispecies small mesh trawl fishery. Section VI presents a summary and conclusions.

2. Production, Efficiency, and Capacity with Undesirable Outputs

2.1 Early Research on Undesirable Outputs

There is a long and rich history of research on economic aspects of undesirable outputs. [1] Most of the early research, however, focused on how to internalize the cost of reducing undesirable outputs to desired levels (e.g. surcharges). For example, Bubbis (1963) demonstrated that surcharges substantially reduced waste discharges from industry. Kneese and Bower (1968) concluded that surcharges encourage plants to make changes resulting in reductions in the volume of effluent, and surcharges may actually lower production costs over time. Etheridge (1973) developed an economic theory of the firm, which specifically incorporated aspects of reducing undesirable outputs. Ayers and Kneese (1969) considered the appropriate level of pricing undesirable outputs within a general equilibrium framework.

The research of the 1960s and 1970s, however, did not explicitly attempt to assess technical efficiency, economic efficiency, or capacity adjusted for undesirable outputs. Pittman (1983) offered a framework for assessing productivity when some outputs are undesirable and cannot be freely or costlessly disposed (i.e., production is characterized by weak disposability of outputs). Pittman's focus, however, was on productivity and developing metrics, which penalized the performance of producers for generating undesirable outputs. The approach of Pittman was to modify the Caves et al. (1982a, 1982b) version of the multilateral productivity index, which was a Törnqvist multilateral productivity index.

2.2 Weak Disposability and Undesirable Outputs and Inputs

Building upon the subsequent work of Pittman (1983), Färe et al. (1989a) introduced the notion of hyperbolic output efficiency measures, which provides an asymmetric treatment of desirable and undesirable outputs. The hyperbolic measure allows inputs to contract, and outputs to expand, by different proportions; all desirable outputs expand by a scalar and all non-desirable outputs contract by the inverse of the scalar. Färe et al. (1994) also refer to this as graph efficiency. A major distinction of Färe et al. (1989a), however, was the introduction and imposition of weak disposability.

Weak disposability is the notion that there is a cost associated with disposing of nondesirable outputs or undesirable inputs. In other words, if both desirable and undesirable outputs are jointly produced and the undesirable output cannot be disposed without additional cost, then the desirable outputs also must be reduced in order to reduce the undesirable outputs, given no change in the inputs (Färe and Grosskopf, 2004a). Färe and Grosskopf (p. 47) also offer an alternative interpretation "If we hold inputs constant, then 'cleaning up' undesirable outputs will occur at the margin through reallocation of inputs away from the production of desirable outputs."

In contrast to weak disposability, the concept of strong disposability allows any output to be disposed without imposing any private costs (Färe et al., 1994). Although the disposability discussion has thus far primarily emphasized outputs, there is also an input disposability notion. Strong disposability in inputs is a situation in which inputs may be expanded or increased without reducing output. Weak disposability in inputs forces outputs to be contracted as some inputs are expanded; it is also used to examine input congestion or noneconomic regions of production (e.g., a backward bending production isoquant).

2.2.1 The Production Technology and Disposability Properties

To better facilitate the discussion of methods for estimating and assessing technical efficiency and capacity in the presence of undesirable outputs, it is helpful to introduce various basic concepts of production.[2] In this section, we introduce the notion of a production set, an input set (input correspondence), and an output set (output correspondence). An input set is equivalent to a factor requirements function, and the output set is equivalent to the transformation function.

2.2.1.1 Some Basics: Inputs and Outputs

The production of goods and services (i.e., outputs) requires inputs (i.e., resources). Traditional examples of inputs include capital, labor, energy, and materials; natural resources such as fish stocks, are also inputs. We designate an input as x_n, n = 1,…,N, where x_n is the nth input among N inputs. Alternatively, if we consider all inputs, we designate a vector $x = (x_1,\ldots,x_N)$. We also have outputs, which we designate as y_m, m = 1,…,M, and M is the number of outputs. If we reference all outputs, we consider a vector of outputs, $y = (y_1,\ldots,y_M)$. To facilitate future discussion, we also introduce the notion of a decision-making unit or DMU. We consider k DMUs, where k = 1,…,K. For each DMU, we have $x^k = (x_{k1},\ldots,x_{kN})$ and $y^k = (y_{k1},\ldots,y_{kM})$. The input x_{kn} is the amount of the nth input used by the kth producer or DMU, and y_{k1} is the amount of the first output produced by the kth producer or DMU.

2.2.1.2 The Input Requirement and Output Possibility Sets

A production technology may be represented by either an input requirement set or the output correspondence or possibility set.[3] We let L(y) be the input correspondence or requirement sets. The input correspondence, $L:\Re^M_+ \Rightarrow 2^{\Re^N_+}$ maps outputs $y \in \Re^M_+$ into subsets $L(y) \subseteq \Re^N_+$. The input set, L(y), denotes the collection of all input vectors $x \in \Re^N_+$ that yield at least output vector $y \in \Re^M_+$ (Färe et al. 1994). The input sets or correspondence may be illustrated by the simple notion of a production isoquant, which depicts the combinations of different levels of different inputs yielding the same level of output (Figure 2.1).

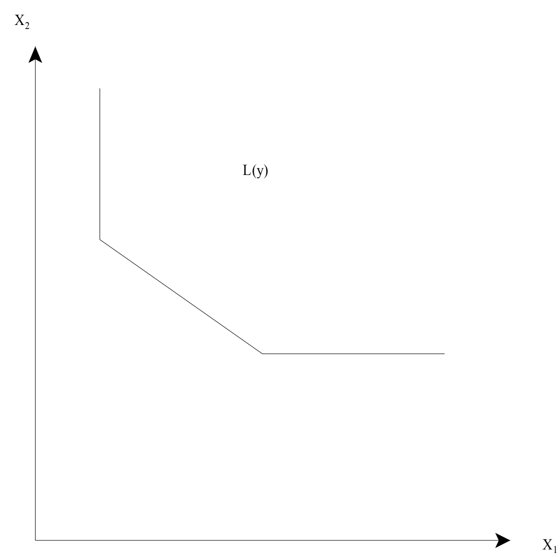

Figure 2.1 The Input Correspondence

The output correspondence or possibility set $P: \Re^N_+ \Rightarrow 2^{\Re^M_+}$ maps inputs $x \in \Re^N+$ into subsets $P(x) \subseteq \Re^M_+$. The set P(x) is the output set, and it indicates the combination or collection of all output vectors, $y \in \Re^M_+$, which can be produced from the input vector $x \in \Re^N_+$. The production or output set is graphically depicted in Figure 2.2.

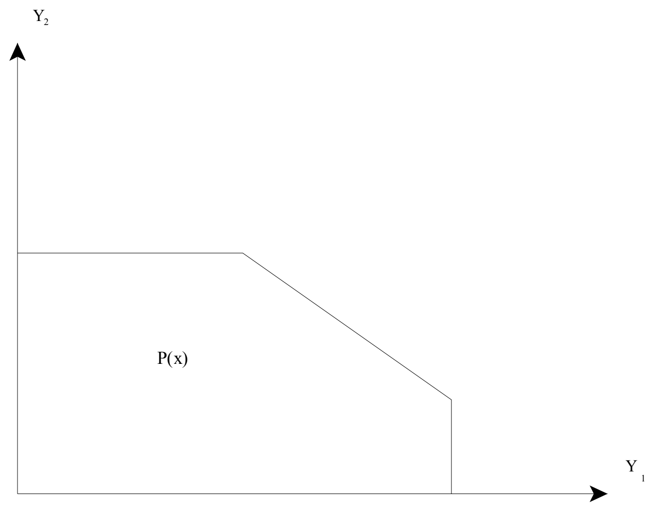

Figure 2.2 The Output Correspondence or Production Possibility Set

It is useful to introduce the basic concepts of the Graph of the technology even though it is not extensively discussed in this paper. The Graph is the collection of all feasible input-output vectors. The Graph may be derived from either the input correspondence or the output set (Färe et al. 2004a). Although all three model the same production technology, they emphasize different aspects of the technology. The input set emphasizes input substitution, the output set focuses on output substitution; and the Graph facilitates determination of both input and output substitution. Following Färe et al. (1994), the input set, the output set, and the Graph of the technology are depicted in Figure 2.3. The Graph of the technology is the area bounded by the x-axis and the line (0A). The input set is $L(Y^0) = [x^0,+\infty]$, and the output set is $P(x^0) = [0,y^0]$.

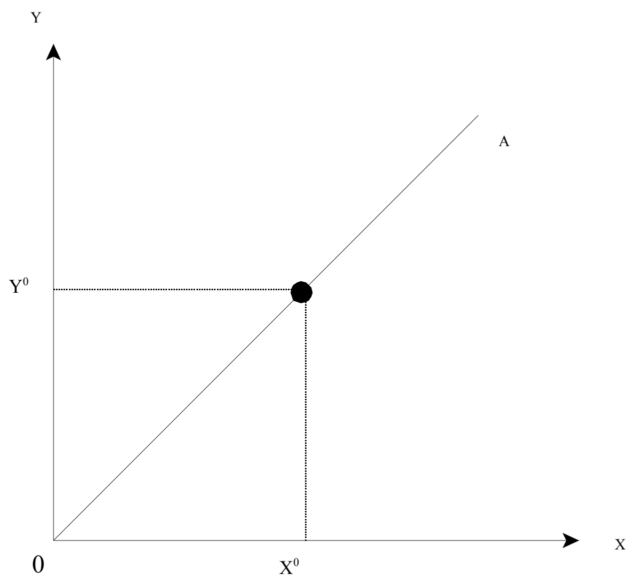

Figure 2.3 The Input and Output Sets and the Graph Technology

2.2.1.3 The Production Function and Input and Output Sets

The production function, y = f(x), represents the technological possibilities (i.e., the process by which inputs are transformed into outputs), and this function is defined by some basic properties.[4] While not exhaustive or globally maintained, four basic properties (Chambers 1988; Coelli et al. 2005)[5] are: (1) nonnegativity—the value of f(x) is a finite, nonnegative, real number; (2) weak essentiality—the production of positive output is impossible without the use of at least one input; (3) nondecreasing in x—also referred to as "monotonicity" or "strong disposability" in inputs, which means that additional units of an input will not decrease output; and (4) concave in x—any convex combination of the vectors x^0 and x^1 will produce an output that is no less than the same convex combination of $f(x^0)$ and $f(x^1)$.

As previously illustrated, the production technology can also be represented by the input and output sets. Properties of the input set are as follows: (1) L(y) is closed for all y; (2) L(y) is convex for all y; (3) inputs are said to be weakly disposable (i.e., cannot be disposed of without incurring a cost) if $x \in L(y)$ then, for all $\theta \geq 1.0$, $\theta x \in L(y)$; and (4) inputs are strongly disposable (inputs can be disposed of without incurring a cost) if $x \in L(y)$ and if $x^* \geq x$ then $x^* \in L(y)$.[6] Properties of the output set are as follows:[7] (1) $0 \in P(x)$—it is not possible to produce zero outputs by using a given set of inputs; (2) positive output levels require positive levels of inputs; (3) P(x) is strongly disposable if $y \in P(x)$ and $y^* \leq y$ then $y^* \in P(x)$; (4) P(x) satisfies strong disposability in inputs if y can be produced from x, and then y can be produced from any $x^* \geq x$; (5) the set P(x) is closed; (6) the set P(x) is bounded; and (7) P(x) is convex.

2.2.2 Strong and Weak Disposability

There are two basic notions of disposability which are important for examining the production technology (i.e., the relationship between inputs and outputs). The customary and usual notion of disposability is that of strong disposability. Both strong and weak disposability can be examined from either an input orientation (i.e., the input set) or an output orientation (i.e., output set). They can also be examined from the perspective of the Graph technology (i.e., both the input and output sets).

If the technology exhibits strong disposability in inputs, producers may dispose of unwanted inputs without incurring a cost. Alternatively, with weak disposability, the production isoquant may actually bend backwards, which is referred to as input congestion. Strong disposability of inputs implies that if inputs are either held the same or increased, output levels will not decrease. Another way of describing strong disposability of inputs is that an increase in inputs cannot decrease or "congest" outputs (Färe and Grosskopf 2000). Weak disposability of inputs allows that there may be too much input such that output is reduced or that there is a cost of disposing of unwanted inputs. Strong disposability implies weak disposability, but not the converse.

Strong disposability in outputs implies that unwanted outputs can be easily disposed of without cost. Weak disposability, on the other hand, implies that outputs cannot be disposed of without incurring a cost. Weak disposability of outputs is also referred to as output congestion. In general, weak disposability in outputs implies that a reduction in some output requires a corresponding reduction in the other outputs or that it is not possible to reduce one output without reducing some other outputs. For technologies producing both desirable and undesirable outputs, weak disposability is often imposed on the underlying technology, such that reductions in the undesirable outputs require joint reductions in the desirable outputs. Returning to the production possibilities set depicted in Figure 2.2, weak disposability would imply that it would not be possible to reduce Y_1 without reducing Y_2, or that the output set would bend down. The notion of weak disposability will be discussed in greater detail later in this report.

2.3 Efficiency and Capacity

Efficiency is an important concept for production. In simple terms, efficiency is a metric indicating how well a firm is utilizing its inputs to produce outputs. Unfortunately, there are multiple efficiency metrics, but in this report we are concerned with technical efficiency (TE) relative to input usage and technical efficiency relative to output levels (i.e., input and output orientations).[8] First, however, we introduce the notion of a frontier (i.e., the production frontier).

2.3.1 Technical Efficiency and the Frontier

The production frontier relates and depicts the combinations of inputs and outputs, such that input levels are minimized for a given output, or output levels are maximized for a given input level (Figure 2.4). All points along the frontier (0A), represent the maximum potential output y given the levels of the factors x of production, such as capital, labor, energy, and materials.

All points in the interior of the frontier (OA) represent inefficient production (e.g., point B). Three orientations are possible, but attention is restricted to an input orientation and output orientation. For output level y_b, x_b represents an inefficient utilization of input x. Input x could be reduced from x_b to x_c and still produce y_b. Alternatively, at input level x_b, output could be expanded to y_d. The contraction of input x from x_b to x_c represents an input orientation to assessing efficiency, and the expansion of output from y_b to y_d represents an output orientation to assessing technical efficiency.

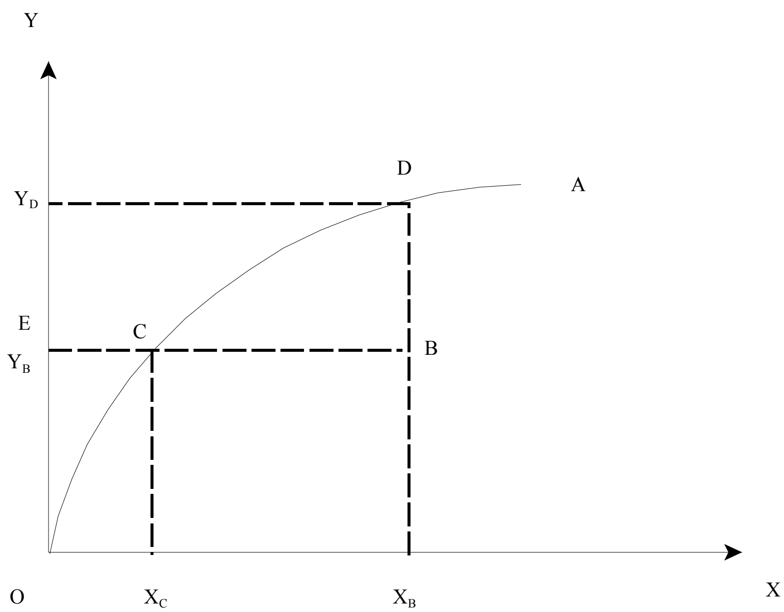

Figure 2.4. The Frontier Production Function

Technical efficiency, from an input orientation, equals the ratio EC/EB, and technical efficiency from an output orientation equals the ratio X_BB/X_BD. Technical efficiency, from an input orientation, provides a metric indicating the maximum contraction in inputs, given no change in outputs. In contrast, TE, from an output orientation, indicates the maximum expansion in outputs, given no change in inputs.[9]

<u>2.3.2 Distance Functions: Input, Output, and Directional</u>

Although it is customary to express the technology in terms of levels of inputs (x) and outputs (y), distance functions are quite useful for describing the technology and for easily linking it to measures of efficiency and productivity. More important, distance functions can be used to describe a multi-input, multi-output technology without having to specify a specific behavioral objective. An input distance function may be used to characterize the technology by considering the maximum proportional contraction of the input vector, given existing levels of outputs. An output distance function can characterize the technology corresponding to the maximal proportional expansion of the output vector, given existing levels of inputs.[10] Alternatively, a directional vector permits the simultaneous maximum contraction of inputs and expansion of outputs by a given level (Färe and Grosskopf 2004a).

We define the input distance function as $D_i(x,y) = \max\ \{\rho: (x/\rho) \in L(t)\}$,[11] where L(y) represents the set of all inputs, which can produce a vector of all outputs (y). Some general properties of the input distance function are as follows: (1) it is non-decreasing in x and non-increasing in y; (2) it is linearly homogeneous in inputs (x); (3) it is concave in x and quasi-concave in y; (4) if x belongs to the input set of y, then the distance function is greater than or equal to 1.0 in value; and (5) if x is on the frontier of the input set, the distance function equals 1.0. For the purpose of assessing TE, we normally consider the inverse of the distance function, $\theta = 1/D_i(x,y)$ as a measure of TE. Given an input orientation, θ is a measure of inefficiency, and $1 - \theta$ indicates the percentage by which all inputs can be radially contracted with no change in the level of production (i.e., the output levels).

Similarly, the output distance function may be defined as $D_o(x,y) = \min\ \{\delta: (y/\delta) \in P(x)\}$.[12] A few properties of the output distance function are as follows: (1) it equals 0.0 for all nonnegative values of x; (2) it is nondecreasing in y and nonincreasing in x; (3) it is linearly homogeneous in y; (4) it is quasi-convext in x and convex in y; (5) it is less than or equal to 1.0 in value if y is part of the production possibility set of x; and (6) if y is on the frontier (i.e., technically efficiency), the value of $D_o(x,y) = 1.0$. As is the case for the input-oriented efficiency metric, TE is normally measured as the inverse of $D_o(x,y)$, and $1/D_o(x,y) - 1$ indicates the proportion by which outputs could be expanded with change in inputs.

A third notion of a distance function is the directional technology distance function (Färe and Grosskopf, 2004a). A directional distance function facilitates expression of the frontier by recognizing the simultaneous proportionate contraction of inputs and expansion of outputs.[13] Since the directional vector is an integral aspect of this report, we devote considerable attention to it.

Following Färe and Grosskopf (2004a), we introduce and further discuss the directional technology distance function. We may denote the directional distance function as

$$\vec{D}_T(x, y, g_x, g_y) = \sup\{\beta : (x - \beta\, g_x, y + \beta\, g_y) \in T\}.$$

The directional technology distance function expands outputs in the direction g_y and contracts inputs in the direction g_x; β is the proportion by which inputs are contracted and outputs expanded.

In figure 2.5 we consider the simple case of a single input (x) and a single output (y). The first quadrant depicts the frontier technology—0T. The technology, including inefficient production, is the area between the x-axis and 0T. Our directional vector, G = (G_x,G_y), indicates the direction of change (normally G_y is positive and G_x is negative). The value of the distance function equals $0_a/0_g$, where 0g is the ray from the origin to (G_x,G_y). We say that production is efficient when the value of the directional distance function equals zero. Values greater than zero are associated with technical inefficiency (i.e., production is not occurring along the frontier) and represent the radial expansion in outputs and radial contraction in inputs (e.g., a value of .25 indicates that the producer could expand outputs by 1/4 and contract inputs by 1/4). The directional vector can also be used to depict the technology from either an input or output orientation. An input orientation simply requires setting G_y to 0.0 and an output orientation requires setting G_x to zero. The values of the input directional vectors directly equal the proportion by which inputs can be contracted; and the values of the output directional vector directly equal the proportion by which outputs can be expanded.

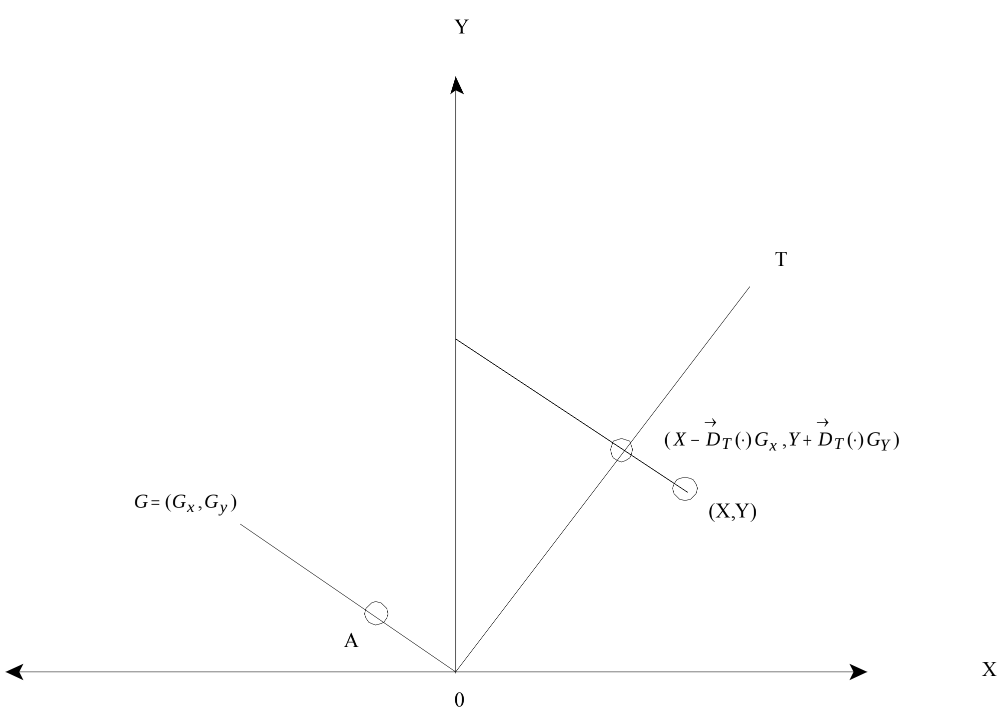

Figure 2.5 Directional Distance Technology

Basic properties of the directional distance function include the following: (1) the translation property, which states that if the input output vector (x,y) is translated into $D_T(x-\alpha g_x, y+\alpha g_y)$, the value of the distance function is reduced by the scalar α; (2) the directional distance function is homogeneous of degree 1.0 in the directional vector; (3) the representation property, which is the condition that when inputs and outputs are freely or strongly disposable, the distance function completely characterizes the technology; (4) if one level of the vector of inputs (e.g., x') is greater than or equal to another level of the vector of inputs (x), the directional vector corresponding to x' is greater than or equal to the value of the directional vector corresponding to x; (5) if y' greater than or equal to y, the directional distance function for y' is less than or equal in value to the value of the directional distance function corresponding to y; and (6) for a scalar increase in both inputs and outputs (λ) the value of the directional vector increases by λ, and thus, the technology exhibits constant returns to scale.[14]

In section 3.0, various methods are introduced for estimating and assessing technical efficiency and capacity. Although emphasis will be given to data envelopment analysis, other methods, such as the deterministic and stochastic frontier, will also be discussed.

3. Estimating Efficiency and Capacity

3.1 Methods for Estimating Technical Efficiency and Capacity

Despite the long and extensive history of research on technical efficiency, only two or possibly three basic methods exist for estimating technical efficiency.[15] One of the earliest methods was that by Farrell (1957), which was the precursor to data envelopment analysis (DEA) introduced by Charnes et al. (1978). Farrell (1957) used linear programming (LP) to construct the efficient unit isoquant from observed input/output ratios. The Farrell framework does not require specification of a functional form relating outputs to inputs to estimate efficiency. Other methods are the deterministic full frontier, the statistical frontier, and the stochastic frontier.

The basic notion of estimating efficiency is to determine the frontier production function (i.e., the maximum output given any input vector, or the minimum input usage required to product any given output vector) (Kumbhakar and Lovell, 2000). Another alternative notion of efficiency is the frontier corresponding to the maximum output and minimum input levels. Koopmans (1951), Debreu (1951), and Shephard (1953, 1970), however, all introduced notions of technical efficiency. Koopmans (1951) stated "A producer is technically efficient if, and only if, it is impossible to produce more of any output without producing less of some other output or using more of some input." The Koopmans definition has become equated to the Pareto-Koopmans concept of efficiency. Debreu (1951) and Shephard (1970) used distance functions as a way of modeling multiple-output technologies, and as a way to measure the radial distance of an existing combination of inputs and outputs from a frontier. Debreu (1951) emphasized the expansions of outputs, and Shephard (1970) focused on the contraction of inputs.

All the various methods and concepts have their advantages and disadvantages.[16] Except for the resurgence of the use of the deterministic frontier (i.e., parameters corresponding to a specified frontier function are estimated via mathematical programming but the estimates are adjusted by corrected ordinary least squares), DEA and the stochastic frontier appear to be the two primary approaches used to estimate and assess technical efficiency and capacity, with DEA being the primary approach used to estimate capacity (Färe et al., 1993; Kirkley et al., 2002; Felthoven and Morrison-Paul, 2004; Färe et al., 2006). In the next section, we introduce the various approaches and methods but primarily focus on the use of DEA, the stochastic frontier, and the modified deterministic frontier.

3.2 Methods for Estimating Efficiency and Capacity

Although DEA or similar variants of DEA were used to estimate efficiency prior to the other approaches, here we will first discuss direct production function approaches. The deterministic full frontier approach is first discussed, and we introduce the notion of the stochastic production frontier (SPF). Finally, we then provide a brief introduction and overview of DEA.

3.2.1 The Deterministic Full Frontier

Aigner and Chu (1968) initially introduced the deterministic frontier. This approach requires specification of a production function (i.e., a mathematical function explicitly relating the level of output to the levels of various inputs). That is, $y = f(x)\, e^{-u}$, where y is the output; x is a vector of inputs; f is a function relating outputs to inputs; and u is a metric used to estimate TE. For a multiplicative specification (e.g., the Cobb-Douglas), TE equals e^{-u}. Färe et al. (2005), however, have recently illustrated how TE could be estimated with the deterministic framework by using an additive rather than a multiplicative specification of the underlying technology. For the purpose of introducing concepts, we focus only on the multiplicative model.

We assume a single output and multiple input production technology (e.g., with two inputs, we have $y = \beta_0\, x_1^{\beta 1} x_2^{\beta 2} e^{-u}$, where y is an output; x_1 and x_2 are inputs; u is an inefficiency term; and the βs are parameters to be estimated). Technical efficiency equals e^{-u}. The frontier function can be estimated via several methods. Aigner and Chu (1968) suggested linear LP and quadratic programming (QP) models. The LP model requires minimization of the sum of deviations between the frontier and the observed output levels. More formally, the goal of the LP model is to calculate the parameters for which the sum of the proportionate deviations of the observed output of each producer beneath maximum feasible output is minimized (Kumbhakar and Lovell, 2000).[17] This model is as follows:

$$\min \sum_i u_i,\ \ u_i = \hat{\beta}_0 + \hat{\beta}_1 \ln x_{1j} + \ldots + \hat{\beta}_N \ln x_{Nj} - \ln y_j$$

$$\text{subject to } \left[\beta_0 + \sum_{n=1}^{N} \beta_n \ln x_{ni} \right] \geq \ln y_i$$

The QP problem is the same, except that it determines the parameters that minimize the sum of the squared proportionate deviations.

Other approaches have also been proposed to estimate the deterministic frontier. Winsten (1957) proposed a two-step estimation procedure. In step 1, the parameters are estimated by ordinary least squares, and in step 2, the intercept is estimated by corrected ordinary least squares (COLS), and the COLS intercept bounds the data from above (i.e., forms a frontier). Afriat (1972) and Richmond (1974) both proposed that the frontier be estimated by ordinary least squares, but assuming that the disturbances follow an explicit one-sided distribution (e.g., the exponential or half normal). Corbo and de Melo (1986) also refer to this approach as the statistical frontier.

A recognized criticism of the deterministic full frontier framework is that all noise or random variation is counted as inefficiency. To counter this criticism, Aigner et al. (1977) and Meeusen and van den Broeck (1977) proposed the notion of stochastic production frontier models. This approach explicitly allows the estimation of TE, while recognizing that noise or random events can affect output.

3.2.2 The Stochastic Frontier

The stochastic frontier was introduced by both Aigner et al. (1977) and Meeusen and van den Broeck (1977). Their specification explicitly recognized that external shocks or noise could affect production, and thus, it was important to be able to separate the influence of exogenous events from technical efficiency. They both proposed a specification, which included an error term (ϵ) composed of noise (v) and technical inefficiency (u).

Referring back to the Cobb-Douglas specification, the SPF model is as follows:

$$\ln y_i = \beta_0 + \sum_n \beta_n \ln x_{ni} + v_i - u_i ,$$

where v_i is a two-sided, normally distributed noise component, and u_i is the non-negative technical inefficiency term. Inefficiency is subsequently estimated such that each estimate of u_i yields an estimate of technical inefficiency for every observation. The inefficiency term, u_i, may be assumed to follow a half-normal, exponential, gamma, or truncated normal distribution.[18] Estimation is normally accomplished by maximum likelihood, but Kumbhakar and Lovell (2000) offer a method of moments approach for estimating the stochastic frontier.

A criticism of the stochastic frontier has been how to estimate efficiency when there is more than one output. One approach for dealing with multiple outputs is the distance function approach. When there is more than one output, however, there is a concern about potential endogeneity (i.e., dependent variables on both sides of an equation) vs. exogeneity. Kumbhakar and Lovell (2000), suggest that the endogeneity problem is irrelevant. Coelli and Perelman (2000) also offer the same conclusion. Atkinson et al. (2003) claim that recommended procedures for addressing the endogeneity issue may not be appropriate, and advocate the use of non-linear three stage least squares.

Since the Cobb-Douglas specification is often viewed as having several limitations (e.g., unitary elasticity of substitution among inputs and global returns to scale over all levels of inputs and outputs), we introduce the notion of a translog specification. For the sake of clarity, we also further discuss the notion of the translog input and output distance functions.[19]

The translog is but one form of the family of flexible functional forms (FFFs) often used to specify the production function or frontier. The generalized form of the flexible function form is

$$f(y) = \beta_0 + \sum_{i=1}^{n} \beta_i g_i(x_i) + \frac{1}{2} \sum_{i=1}^{n} \sum_{n=1}^{M} \beta_{ij} g_i(x_i) g_j(x_j),$$

where each g_i is a known twice-continuously differentiable function of x_i, and $b_{ij} = b_{ji}$. Widely used FFF specifications include the quadratic, normalized quadratic, translog, and generalized Leontief; all involve different transformations (e.g., in the translog, g_i is a log transformation).[20]

The preceding specification, however, is for a single output and multiple input technology. For the purpose of estimating TE, we typically consider the multiplicative translog function and estimate with our composite error term, which includes noise and inefficiency. We can, however, specify our technology by using an output distance function, D_{oi}.[21] Following Coelli (undated), we specify a k input, m output translog output distance function:

$$\begin{aligned} \ln D_{Oi} = \alpha_0 + \sum_{m=1}^{M} \alpha_m \ln y_{mi} + \frac{1}{2} \sum_{n=1}^{N} \sum_{m=1}^{M} \alpha_{mm} \ln y_{mi} \ln y_{ni} + \sum_{k=1}^{K} \beta_k \ln x_{ki} x + \\ \frac{1}{2} \sum_{k=}^{K} \sum_{l=1}^{K} \beta_{kl} \ln x_{ki} \ln x_{li} + \sum_{k=l}^{K} \sum_{m=1}^{M} \delta_{km} \ln x_{ki} \ln y_{mi}. \end{aligned}$$

Since an output distance function is specified, restrictions must be imposed on the translog output distance function to ensure linear homogeneity in outputs. The required restrictions are as follows:

$$\sum_{m=1}^{M} \alpha_m = 1, \ \sum_{n=1}^{M} \alpha_{mn} = 0, \ m = 1,2,..., M, \text{ and } \sum_{m=1}^{M} \delta_{km} = 0, \ k = 1,2,..., M.$$

As is apparent, the output distance function has outputs on the right side of the specification. These are normally viewed as dependent or endogenous variables. Also, and more important, is that the value of the output distance function is unobserved. To address these two problems, we can simply normalize the output distance function by dividing all outputs by a reference output (e.g., y_2). We can then add the negative of the natural logarithm of D_{oi} to the right hand side of the specification, which becomes our term for inefficiency. Last, for the purpose of estimating the stochastic frontier, we add a normally distributed error term, v_i. The function we estimate is then as follows:

$$- \ln y_{2i} = \alpha_0 + \sum_{m=1}^{M} \alpha_m \ln(y_{mi} / y_{2i}) + \frac{1}{2} \sum_{m=1}^{M} \sum_{n=1}^{N} \alpha_{mn} \ln(y_{mi} / y_{2i}) + \sum_{k=1}^{K} \beta_k \ln x_{ki} +$$
$$\frac{1}{2} \sum_{k=1}^{K} \sum_{l=1}^{K} \beta_{kl} \ln x_{ki} \ln x_{li} + \sum_{k=1}^{M} \sum_{m=1}^{M} \delta_{km} \ln x_{ki} \ln(y_{mi} / y_{2i}) + v_i - \ln D_{Oi} .$$

Technical efficiency is then estimated by the expected value of e^{-ui} or the expected value of $e^{- \ln Doi}$.

As previously indicated, there is a potential problem of endogeneity. Several authors have argued that normalization by y_{ij} is appropriate to avoid the endogeneity problem. Others have argued that no type of normalization solves the problem, and that non-linear three stage least squares is required to estimate the parameters of the distance function. Coelli and Perelman (2000), however, have argued that since ratios are being used, they may be assumed to be exogenous. This conclusion now appears to be relatively well accepted.

3.2.3 Data Envelopment Analysis

Data envelopment analysis is a mathematical programming approach for assessing technical efficiency and various economic performance metrics. Charnes et al. (1978) formally introduced DEA, but their work was really an extension of the works of Shephard (1953, 1970) and Farrell (1957). Data envelopment analysis facilitates the construction of a non-parametric piece-wise frontier over the existing data. Efficiency measures may then be determined by examining ratios or distances between observed input and output combinations and frontier input and output combinations. Since there is such an extensive literature on DEA, we provide only a brief introduction to DEA in this section.[22]

Figure 3.1 depicts the frontier of a single output, single input technology. Data envelopment analysis seeks to generate a linear piece-wise surface for the frontier. All points on the frontier represent technically efficient combinations of inputs and outputs, and all points to the interior of the frontier represent inefficient combinations of inputs and outputs. Data Envelopment Analysis seeks to determine the maximal radial contraction (expansion) of inputs (outputs), while still remaining with the feasible input (output) set (Coelli et al., 2005).[23] The projection of observed inputs (outputs) onto the frontier is done from an input (output) orientation. Non-orienting projections, however, are also possible with alternative types of DEA models. Unlike regression, which determines a statistical relationship between dependent and independent variables at the conditional mean level, DEA determines optimal solutions for every observation in a data set.

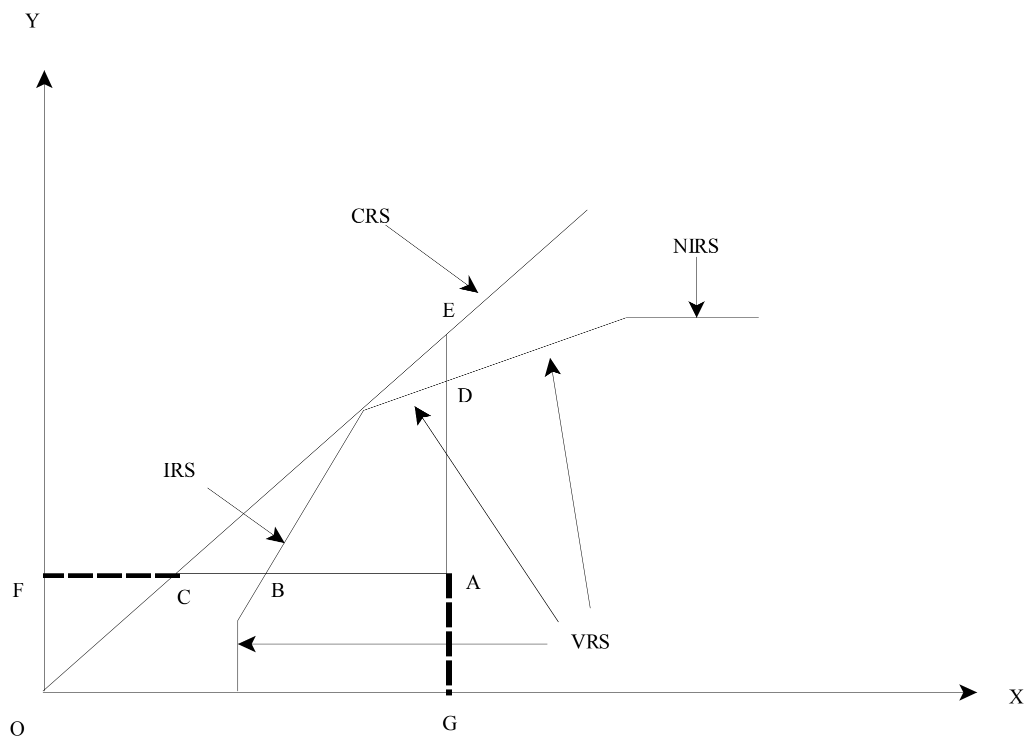

Figure 3.1 Input/Output Orientation and the Frontier.

Figure 3.1 depicts the frontier for three types of returns to scale (i.e., the percentage change in output given a one percent change in all input levels). The straight line from the origin represents constant returns to scale (i.e., output increases by 1% for a 1% increase in all inputs). The segmented line represents variable returns to scale (VRS), increasing returns to scale (IRS), and non-increasing returns to scale (NIRS).

Depending upon the orientation, DEA facilitates the determination of maximum contractions and expansions of inputs and outputs. From an input orientation and assuming VRS, DEA determines the ratio fb/fa, which indicates the percentage of inputs required to produce an output level corresponding to point f; the CRS reduction is fc/fa. The percentage by which the original input level can be reduced equals 1.0 – fb/fa for the VRS case, and 1.0 – fc/fa for CRS. The output-oriented measure of TE for the VRS case equals the ratio ga/gd, and ga/ge for CRS. The percentage by which outputs could be expanded equals gd/ga – 1.0 for the VRS case, and ge/ga – 1.0 for CRS.

Our concept of efficiency is that of weak efficiency. Strong efficiency, however, is also possible. If our projection of inputs or outputs coincided with one of the flat vertical or horizontal sections of the frontier technology, we would have slacks with values greater than zero.[24]   Production is said to be weakly efficient if production is technically efficient and slacks are not equal to zero. In contrast, production is said to be strongly efficient if production is technically efficient and all slacks equal 0.0. While distinguishing strong from weak efficiency is important, we focus primarily of DEA methods to estimate weak efficiency.[25]

There are numerous types of DEA models for estimating and assessing technical and economic efficiency. Here, we focus on the envelopment model and ignore the presence of slacks; the data envelopment analysis program (DEAP) of Coelli (1996), however, offers an envelopment algorithm which attempts to resolve the non-zero slack issue. Initially, we consider the DEA envelopment model from the input orientation. We consider the DEA envelopment model from the output orientation and then introduce the non-orienting (i.e., directional distance DEA model), which allows inputs to be contracted and outputs to be expanded. We also provide a brief introduction and description of the hyperbolic (i.e., graph efficiency) model.

3.2.3.1 DEA and Input Orientation

We initially designate vectors of inputs as x and outputs as y. We specify that there are M outputs and N inputs. We have j observations, firms, or decision-making units (i.e., each pair of x_j,y_j represents the levels of x and y for the jth observation). Our DEA seeks to determine the value which inputs can be radially contracted; we will refer to that value as λ. Alternatively, we seek to determine the maximum radial contraction in inputs given the existing levels of outputs. In the input orientation, λ is a measure of technical efficiency and equals the percentage of total inputs required to be efficient. If $\lambda = 1.0$, production is said to be technically efficient. Values less than 1.0 imply inefficient production. The value $1 - \lambda$ indicates the percentage by which all inputs can be reduced and still produce the same level of output, y.

The DEA problem is a simple linear programming problem:[26]

$$\min_{z} \lambda$$

subject to

$$y_{jm} \leq \sum_{j=1}^{J} z_j y_{jm},\ m = 1,2,\ldots,M$$

$$\sum_{j=1}^{J} z_j x_{jn} \leq \lambda x_{jn},\ n = 1,2,\ldots,N$$

$$z_j \geq 0,\ j = 1,2,\ldots,J$$

where z is a vector of intensity variables, which indicates the intensity levels at which each of the J decision making units are conducted. Values of z are used to construct the reference (i.e., benchmark) frontier. The above problem, as specified, imposes constant returns to scale. Imposing the constraint that the sum of the z_i's must equal 1.0 imposes variable returns to scale; imposing the constraint that the sum must be less than or equal to 1.0 imposes nonincreasing returns to scale; and imposing the constraint that the sum must be greater than or equal to 1.0 imposes nondecreasing returns to scale.[27] The problem may be solved by using linear programming and is solved for every jth unit or observation.

3.2.3.2 DEA and Output Orientation

The output oriented DEA problem seeks to determine the maximum radial expansion of outputs given the existing levels of inputs. This is another simple linear programming problem, which is solved for every observation:

$$\max_{z} \theta$$

subject to

$$\theta y_{jm} \leq \sum_{j=1}^{J} z_j y_{jm},\ m = 1,2,\ldots,M$$

$$\sum_{j=1}^{J} z_j x_{jn} \leq x_{jn},\ n = 1,2,\ldots,N$$

$$z_j \geq 0,\ j = 1,2,\ldots,J$$

If θ = 1.0 in value, production is technically efficient; if θ is greater than 1.0, production is inefficient.[28] The same restrictions used to impose the various returns to scale in the input oriented DEA problem can be imposed on the output oriented problem to ensure that the technology is consistent with the desired returns to scale. The above problem imposes constant returns to scale. In this output oriented problem, as specified, θ is greater than or equal to 1.0, and the value of θ - 1.0 indicates the percentage by which the original output levels can be radially expanded (e.g., if $\theta = 1.5$, then outputs can be expanded by 50% with no change in inputs).

3.2.3.3 DEA and Directional Distance Technology

Although Luenberger (1992, 1995) introduced the directional technology distance function, Chambers et al. (1996) highly popularized the concept, and Färe and Grosskopf (2004a) formalized the theoretical concepts of the directional technology distance function. The directional vector is distinguished from the input and output orientations by the fact that both inputs and outputs are radially scaled to achieve technical efficiency. That is, inputs are contracted and outputs are expanded by the same scalar.

Estimation of technical efficiency using the directional technology distance function can be accomplished by solving the following linear programming problem:[29]

$$\max_{z} \beta$$

subject to

$$\sum_{j=1}^{J} z_j y_{jm} \geq y_{jm} + \beta g_{ym} \quad , m = 1,2,\ldots,M$$

$$\sum_{j=1}^{J} z_j x_{jn} \leq x_{jn} - \beta g_{xn}, \; n = 1,2,\ldots,N$$

$$z_j \geq 0, \; j = 1,2,\ldots,J$$

The $g = (g_x,g_y)$ functions are the directional distance functions and indicate the direction of expansion or contraction. A value of 1.0 indicates an expansion, and a value of –1.0 indicates a contraction. The value of β is a measure of efficiency. If β equals 0.0, production is efficient and changes in input and output levels are not necessary to achieve efficient production; for values of β greater than 0.0, output can be expanded by a percentage equal to β, and inputs may be contracted by the same percentage.

The directional technology distance function is an important concept because it can be used to estimate profit efficiency and technical efficiency in the presence of undesirable outputs. The preceding LP formulation, which will be further explored in section 4.0 of this report, can be modified such that desirable outputs can be expanded while both undesirable outputs and conventional inputs can be contracted. It can also be modified to permit only desirable outputs to be expanded and undesirable outputs to be reduced with no change in variable input usage. In section 4.0, we introduce the directional technology distance function and introduce how it can be used to estimate both technical efficiency and capacity when producers produce both desirable and undesirable outputs.

3.2.4 Methods for Estimating and Assessing Capacity

There are two basic notions of capacity: an economic concept, and a technological-economic concept (called a "primal" concept). The economic concept explicitly recognizes that input and output prices affect decision-making behavior, and subsequently, they effect the utilization of capital, labor, energy, and materials and the production of outputs.[30] In addition, the economic concept also directly links capacity output to economic decision-making behavior. In contrast, there is a widely used primal concept, in which existing technology and fixed factors constrain maximum potential output, but there are no limitations on the variable factors of production (Johansen, 1968).

Prior to the work by Färe (1984), the economic concept of capacity was the most often estimated and assessed. Initially, capacity was estimated based on first-order conditions derived from some assumed economic behavioral objective (e.g., cost minimization). Later, the economic theory of duality was used to estimate capacity (e.g., Morrison (1985a,1985b). Klein (1960), however, introduced an early framework for estimating and assessing the primal notion of capacity, and Klein and Long (1973) formalized a peak-to-peak approach for estimating capacity output. In 1984, Färe offered a framework for estimating the Johansen notion of capacity output, capacity utilization, and the optimal rate of variable input utilization.

In this report, we focus on the Johansen concept of capacity and the analytical framework offered by Färe (1984) and Färe et al. (1989b) for estimating capacity, capacity utilization, and the optimal rate of variable input utilization. This is because a primary concern of the present research is the assessment of capacity in fisheries for which economic data necessary to estimate the economic concept of capacity are seldom available. We also present a comparative framework based on the stochastic frontier developed by Kirkley et al. (2002) and a nonfrontier approach offered by Felthoven and Morrison-Paul (2004).

3.2.4.1 The Färe/Johansen Concept of Capacity and DEA

Färe (1984) originally offered a DEA (linear programming framework) for estimating capacity output and capacity utilization. Färe et al. (1989b) later offered a more completed development of the framework and included a procedure for estimating an unbiased measure of capacity utilization. Färe (1984) and Färe et al. (1989b) offered procedures for estimating three important metrics related to capacity: (1) capacity output, (2) an unbiased measure of capacity utilization, and (3) a measure of variable input utilization.

The Färe (1984) and Färe et al. (1989b) framework was a relatively simple output-oriented DEA model:

$$\max_{z,\lambda} \theta$$

subject to

$$\theta y_{jm} \le \sum_{j=1}^{J} z_j y_{jm}, \; m = 1,2,\ldots,M$$

$$\sum_{j=1}^{J} z_j x_{jn} \le x_{jn}, \; n \in F_x$$

$$\sum_{j=1}^{J} z_j x_{jn} = \lambda_{jn} x_{jn}, \; n \in V_x$$

$$z_j \ge 0, \; j = 1,2,\ldots,J$$

$$\lambda_{jn} \ge 0, \; n \in V_x$$

where θ is the proportion by which outputs can be expanded to yield the capacity output (e.g., if the reported output equaled 100 units and θ equaled 1.5, the capacity output would equal 150 units); z is a vector of the intensity variables, which permits the construction of convex combinations of outputs and inputs; λ is a measure of the proportionate expansion or contraction of the variable factors, V_x; F_x is a vector of the fixed factors; y_{jm} is the mth output of the jth decision making unit; and x_{jn} is the nth input of the jth decision making unit. The second constraint applies only to the fixed factors, and the third constraint applies only to the variable factors. The same constraints previously discussed for the input and output oriented DEA models can be used to specify the returns to scale. The LP model can, however, be estimated with or without the constraint on the variable factors. The variable factor constraint simply ensures that the variable factors do not restrict output. It also facilitates a direct calculation of the variable inputs levels required to produce the capacity output.

Färe et al. (1989b) also offered an unbiased measure of capacity utilization (CU). The conventional measure of capacity utilization equals the observed output (level of production) divided by the capacity output, and it indicates the utilization of the capital stock (i.e., the plant and equipment). Färe et al., however, suggested that the conventional measure of CU might be misleading because of technical inefficiency (i.e., inefficient production, rather than substantial underutilization of the capital stock, might be a reason why firms do not produce the capacity output). To address this potential bias, Färe et al. suggested that a more appropriate metric of CU is the ratio of technically efficient output to capacity output, or more specifically, the ratio of the technical efficiency score from the output oriented DEA model to the value of θ from the DEA model used to estimate capacity output. The value of the unbiased measure of CU is restricted to less than or equal to 1.0 in value. If the unbiased measure is less than 1.0 (e.g., 0.90), it implies that approximately x% (e.g., 90%) of the capacity output could be realized through improvements in technical efficiency. The remaining increase in output would require expansion of the variable inputs.

Another useful metric relative to capacity is the variable input utilization rate proposed by Färe et al. (1989b, 1994). This metric equals the ratio of the optimal level of variable input necessary to produce the capacity output to the actual level of the variable input used to produce the reported output:

$$\lambda_{jn}^{*} = \frac{\sum_{j=1}^{J} z_j^{*} x_{jvi}}{x_{jvi}}, \; n \in V_x .$$

If the rate exceeds 1.0, a firm is using too little of a given variable input, and if the rate is less than 1.0 in value, a firm is using too much of the variable input. A value of 1.0 implies that a firm is using the appropriate level of the variable input to produce the capacity output.

3.2.4.2 Capacity, The Stochastic Frontier, and Nonfrontier Primal Measure

A frequent criticism of DEA is that it does not adequately address noise or stochastic events. Alternatively, all noise is imputed as technical inefficiency. There is also a concern that DEA overestimates capacity. Despite an extensive amount of research on developing stochastic DEA, there does not appear to be a consensus on an acceptable stochastic DEA.[31]

Kirkley et al. (2002, 2004) offer a comparative framework based on the stochastic production frontier, for estimating capacity in fisheries. They also construct the unbiased CU measure and determine the optimal level of variable input utilization. They specified a translog frontier but distinguished fixed (F) factors from variable (V) factors. The variables included in the analysis were K or the fixed capital stock; V, a vector of variable inputs; S as a vector of nondiscretionary stock inputs not within the control of the vessel operator; and R as a vector of external control or shift variables (such as season or year). The translog specification was as follows:

$$\ln y_i = \alpha_0 + \sum_k \alpha_k \ln K_k + \alpha_s \ln S + \sum_n \alpha_n \ln V_n + \sum_r \alpha_r R_r + \sum \gamma_{Sn} \ln S \ln V_n$$
$$+ \sum_r \gamma_{Sr} \ln S R_r + \sum_n \sum_r \gamma_{nr} \ln V_n R_r + \sum_n \beta_{nn} (\ln V_n)^2 + \sum_r \beta_{rr} R_r^2$$

The full translog specification was used to estimate technical efficiency and the production frontier. The same function, but with the variable inputs omitted, was used to obtain estimates of capacity output. Estimates of capacity from the stochastic frontier were then compared to estimates of capacity output from DEA. The results indicated considerable differences in the two estimates, with the DEA estimates of capacity being higher than those obtained by using the stochastic frontier. The empirical work by Kirkley et al. (2002, 2004) pertained to a single output fishery—the sea scallop fishery. A stochastic distance function approach, however, could also be used when there are multiple outputs. There remains the problem, however, of omitted variable bias.

Felthoven and Morrison-Paul (2004) offer an alternative specification and estimation of capacity. They adopt an approach similar to that of Kirkley et al. (2004) but do not consider the stochastic production frontier. Their focus is on maintaining the existing levels of technical inefficiency and obtaining estimates indicative of customary and usual operating procedures. They specify a generalized quadratic transformation function (i.e., multiple product technology). They subsequently calculate capacity output by using the assumption that variable inputs could increase by 25-50% beyond their reported levels, and then they determine the level of variable input usage at which the marginal products of the variable inputs equal 0.0. Similar to most other studies on production involving multiple outputs, this one also has the potential criticism of having endogenous variables on both sides of the equation being estimated. In addition, the concept of capacity is determined not directly by the fixed factors but rather by the marginal products of the variable inputs being equal to 0.0.

4. Efficiency, Capacity, and Undesirable Outputs

4.1 Assessing Efficiency and Capacity with Undesirable Outputs

Undesirable outputs or the production of undesirable outputs occur in many industries. Traditional examples of undesirable outputs include emissions of harmful substances in air, water, and ground. Although the production of undesirable outputs is widespread, most research attention has been given to the empirical analysis of technical efficiency in the presence of undesirable outputs in electric generating facilities (e.g., Lee et al., 2002; Färe et al., 2004b). Färe et al. (2006), however, examined the technical efficiency of undesirable outputs in fisheries.

The issue of addressing undesirable outputs apparently arose out of concern that the evaluation of the performance of producers was recognized as efficient regardless, of their production of undesirable outputs. As a result, producers with high levels of undesirable outputs were not penalized relative to the assessment of technical and economic efficiency (Färe et al. 1989a). Pittman (1983) was among the earlier researchers to introduce a framework for assessing a firm's level of performance while explicitly considering both desirable and undesirable outputs. Pittman, however, evaluated performance by using a multilateral productivity index without explicit recognition of technical efficiency and without penalizing efficiency for undesirable outputs (i.e., under Pittman’s framework, both desirable and undesirable outputs were allowed to increase).

Färe et al. (1989a) introduced one of the earliest frameworks for assessing TE when some outputs are undesirable. The Färe et al. approach was based on mathematical programming, and more specifically, a type of DEA.[32] Färe et al. approached the estimation of TE with undesirable outputs from the perspective of hyperbolic output efficiency (i.e., graph efficiency). With this framework, efficiency could be estimated conditional upon the simultaneous expansion of desirable outputs and contraction of undesirable outputs.

Färe et al. (1993) later introduced the use of a parametric output distance function to estimate TE, and more importantly, to estimate the shadow values of undesirable outputs. Färe et al. (1993) specified a translog functional form for the production technology with an output distance function on the left hand side. The Aigner and Chu (1968) linear programming approach was used to estimate the parameters of the translog function form. Restrictions imposed on the specification included lineary homogeneity, weak disposability, and nonpositive shadow prices for undesirable outputs. Coggins and Swinton (1996) applied the approach of Färe et al. (1993) to estimate the shadow prices of SO_2 allowances for Wisconsin coal-burning utility plants. Kwon and Yun (1999) also estimated TE and shadow prices in the presence of undesirable outputs by using the translog specification and the method of Färe et al. (1993). Huang and Leung (2006) also used the same approach to estimate efficiency and shadow prices for Hawaii's longline fishery, which included the bycatch of sea turtles as undesirable outputs.

Chung et al. (1997) provided a framework for estimating efficiency and productivity with undesirable inputs by using directional distance vectors. The Chung et al. framework explicitly allowed the simultaneous expansion of desirable outputs and contraction of undesirable outputs by the same proportion. Data envelopment analysis was used to estimate efficiency and calculate productivity based on estimates of the directional distance vectors.

Lee et al. (2002) also applied the directional distance function framework to analyze TE for production involving undesirable outputs, but unlike Chung et al. (1997), imposed restrictions such that desirable outputs had to be reduced along with reductions in undesirable outputs. The work by Chung et al. allowed desirable outputs to be expanded while undesirable outputs were contracted. Lee et al. analyzed performance by electricity generation plants in Korea.

Färe et al. (2004b) recently offered another non-stochastic, parametric approach for assessing technical efficiency and the shadow prices of undesirable outputs. This framework specified a generalized quadratic function as the production technology, and the dependent variable was a directional distance vector with directions of +1.0 for desirable outputs and –1.0 for undesirable outputs.

4.2 Estimating Capacity in Fisheries with Undesirable Outputs

Although a wide array of approaches have been developed to assess technical efficiency in the presence of undesirable outputs, we focus on two methods in this study—the directional distance function approach of Chambers et al. (1996), and the graph technology (i.e., hyperbolic efficiency) of Färe et al. (1993).[33] We also introduce and briefly discuss an alternative DEA model proposed by

Seiford and Zhu (2002) to assess efficiency in the presence of undesirable outputs. The focus of our discussion and research, however, is on capacity and technical efficiency.

We consider the weak Johansen (1968) notion of capacity which was introduced by Färe (1984). That is, capacity output is the maximum potential output that can be produced per unit of time with existing plant and equipment, given that the availability of variable factors of production is not restricted (Färe et al., 1994, p. 261). Our notion of capacity is illustrated in Figure 4.1.

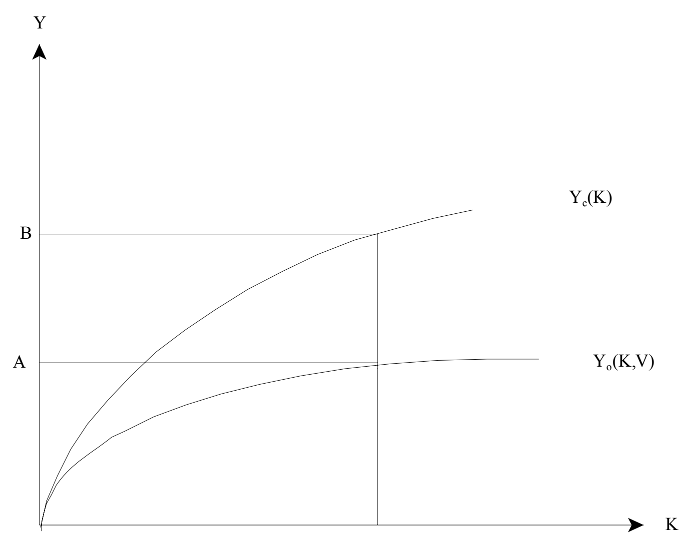

Figure 4.1. Actual and Capcity Output

The vertical axis depicts output, and the horizontal axis depicts the fixed input (e.g., the capital stock). The line segment Y_O(K,V) represents the observed output (A) corresponding to the capital stock and variable (V) factors of production. The other line segment Y_C(K) represents the capacity (B) output corresponding to the capital level K, but without limitations on the variable (V) factors of production. Alternatively, Y_C(K) is the maximum potential output that can be produced by K given the full utilization of the variable factors of production (i.e., the levels of the variable factors required to produce the capacity output).

One approach for estimating capacity output is to apply DEA, as suggested in section 3.2.4.1. This is a relatively simple linear programming problem. We seek the maximum radial expansion of outputs subject only to constraints imposed by the fixed factors of production (e.g., capital). Variable factors, such as energy, materials, and labor, are allowed to expand or increase as necessary to produce the capacity output.

The standard DEA problem, however, does not address the problem of estimating capacity in the presence of undesirable outputs. In this section, we consider two alternative DEA problems, which were introduced by Färe et al. (1989a) and Färe and Grosskopf (2004a). The first approach of Färe et al. (1989a) is based on the hyperbolic efficiency measure, and the Färe and Grosskopf (2004a) approach is based on a directional output distance vector. We also present the additive modeling approach of Seiford and Zhu (2002).

<u>4.2.1 The Hyperbolic Efficiency Measure</u>

Färe et al. (1989a) offer a hyperbolic efficiency measure, which permits desirable outputs to be expanded and undesirable outputs and inputs to be contracted. Unfortunately, the hyperbolic efficiency metric is a nonlinear problem, and thus requires some modifications to be solved via linear programming.[34] We have M^g desirable outputs, M^b undesirable outputs, N outputs, and J observations. We seek an expansion in desirable outputs and a contraction in both undesirable outputs and inputs. The generalized hyperbolic output efficiency problem of Färe et al. (1989a) is as follows:

$$H_O^A(y_j^g, y_j^b, x_j) = \max_z \lambda$$

subject to:

$$\lambda y_{jm}^g \le \sum_{j=1}^{J} z_j y_{jm}^g, m = 1,2,..., M^g$$

$$\lambda^{-1} y_{jm}^b \le \sum_{j=1}^{J} z_j y_{jm}^b, m = 1,2,...., M^b$$

$$\sum_{j=1}^{J} z_j x_{jn} \le \lambda^{-1} x_{jn}, n = 1,2,...., N$$

The problem is nonlinear, but can be made linear by using a first-order Taylor's series approximation for the nonlinear constraint (Fare et al. 1989a; Ray 2004). Define $f(\lambda) = 1/\lambda$, and then at $\lambda = \lambda_0$, we have

$$f(\lambda) \approx f(\lambda_0) + f'(\lambda_0)(\lambda - \lambda_0) = \frac{2\lambda_0 - \lambda}{\lambda_0}.$$

At $\lambda_0 = 1$, we have $f(\lambda)$ approximately equal to $2 - \lambda$.

In order to estimate our capacity model, we need to modify the above model by making it linear, by imposing weak subvector disposability on the undesirable outputs (i.e., disposing of undesirable outputs is not free), and by breaking up the constraint on the inputs so only the fixed factors can bind production. Additionally, we can also impose variable returns to scale, if we choose. Making these changes to the above model yields the following DEA problem for estimating capacity with weak subvector disposability and variable returns to scale imposed:

$$
\begin{aligned}
& H_O^A(y_j^g, y_j^b, x_j) = \max_z \lambda \\
& \text{subject to:} \\
& \lambda y_{jm}^g \le \sum_{j=1}^{J} z_j y_{jm}^g, \ m = 1,2,\ldots, M^g \\
& 2y_{jm}^b - \lambda y_{jm}^b - \sum_{j=1}^{J} z_j y_{jm}^b = 0, \ m = 1,2,\ldots., M^b \\
& \sum_{j=1}^{J} z_j x_{jn}^f - x_{jn}^f \le 0, \ n = 1,2,\ldots., N^F \\
& \sum_{j=1}^{J} z_j x_{jn}^v - \delta x_{jn}^v \le 0, \ n = 1,2,\ldots., N^V \\
& \sum_{j=1}^{J} z_j = 1.
\end{aligned}
$$

The second constraint imposes the Taylor's series expansion and imposes weak subvector disposability by changing the constraint to a strict equality. In the above problem, the fixed and variable factors of production are split into two constraints, and δ is included in the fourth constraint to facilitate the estimation of the full utilization levels of the variable inputs. The problem imposes variable returns to scale by restricting the sum of the intensity variables to equal one in value in the last equation. We, thus, end up with what Färe et al. (1989a) refer to as a hyperbolic output measure. Färe et al. illustrate that the potential loss in output caused by an absence of strong disposability equals the reported output times the difference between the hyperbolic efficiency measure with strong disposability and the hyperbolic efficiency measure with weak disposability. In addition, a producer-specific measure of the potential loss in revenue may be calculated by multiplying the output price times the loss caused by an absence of strong disposability.

4.2.2 Directional Distance Functions.

A second approach for estimating capacity with undesirable outputs involves directional distance vectors, or as suggested in Färe and Grosskopf (2004a), the directional output distance function. The Färe and Grosskopf approach requires null-jointness in desirable and undesirable outputs. The term "null-jointness" means that the positive production of a desirable output requires the positive production of a undesirable output, or that if the level of a undesirable output is zero, then the level of a desirable output must also be zero. The hyperbolic efficiency measure does not require null-jointness in desirable and undesirable outputs. The following model is a candidate directional output distance function approach :

$$\max_{z} \beta$$

subject to

$$\sum_{j=1}^{J} z_j y_{jm} \geq y_{jm} + \beta g_{ym}, \quad m = 1,2,\ldots,M^g$$

$$\sum_{j=1}^{J} z_j y_{jn} = y_{jn} - \beta g_{ym}, \quad m = 1,2,\ldots,M^b$$

$$\sum_{j=1}^{J} z_j x_{jn} \leq x_{jn}, \quad n = 1,2,\ldots,N$$

$$z_j \geq 0, \; j = 1,2,\ldots,J$$

Note again that to obtain estimates of capacity, we restrict the third constraint to only fixed factors (i.e., the variable factors need not be included in the estimation). We also impose weak subvector disposability with the second equality constraint. Adding the restriction that the sum of the intensity variables must equal one imposes variable returns to scale. If the value of the directional vector is set equal to the observed values of the desirable and undesirable outputs (i.e., $g_{ym}=y_m$), β indicates the proportionate expansion in desirable outputs and contraction in undesirable outputs.[35] That is, capacity output equals (1+β)*Y_{GO} (observed desirable output). The reduction in undesirable outputs equals (1-β)*Y_{BO} (observed undesirable output). If β=0.0, production is efficient, or in the case of capacity output, production cannot be expanded, and the firm is producing the capacity output. The potential loss in desirable output is calculated as the product of the observed output times the difference between the values of (1+β) corresponding to strong and weak disposability.

4.2.3 The Seiford-Zhu Approach

Seiford and Zhu (2002) proposed an alternative model for assessing efficiency in the presence of undesirable outputs.[36] They proposed a modified Banker et al. (1984) model, which is an additive model with variable returns to scale. Their model permits both the expansion and contraction of desirable and undesirable outputs. Their approach also does not require null-jointness and thus is of some interest for estimating capacity output in fisheries, which often involves observations with zero production of certain desirable and undesirable outputs or zero levels of any undesirable outputs for some observations.

The approach of Seiford and Zhu is another DEA type problem:

$$
\begin{aligned}
&\text{Max } h \\
&\text{subject to } \sum_{j=1}^{J} \lambda_j y_{rj}^{g} \geq h\ y_{r0}^{g} \\
&\sum_{j=1}^{J} \lambda_j y_{rj}^{\bar{b}} \geq h\ y_{r0}^{\bar{b}} \\
&\sum_{j=1}^{J} \lambda_j x_{ij} \leq x_{i0} \\
&\sum_{j=1}^{J} \lambda_j = 1 \\
&\lambda_j \geq 0,\ j = 1,\dots,n
\end{aligned}
$$

To estimate h, it is necessary to change the undesirable outputs, which are indicated by b. In this case, we first make all the undesirable outputs negative by multiplying their levels by –1.0. We next find the highest level of a undesirable output and add it, together with 1.0, to the original negative value to form our y^b. In steps, we multiply the reported undesirable output levels by –1.0; we then form a new undesirable output by adding the maximum value of a undesirable output over all observations plus 1.0 (we call this v_r) to our negative levels of reported undesirable outputs. The efficiency scores (h) for this problem indicate the expansion and contraction of desirable and undesirable outputs; the values of h are greater than or equal to 1.0 in value. More formally, the efficient levels of desirable outputs equal the efficiency score (h) times the reported or observed desirable output plus the value of the slack for the given output. For the undesirable outputs, the efficient level equals v_r –(h times the undesirable output plus the values of the slack variables for the undesirable outputs). As noted by Färe and Grosskopf (2004b), however, the Seiford and Zhu (2002) approach does not impose weak disposability and thus may be limited in assessing efficiency or capacity in the presence of undesirable outputs.

5.0 Estimates of Capacity: The New England Georges Bank Otter Trawl Fishery

5.1 Overview of Estimation Procedures

In section 5, we present estimates of capacity output based on four estimation procedures. First, we present estimates of capacity output which ignore the production of undesirable outputs (such as bycatch of nonmarketable species or products). We next present estimates derived using the directional output distance function approach of Färe and Grosskopf (2004a). In this case, we follow the framework offered by Lee et al. (2002) in which various directions are considered for desirable and undesirable outputs . For example, in the more widely considered framework, desirable outputs are allowed to increase while undesirable outputs are restricted to decrease or remain unchanged. In another framework, both desirable and undesirable outputs are allowed to decrease. We also estimate capacity conditional on weak and strong disposability for the case of allowing desirable outputs to expand and undesirable outputs to contract. We next present estimates based on the graph technology approach of Färe et al. (1989a). While this is a non-linear programming problem, we use the linear approximation offered in Färe et al. (1989a). Estimation of graph efficiency or capacity is estimated subject to both weak subvector and strong disposability in the undesirable outputs. The final set of estimates is derived using the approach of Seiford and Zhu (2002), and we consider only the case of strong disposability

The various estimates are presented because each approach is different, and each has both advantages and disadvantages relative to the other methods. For example, the directional distance function approach is relatively easy to use to estimate capacity and efficiency, but it requires null-jointness in desirable and undesirable outputs (i.e., positive levels of desirable outputs can only be produced if positive levels of undesirable outputs are produced). This is unlikely to characterize data available on fisheries production. Neither the graph technology approach and the approach of Seiford and Zhu (2002) require null-jointness, which is of substantial concern in examining efficiency and capacity in fisheries because many of the observations may contain all zeros for the undesirable outputs (e.g., bycatch of regulated or non-marketable species). Allowing for zero levels of undesirable outputs better facilitates the estimation of efficiency and capacity in fisheries because many trips or tows (sets) produce no undesirable outputs.

For the directional distance function approach, we also conduct the types of analyses conducted by Lee et al. (2002). They estimated technical efficiency by using four combinations of the directional distance vector. First, they considered the Coggins and Swinton (1996) framework in which both desirable and undesirable outputs are allowed to increase; next they considered the framework of Turner (1995), which restricts the expansion of undesirable outputs to zero but allows the desirable outputs to increase; Lee et al. (2002) then followed Boyd et al. (1996) by allowing undesirable outputs to contract and desirable outputs to expand, which is the more conventional assumption. Lastly they forced contraction of both desirable and undesirable outputs, which they contend maintained the existing levels of technical inefficiency.

For the graph efficiency notion of Färe et al. (1989a), we estimate the initial model specification, which is conditional on no change in inputs but imposes weak subvector disposability in the undesirable output. We then estimate the same model while imposing strong disposability. Because of weak subvector disposability, we estimate the potential loss of output as the difference between the two efficiency measurements times the reported landings. If comprehensive price data were available, we could also estimate the potential loss in revenues by multiplying the potential loss in landings by the corresponding prices.

The Seiford and Zhu (2002) approach is estimated subject only to strong disposability. Färe and Grosskopf (2004b), however, recommend that weak disposability is the more appropriate constraint. We present results of the Seiford and Zhu (2002approach but only for comparative purposes.

5.2 The Georges Bank Otter Trawl Fishery

The New England Otter Trawl fishery is among the oldest, large-scale fisheries of the United States. The fishery targets a large number of species over a relatively large geographic area. The Georges Bank fishery is part of the New England trawl fishery, which exploits marine resources in the Gulf of Maine, Southern New England, and Georges Bank. Georges Bank, however, is the primary resource area.

Georges Bank is a large productive fishing ground situated in the northwest Atlantic, adjacent to the northeastern United States and extending into Canadian waters. Vessels fishing on Georges Bank harvest a wide variety of finfish species. Vessels in the fishery typically land 10 or more species, which may include cod (*Gadus morhua*), haddock (*Melanogrammus aeglefinus*), yellowtail flounder (*Limanda ferruginea*), pollock (*Pollachius virens*), winter flounder (*Pseudopleuronectes americanus*), witch flounder (*Glyptocephalus cynoglossus*), windowpane flounder (*Scophthalmus aquosus*), American plaice (*Hippoglossoides platessoides*), white hake (*Urophycis tenuis*), redfish (*Sebastes spp*.), and monkfish (*Lophius americanus*).

As is characteristic of trawl gear, the Georges Bank otter trawl fishery captures a wide array of non-marketable species.[37] These species are discarded either because there is no market for the species or because of various regulations (i.e., regulatory discards). These discards represent undesirable outputs in this study.

5.2.1 The Available Georges Bank Trawl Data

Unfortunately, discard information is seldom available for a fishery or fleet of vessels operating in the fishery. In this study, we use observer data collected over a three-year period (2003 through 2005). All data were organized at the trip level and reflect landings and discards of all species. There were 12 desirable outputs and 17 undesirable outputs. The 12 desirable outputs included: (1) monkfish, (2) cod, (3) haddock, (4) yellowtail flounder, (5) winter flounder, (6) pollock, (7) white hake, (8) red fish, (9) other flounder, (10) lobsters, (11), scallops, and (12) skates. The 17 undesirable outputs include the following species or aggregations: (1) skates, (2) monkfish, (3) cod, (4) haddock, (5) pollock, (6) redfish, (7) mixed hakes, (8)ocean pout, (9) sea robins and sea ravens, (10) yellowtail flounder, (11) winter flounder, (12) other mixed flounder, (13) summer flounder, (14) lobster, (15) mixed crabs, (16) seaweed, and (17) starfish.[38] In this study, a species can be included as both a desirable and undesirable output because of market conditions and regulations. Market conditions may force vessels to discard some catches because there is only demand for fish above a certain size. At the same time, regulations may force vessels to discard species below a certain size. In other fisheries, there are "no discard" regulations that force vessels to land everything that is caught. Instead of discarding, non-marketable species may be processed on land into other products, such as fish meal or fertilizer. However, vessels in these fisheries may still inadvertently catch certain marine mammals, seabirds, and turtles which would be considered undesirable outputs.

The data set contained a total of 307 observations (individual fishing trips) representing 52 vessels (69 trips) operating in 2003, 50 vessels (67 trips) operating in 2004, and 102 vessels (171 trips) operating in 2005. The total number of individual vessels over the three-year period included in the data set was 129. Vessel size ranged from 44 to 107 feet, gross registered tonnage (GRT) between 5 and 201, and engine horsepower (HP) between 250 and 1,380 HP (Table 5.1). Average annual catch of desirable outputs per vessel was 72.9 thousand pounds in 2003, 63.3 thousand pounds in 2004, and 68.3 thousand pounds in 2005. The corresponding average annual catch per vessel of undesirable outputs was 43.2 thousand pounds in 2003, 37.3 thousand pounds in 2004, and 55.6 thousand pounds in 2005.

The desirable and undesirable catch at the trip level are summarized in Tables 5.2 and 5.3. The catches of all desirable outputs (usually referred to as "landings") combined ranged from 22 to 249,848 pounds per trip between 2003 and 2005 (Table 5.2). The catches of undesirable outputs (discards) on any single trip ranged between 1 and 469,156 pounds (Table 5.3). In terms of total desirable outputs over the three-year period, haddock had the highest level of landings (3.8 million pounds) for the sample data; cod ranked second with 2.0 million pounds; yellowtail flounder was third with 1.8 million pounds; all skates combined ranked fourth with 1.6 million pounds; winter flounder ranked fifth in landings with 1.5 million pounds. In terms of undesirable outputs, skates had the highest level of catch over the three-year period with 8.1 million pounds; mixed flounder was second highest with 311 thousand pounds; cod ranked third with 216 thousand pounds; haddock ranked fourth with 194 thousand pounds; various species of crabs, aggregated together, ranked fifth with 174 thousand pounds. It is stressed that although not every trip caught every desirable or undesirable species, every trip had at least one pound of desirable and one pound of undesirable species.

Table 5.1. Annual summary statistics of Georges Bank sample data, 2003-2005

	Mean Values				Total (Summation) Values per Vessel			
Year	Vessel Length (Feet)	Gross Tonnage (GRT)	Horsepower (HP)	Crew Size (Number)	Days Fished (Hours)	Days at Sea	Desirable Outputs (Pounds)	Undesirable Outputs (Pounds)
2003								
Vessels	52							
Minimum	44	5	300	2	9	1	697	274
Maximum	106	201	1,380	5	597	37	194,925	147,347
Mean	77	145	687	4	141	10	72,873	43,163
Sum[39]	3,979	7,530	35,712	228	7,335	539	3,789,417	2,244,467
2004								
Vessels	50							
Minimum	44	22	250	2	1	1	22	178
Maximum	92	199	1,280	5	376	26	416,129	183,227
Mean	75	140	637	4	125	10	63,334	37,702
Sum	3,769	6,991	31,833	213	6,261	488	3,166,717	1,885,085
2005								
Vessels	102							
Minimum	44	22	275	2	10	1	958	222
Maximum	107	201	1,380	6	490	36	299,237	469,156
Mean	76	138	637	4	161	13	68,282	55,582
Sum	7,738	14,037	64,948	425	16,421	1,285	6,964,791	5,669,387
Total[40]								
Vessels	129							
Minimum	44	5	250	2	1	1	22	222
Maximum	107	201	1,380	6	782	51	676,806	469,156
Mean	75	135	627	4	233	18	107,914	75,961

Table 5.2. Trip level summary from sample data set of Georges Bank otter trawl fishery catches in pounds (desirable outputs) 2003-2005.

Year	Monkfish	Cod	Haddock	Yellowtail Flounder	Winter Flounder	Pollock	White Hake	Redfish	Mixed flounder	Lobster	Scallops	Skates	Desirable
2003													
Trips	69	69	69	69	69	69	69	69	69	69	69	69	69
Mean	5,355	12,254	9,385	4,921	8,815	1,709	996	313	3,209	1,364	225	6,375	54,919
Minimum	0	0	0	0	0	0	0	0	0	0	0	0	697
Maximum	32,414	53,160	69,322	71,592	109,544	23,664	15,506	3,994	26,734	7,058	8,104	41,535	135,140
2004													
Trips	67	67	67	67	67	67	67	67	67	67	67	67	67
Mean	4,760	3,838	15,717	8,394	4,684	981	374	170	2,643	723	650	4,331	47,264
Minimum	0	0	0	0	0	0	0	0	0	0	0	0	22
Maximum	56,130	39,360	118,230	60,090	67,400	24,944	4,900	2,448	60,450	5,174	14,648	31,094	249,848
2005													
Trips	171	171	171	171	171	171	171	171	171	171	171	171	171
Mean	4,074	5,388	12,129	5,273	3,452	909	198	432	2,812	728	451	4,885	40,730
Minimum	0	0	0	0	0	0	0	0	0	0	0	0	958
Maximum	81,800	38,492	139,872	52,820	50,850	69,148	7,724	20,000	24,886	5,864	8,032	65,616	165,654
2003-2005													
N	307	307	307	307	307	307	307	307	307	307	307	307	307
Mean	4,512	6,593	12,295	5,875	4,926	1,104	416	348	2,864	870	443	5,099	45,345
Minimum	0	0	0	0	0	0	0	0	0	0	0	0	22
Maximum	81,800	53,160	139,872	71,592	109,544	69,148	15,506	20,000	60,450	7,058	14,648	65,616	249,848

Table 5.3. Trip level summary from sample data set of Georges Bank otter trawl fishery catches in pounds (Undesirable Outputs) 2003-2005

Year	Skates	Monkfish	Cod	Haddock	Pollock	Redfish	Hakes	Ocean Pout	Sea Robins/ Sea Ravens	Yellowtail Flounder	Winter Flounder	Mixed Flounder	Summer Flounder	Lobster	Mixed Crabs	Seaweed	Starfish	Undesirable
2003																		
Trips	69	69	69	69	69	69	69	69	69	69	69	69	69	69	69	69	69	69
Mean	27,722	513	561	194	1	23	130	345	690	159	8	816	244	369	622	57	74	32,529
Minimum	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	274
Maximum	108,672	3,030	16,605	3,001	20	602	1,060	3,170	4,422	4,608	261	12,446	5,778	1,810	5,100	3,000	897	127,706
2004																		
Trips	67	67	67	67	67	67	67	67	67	67	67	67	67	67	67	67	67	67
Mean	22,814	345	191	945	5	50	221	181	519	716	76	526	101	374	676	51	344	28,136
Minimum	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
Maximum	146,000	2,108	6,934	21,812	154	1,840	2,106	1,970	5,540	21,608	3,500	7,804	3,294	2,550	14,066	1,400	10,042	172,885

Table 5.3 (continued). Trip Level Summary from sample data set of Georges Bank otter trawl fishery catches (pounds), Undesirable Outputs, 2003-2005.

Year	Skates	Monkfish	Cod	Haddock	Pollock	Redfish	Hakes	Ocean Pout	Sea Robins/ Sea Ravens	Yellowtail Flounder	Winter Flounder	Mixed Flounder	Summer Flounder	Lobster	Mixed Crabs	Seaweed	Starfish	Undesirable
2005																		
Trips	171	171	171	171	171	171	171	171	171	171	171	171	171	171	171	171	171	171
Mean	27,192	476	965	689	3	22	135	148	381	410	47	1,282	432	283	504	75	110	33,154
Minimum	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	20
Maximum	460,880	15,220	20,742	16,266	224	676	3,766	3,306	4,025	9,841	2,835	31,068	10,408	3,848	18,650	2,800	1,690	469,156
2003-2005																		
Trips	307	307	307	307	307	307	307	307	307	307	307	307	307	307	307	307	307	307
Mean	26,356	456	705	633	3	28	153	200	481	420	45	1,012	317	322	568	66	153	31,918
Minimum	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
Maximum	460,880	15,220	20,742	21,812	224	1,840	3,766	3,306	5,540	21,608	3,500	31,068	10,408	3,848	18,650	3,000	10,042	469,156

5.2.2 The Four DEA Models for Estimating Capacity

Initially, we estimate capacity by using what many would consider to be the (1) standard approach for estimating capacity or technical efficiency (TE). We specify an output oriented DEA model, and completely ignore the undesirable outputs. We seek the maximal radial expansion of outputs conditional only on the fixed factors binding or restricting the radial expansion; variable inputs are unbounded. Next, we consider (2) the directional distance vector approach, which allows desirable outputs to be expanded and undesirable outputs to be radially contracted by the same proportion allowed for the desirable output expansion. However, we also modify the directional vector approach to allow for the different expansions and contractions examined by Lee et al. (2002). The Lee et al. (2002) approach allows an assessment of technical efficiency and capacity consistent with the expansion/contraction patterns of Coggins and Swinton (1996), Turner (1995), and Boyd et al. (1996). We next use (3) the hyperbolic approach of Färe et al. (1989a), but linearized, to estimate TE and capacity with undesirable outputs. Last, we use (4) the approach of Seiford and Zhu (2002) to estimate capacity. A description of each of the four models can be found in sections 3.2.4.1 and 4.2.

5.2.2.1 The Standard Output-Oriented DEA Model

Our standard DEA model for estimating capacity follows the approach of Färe (1984), Färe et al. et (1989b), and Färe et al. (1994), and is found in section 3.2.4.1. This is a standard output-oriented DEA model, which estimates the maximum radial expansion of outputs conditional only on the fixed factors limiting the output; the variable factors are non-constraining. In this particular model, we ignore all considerations of undesirable outputs; that is, we seek only the expansion of desirable outputs without any consideration of the undesirable outputs. This initial model is used to provide a baseline comparison relative to other models which explicitly consider changes in undesirable outputs.

5.2.2.2 The Directional Distance Function Approach

Färe and Grosskopf (2004a) formally refer to this framework as both the "Directional

Technology Distance Function" and the "Directional Distance Function", and it is discussed in section 4.2.2. This framework permits simultaneous expansion of desirable outputs and contraction of undesirable outputs, and explicitly credits firms for reducing undesirable outputs. This same framework, however, includes both output and input oriented assessments of TE and capacity as special cases. Efficiency scores, however, vary from zero for efficient production to greater than zero for inefficient production, whereas in the output and input oriented models, a score of 1.0 indicates efficient production. To estimate TE with undesirable outputs, we impose an equality constraint on the undesirable outputs, which imposes weak subvector disposability. In order to estimate capacity, we split the input constraint into separate constraints for the fixed and variable factors of production. For the fixed factors, we retain the inequality constraint, but for the variable factors we add an equality constraint, which allows us to determine the level of variable factors necessary to efficiently produce the capacity output. This is done just as in in the preceding output-oriented approach. Thus, we estimate the following model:

$$\max_{z,\lambda} \beta$$

subject to

$$\sum_{j=1}^{J} z_j y_{jm} \geq y_{jm} + \beta g_{ym}, \quad m = 1,2,\ldots, M^g$$

$$\sum_{j=1}^{J} z_j y_{jm} = y_{jm} - \beta g_{ym}, \; m = 1,2,\ldots, M^b$$

$$\sum_{j=1}^{J} z_j x_{jn} \leq x_{jn}, \; n = 1,2,\ldots, N^F$$

$$\sum_{j=1}^{J} z_j x_{jn} = \lambda_{jn} x_{jn}, \; n = 1,2,\ldots, N^V$$

$$\sum_{j=1}^{J} Z_j = 1$$

$$z_j \geq 0, \; j = 1,2,\ldots, J$$

The last constraint imposes variable returns to scale. We also follow Lee et al. (2002) in specifying the directions for the desirable and undesirable outputs, which requires some additional modification of the notation to the directional distance function approach. We use g for the direction of the desirable outputs and b for the direction of undesirable outputs; we thus replace g_{ym} in both equations with g and b and change the negative sign in the undesirable output constraint to a plus sign. Lee et al. (2002) consider four combinations of directions: (1) allow both to expand as in Coggins and Swinton (2002) (g and b both are positive); (2) allow desirable outputs to expand and undesirable outputs to remain unchanged ($b = 0$ and $g > 0$); (3) allow desirable outputs to expand and undesirable outputs to contract ($b < 0$ and $g > 0$); and (4) allow both desirable and undesirable outputs to contract ($b < 0$ and $g < 0$). We point out, however, that the fourth option can eventually force all outputs to zero levels.

5.2.2.3 The Hyperbolic or Graph Efficiency Approach

Capacity and TE are also estimated by using the hyperbolic efficiency approach of Färe et al. (1989a), as shown in section 4.2.1. This approach allows desirable outputs to be expanded and undesirable outputs to be contracted. Unlike the directional distance function approach, however, the expansion and contraction of desirable and undesirable outputs are asymmetrical.

5.2.2.4 The Seiford and Zhu Approach

The Seiford and Zhu approach is described in Seiford and Zhu (2002) and in Zhu (2003), and is also described in section 4.2.3. The problem is modified to estimate capacity by splitting the input constraint into two: one for the fixed inputs and one for the variable inputs. This also allows estimation of the full utilization levels of the variable inputs. This results in the following model:

$$\underset{\lambda,\theta}{Max}\ h$$

$$subject\ to\ \sum_{j=1}^{J} \lambda_j y_{rj}^{g} \geq h\ y_{r0}^{g}$$

$$\sum_{j=1}^{J} \lambda_j y_{rj}^{\bar{b}} \geq h\ y_{r0}^{\bar{b}}$$

$$\sum_{j=1}^{J} \lambda_j X_{ij} \leq X_{io},\ x = 1,....,N^F$$

$$\sum_{j=1}^{J} \lambda_j X_{ij} = \theta_{io} X_{io},\ x = 1,....,N^V$$

$$\sum_{j=1}^{J} \lambda_j = 1$$

$$\lambda_j \geq 0,\ j = 1,...,n$$

The desirable outputs are expanded by h, and the undesirable outputs are contracted by h, but only after adjusting the estimates to reflect the original levels of the undesirable outputs. Alternatively, the undesirable output levels corresponding to the capacity output equal v_r –(h times the transformed undesirable outputs). This approach is used in this study to illustrate another approach for estimating efficiency and capacity in the presence of undesirable outputs, while also allowing for zero valued undesirable outputs.

5.3 A Comparative Analysis of Capacity with Undesirable Outputs

In this section, we present and summarize the various estimates for the Georges Bank Otter Trawl Fishery outlined in section 5.2. We first present the estimates based on the traditional approach, which ignores the undesirable outputs. Then, the estimates from the directional vector approach are presented and explained. We first consider strong disposability and then impose weak subvector disposability and the different options summarized in Lee et al. (2002). We next present the hyperbolic approach of Färe et al. (1989a). We initially derive the estimate subject to strong disposability in the undesirable outputs and then re-estimate it subject to weak subvector disposability. For comparative purposes, we also present the results derived from the Seiford and Zhu (2002) approach. A summary of the sample data is presented in Tables 5.4a and 5.4b. The estimates corresponding to the standard output-oriented approach, the directional distance function approach, the hyperbolic measure, and the Seiford and Zhu approach are presented in Tables 5.5-5.8. We also present summary estimates of the technically efficient output for methods.

We have 12 desirable and 17 undesirable outputs. The fixed factors are vessel length, gross registered tonnage (GRT), and engine horsepower (HP). The variable factors are crew size and days at sea per trip. In addition to reporting estimates of the capacity outputs, we also report estimates of the crew size and days at sea required to produce the capacity outputs. All estimates are subject to variable returns to scale. We select the reported values as our baseline reference (i.e., values used to compare the estimates). Mean and total values corresponding to the sample data set are reported in Tables 5.4a and b. Mean vessel length equaled 76 feet, GRT was 141, and HP was 654. Mean crew size equaled 4.3, and mean days at sea per trip equaled 7.5. In general, we found that unless the technology is strongly disposable, gains in output are extremely limited. Moreover, when such gains in desirable outputs are possible, they are realized mostly by improvements in technical efficiency, not by expansion of the variable factors of production.

5.3.1 The Traditional Output-Oriented Approach

In keeping with the analyses conducted by Seiford and Zhu (2002) and the standard approach which ignores undesirable outputs, we first estimate capacity output for the desirable outputs (Table 5.5). That is, we ignore the undesirable outputs. Estimates (Table 5.5) suggest a need to reduce average crew size by 0.1 and to increase average days at sea per trip by 0.7. The ratio of capacity output to reported output for all the desirable outputs ranged from a low of 1.46 for pollock to a high of 1.93 for mixed skates.

5.3.2 The Directional Distance Function Approach

We initially estimate capacity output conditional on allowing the expansion of both the desirable and undesirable outputs (Tables 5.6a-b). In this case, the potential expansion in desirable outputs is considerably less than that projected with the traditional output-oriented approach. The ratio of capacity output to reported output ranges from a low of 1.24 for pollock to a high of 1.63 for mixed skates. The projected crew size and days at sea necessary to produce the capacity output are approximately the same—4.2 crew members and 8.2 days--as projected by using the output-oriented approach.[41] The lower estimates of capacity outputs determined by using the directional vector approach and by allowing both desirable and undesirable outputs to expand are caused by an expanded output set, as compared to the standard approach which ignores undesirable outputs. That is, the additional outputs are also defining the reference frontier technology.

We also project a considerable expansion in the undesirable outputs; this is consistent with observations in fisheries in which expanded desirable outputs normally result in an increase in undesirable outputs (i.e., bycatch). The capacity outputs are thus considerably lower when estimated with the directional distance function and including all desirable and undesirable outputs then when estimated with only the traditional output-oriented approach which ignores undesirable outputs.[42] The ratio of the capacity output to the reported output for all undesirable outputs ranged from a low of 1.15 for winter flounder to a high of 1.47 for mixed skates.

We next estimate capacity output by allowing the desirable outputs to expand and the undesirable outputs to contract, but also by imposing strong disposability or an inequality constraint on both desirable and undesirable outputs (Tables 5.6c-d). In the case of these 12 desirable outputs, capacity output can be expanded by only 1.0% for three species—mixed flounder, white hake, and monkfish. The capacity output levels for the other nine species approximately equal the reported output. In terms of reductions in the undesirable outputs, the corresponding capacity output for pollock equals 95.0% of the reported outputs, and for eight of the undesirable outputs, capacity output equals 99.0% of the reported capture. No reductions are feasible for the eight remaining undesirable outputs. The full-utilization levels of the crew members and days at sea are 4.3 and 7.5, respectively.

The above model was next estimated subject to weak subvector disposability (i.e., an equality constraint was used for all undesirable outputs) (Tables 5.6e-f). This is the more widely used model for estimating technical efficiency and capacity when there are undesirable outputs. Estimates for this model suggest that it is not possible to reduce undesirable outputs without forcing a reduction in desirable outputs. The ratios of all estimated desirable and undesirable outputs (when measured at two decimal places) to the reported outputs all equaled 1.0 in value. Following the methods of Färe et al. (1989a), regulations to reduce bycatch would only be binding for 7 of 307 trips if we consider strong disposability in undesirable outputs, but subject to a reduction; that is, the ratio of the strongly disposable technology, assuming a reduction in undesirable outputs, to the weakly disposable technology is greater than 1.0 in value for only seven observations. If, however, the potential loss in output is assessed relative to the expansion of desirable and undesirable outputs, as recommended by Färe et al. (1989a), we now find that 203 trips would have been affected by regulating undesirable outputs. The full utilization levels of crew size and days at sea equal the reported levels of 4.3members and 7.5 days, respectively.

We next estimated capacity output following the restrictions of Turner (1995), in which desirable outputs are allowed to expand but undesirable outputs are held constant (i.e., these are not allowed to decrease) (Tables 5.6g-h). In this case, the estimated capacity output is 1.0% higher than the reported output for monkfish, cod, haddock, yellowtail, pollock, mixed flounder, and lobster; the capacity output for white hake is 2.0% higher than the reported outputs. All capacity output levels for the undesirable outputs equal the reported levels, as imposed via the constraints. The full utilization levels of crew and days at sea equal the reported levels—4.3 crew members and 7.5 days.

The last directional distance function approach considered the contraction of both undesirable and desirable outputs (Tables 5.6i-j). Lee et al. (2002) suggested examining efficiency when both desirable and undesirable outputs are forced to contract. The findings from allowing the joint contraction is likely to be consistent with the perceptions of most stock assessment scientists; that is, it is not possible to reduce undesirable outputs without reducing desirable outputs, without substantial gear modifications, or without new regulations. The ratio of the estimated capacity output to the reported output for the desirable outputs ranged from 0.37 for pollock to 0.66 for sea scallops; and the ratio of the capacity output to the reported output for the undesirable outputs ranged from 0.35 for seaweed to 0.71 for yellowtail flounder. The full-utilization levels for the variables inputs equaled 4.0 crew members and 5.4 days at sea.

5.3.3 The Hyperbolic Approach

As stated in earlier sections of this report, the hyperbolic measure requires a nonlinear mathematical programming specification. The programming problem, however, can be linearized as illustrated in Färe et al. (1989a) and Zhu (2003). We estimate capacity output by using the linearized version, but we also consider both strong and weak disposability in the undesirable outputs (Tables 5.7a-b and 5.7c-d). In addition, we follow Färe et al. (1989a) by requiring undesirable outputs to equal reported undesirable output levels or be reduced.

In the case of strong disposability, the ratio of capacity output to reported output for the desirable outputs ranged from a low of 1.38 for pollock to 1.87 for skates. The ratio of capacity output to reported output for the undesirable species ranged from 0.36 for starfish to 0.84 for yellowtail flounder. The full utilization levels of crew and days at sea equaled 4.2 members and 8.2 days, respectively.

The results were considerably different when weak subvector disposability was imposed. In this case, all ratios of capacity output to reported output for both the desirable and undesirable outputs equaled 1.0. Again, following Färe et al. (1989a), we constructed the ratio of the efficiency scores from the strongly disposable model to the model with weak subvector disposability imposed. In this case, we found the ratio of the estimates corresponding to the strongly disposable technology to those derived from the model with weak subvector disposability to exceed 1.0 in value for 212 trips, which is slightly more than we determined from the directional vector approach. The 203 potential trips, which would be affected by regulations on undesirable outputs as determined via the directional distance function approach, were also determined to potentially be affected according to the hyperbolic efficiency approach.

Färe et al. (1989a) suggest that the potential losses from a lack of weak disposability equal the difference between technically efficient output levels corresponding to strong and weak disposability (i.e., the [efficient output | strong disposability – efficient output | weak disposability] times the reported output). In this case, the losses could be quite substantial: (1) monkfish—781,270 lbs, (2) cod—1,465,883 lbs, (3) haddock—3,048,515 lbs, (4) yellowtail—1,111,088 lbs, (5) winter flounder—1,085,505 lbs, (6) pollock—129,040 lbs, (7) white hake—60,769 lbs, (8) redfish—45,628 lbs, (9) mixed flounder—628,754 lbs, (10) lobster—168,029 lbs, (11) sea scallops—55,420 lbs, and (12) mixed skates—1,365,153 lbs. Alternatively, the effect of regulations could reduce the desirable outputs by as much as 32,394 pounds per trip; the reported total desirable output per trip equaled 45,345 pounds.

5.3.4 The Approach of Seiford and Zhu

This approach was used to estimate capacity output because it is easily accomplished with the simpler output-oriented DEA model. It is only necessary to scale the undesirable outputs such that all observations are positive in value. This approach, however, yields estimates identical to those obtained by using a directional distance function with weak subvector disposability imposed (Tables 5.8a-b). That is, all ratios of the estimated capacity output of desirable and undesirable outputs to reported levels of desirable and undesirable outputs equal 1.0 in value.

Table 5.4a. Summary statistics of Georges Bank otter trawl fishery sample data, desirable outputs

	Length (ft.)	Gross Tons	Horsepower	Crew Size	Days at Sea	Monkfish Lbs.	Cod Lbs.	Haddock Lbs.	Yellowtail Lbs.	Winter Flounder Lbs.	Pollock Lbs.	White Hake Lbs.	Redfish Lbs.	Mixed Flounder Lbs.	Lobster Lbs.	Scallops Lbs.	Skates Lbs.
Total	23,399	43,287	200,782	1,316	2,312	1,385,084	2,023,959	3,774,670	1,803,564	1,512,261	339,049	127,724	106,780	879,320	267,048	136,140	1,565,327
Mean per Trip	76	141	654	4.3	7.5	4,512	6,593	12,295	5,875	4,926	1,104	416	348	2,864	870	443	5,099

Table 5.4b. Summary statistics of Georges Bank otter trawl fishery sample data, undesirable outputs

	Skates	Monkfish	Cod	Haddock	Pollock	Redfish	Hakes	Ocean Pout	Sea Robins/ Ravens	Yellowtail Flounder	Winter Flounder	Mixed Flounder	Summer Flounder	Lobster	Mixed Crabs	Seaweed	Starfish
Total Pounds	8,091,245	139,945	216,463	194,414	896	8,678	46,936	61,259	147,600	129,079	13,723	310,767	97,432	98,915	174,346	20,202	47,037
Mean Pounds per Trip	26,356	456	705	633	3	28	153	200	481	420	45	1,012	317	322	568	66	153

Table 5.5. Estimated capacity, technically efficient output and variable input utilization via the standard output-oriented model, no undesirable outputs

Standard Output-Oriented			Pounds											
	Crew Size	Days at Sea	Monkfish	Cod	Haddock	Yellowtail Flounder	Winter Flounder	Pollock	White Hake	Redfish	Mixed Flounder	Lobster	Scallops	Skates
Capacity Output	1,289	2,522	2,236,685	3,603,240	6,978,677	2,977,892	2,682,852	495,214	195,017	159,375	1,572,057	446,898	197,410	3,024,484
Mean per Trip	4.2	8.2	7,286	11,737	22,732	9,700	8,739	1,613	635	519	5,121	1,456	643	9,852
Efficient Output			2,063,956	3,186,605	6,016,853	2,697,062	2,372,359	449,210	183,170	146,396	1,418,494	402,015	185,401	2,606,697

Table 5.6a. Estimated capacity and technically efficient output for desirable outputs, variable input utilization, by using the directional distance function approach, imposing strong disposability (SD) by expanding desirable and undesirable outputs

Directional Distance Function (SD)			Pounds												
	Crew Size	Days at Sea	Monkfish	Cod	Haddock	Yellowtail Flounder	Winter Flounder	Pollock	White Hake	Redfish	Mixed Flounder	Lobster	Scallops	Skates
Capacity Output	1,286	2,519	1,863,346	3,024,889	5,759,940	2,529,466	2,153,941	419,574	167,485	136,845	1,304,886	373,245	171,697	2,544,844
Mean per Trip	4.2	8.2	6,070	9,853	18,762	8,239	7,016	1,367	546	446	4,250	1,216	559	8,289
Efficient Output			1,759,258	2,763,893	5,170,281	2,322,774	1,963,370	401,089	159,803	129,214	1,198,715	346,278	163,099	2,239,751

Table 5.6b. Estimated capacity and technically efficient output for undesirable outputs, by using the directional distance function approach, imposing strong disposability (SD), by expanding desirable and undesirable outputs

Directional Distance Function (SD)				Pounds													
	Skates	Monkfish	Cod	Haddock	Pollock	Redfish	Hakes	Ocean Pout	Sea Robins/ Sea Ravens	Yellowtail Flounder	Winter Flounder	Mixed Flounder	Summer Flounder	Lobster	Mixed Crabs	Seaweed	Starfish
Capacity Output	11,882,256	187,079	261,594	253,815	1,108	11,331	57,658	81,378	208,564	165,327	15,833	441,700	129,981	143,895	211,695	20,202	47,037
Mean per Trip	38,704	609	852	827	4	37	188	265	679	539	52	1,439	423	469	690	66	153
Efficient Output	10,828,889	174,680	249,575	231,990	1,062	10,660	54,697	75,323	189,441	156,648	15,290	407,324	121,535	130,203	205,403	23,899	55,894

Table 5.6c. Estimated capacity and technically efficient output for desirable outputs, variable input utilization, by using the directional distance function approach, by imposing strong disposability (SD), and by expanding desirable and contracting undesirable outputs

Directional Distance Function (SD)			Pounds											
	Crew Size	Days at Sea	Monkfish	Cod	Haddock	Yellowtail Flounder	Winter Flounder	Pollock	White Hake	Redfish	Mixed Flounder	Lobster	Scallops	Skates
Capacity Output	1,319	2,297	1,392,623	2,028,603	3,786,983	1,811,942	1,513,712	339,871	128,590	106,972	883,955	267,647	136,334	1,568,958
Mean per Trip	4.3	7.5	4,536	6,608	12,335	5,902	4,931	1,107	419	348	2,879	872	444	5,111
Efficient Output			1,391,818	2,027,654	3,785,428	1,808,063	1,513,133	339,824	128,556	106,967	883,254	267,302	136,255	1,566,849

Table 5.6d. Estimated capacity and technically efficient output for undesirable outputs, directional distance function approach, by imposing strong disposability (SD), and by expanding desirable and contracting undesirable outputs

Directional Distance Function (SD)					Pounds													
	Skates	Monkfish	Cod	Haddock	Pollock	Redfish	Hakes	Ocean Pout	Sea Robins/ Sea Ravens	Yellowtail Flounder	Winter Flounder	Mixed Flounder	Summer Flounder	Lobster	Mixed Crabs	Seaweed	Starfish
Capacity Output	8,052,440	139,216	216,213	193,467	855	8,614	46,687	60,910	147,108	128,426	13,722	307,766	97,340	98,067	173,420	20,202	47,037
Mean per Trip	26,229	453	704	630	3	28	152	198	479	418	45	1,002	317	319	565	66	153
Efficient Output	8,073,294	139,562	216,239	193,586	856	8,615	46,828	60,953	147,307	128,511	13,722	309,443	97,398	98,268	173,496	20,158	47,015

Table 5.6e. Estimated capacity and technically efficient output for desirable outputs, and variable input utilization, by using the directional distance function approach, imposing weak disposability (WD), by expanding desirable outputs, and contracting undesirable outputs

Directional Distance Function (WD)			Pounds											
	Crew Size	Days at Sea	Monkfish	Cod	Haddock	Yellowtail Flounder	Winter Flounder	Pollock	White Hake	Redfish	Mixed Flounder	Lobster	Scallops	Skates
Capacity Output	1,316	2,312	1,385,094	2,024,030	3,775,647	1,803,565	1,512,294	339,050	127,724	106,780	879,374	267,059	136,334	1,568,958
Mean per Trip	4.3	7.5	4,512	6,593	12,299	5,875	4,926	1,104	416	348	2,864	870	444	5,111
Efficient Output			1,385,094	2,024,030	3,775,647	1,803,565	1,512,294	339,050	127,724	106,780	879,374	267,059	136,140	1,565,959

Table 5.6f. Estimated capacity and technically efficient output for undesirable outputs, by using the directional distance function approach, imposing weak disposability (WD), by expanding desirable outputs, and contracting undesirable outputs

Directional Distance Function (WD)				Pounds														
	Skates	Monkfish	Cod	Haddock	Pollock	Redfish	Hakes	Ocean Pout	Sea Robins/ Sea Ravens	Yellowtail Flounder	Winter Flounder	Mixed Flounder	Summer Flounder	Lobster	Mixed Crabs	Seaweed	Starfish
Capacity Output	8,088,044	139,930	216,450	194,382	896	8,678	46,936	61,241	147,585	129,070	13,723	310,733	97,421	98,914	174,335	20,200	47,037
Mean per Trip	26,345	456	705	633	3	28	153	199	481	420	45	1,012	317	322	568	66	153
Efficient Output	8,088,044	139,930	216,450	194,382	896	8,678	46,936	61,241	147,585	129,070	13,723	310,733	97,421	98,914	174,335	20,200	47,035

Table 5.6g. Estimated capacity and technically efficient output for desirable Outputs, and variable input utilization, by using the directional distance function approach, imposing strong disposability (SD), expanding desirable outputs, and by not changing undesirable outputs

Directional Distance Function (SD)			Pounds											
	Crew Size	Days at Sea	Monkfish	Cod	Haddock	Yellowtail Flounder	Winter Flounder	Pollock	White Hake	Redfish	Mixed Flounder	Lobster	Scallops	Skates
Capacity Output	1,319	2,298	1,403,438	2,036,366	3,804,218	1,827,624	1,516,178	341,145	130,120	107,275	890,251	268,574	136,737	1,568,958
Mean per Trip	4.3	7.5	4,571	6,633	12,392	5,953	4,939	1,111	424	349	2,900	875	445	5,111
Efficient Output			1,401,413	2,034,444	3,800,616	1,820,611	1,515,124	340,985	129,977	107,247	888,697	267,977	136,592	1,569,219

Table 5.6h. Estimated capacity and technically efficient output for undesirable outputs, by using the directional distance function approach, imposing strong disposability (SD), by expanding desirable outputs, and by not changing undesirable outputs

Directional Distance Function (SD)					Pounds													
	Skates	Monkfish	Cod	Haddock	Pollock	Redfish	Hakes	Ocean Pout	Sea Robins/ Sea Ravens	Yellowtail Flounder	Winter Flounder	Mixed Flounder	Summer Flounder	Lobster	Mixed Crabs	Seaweed	Starfish
Capacity Output	8,091,245	139,945	216,463	194,414	896	8,678	46,936	61,259	147,600	129,079	13,723	310,767	97,432	98,915	174,346	20,202	47,037
Mean per Trip	26,356	456	705	633	3	28	153	200	481	420	45	1,012	317	322	568	66	153
Efficient Output	8,091,245	139,945	216,463	194,414	896	8,678	46,936	61,259	147,600	129,079	13,723	310,767	97,432	98,915	174,346	20,202	47,037

Table 5.6i. Estimated capacity and technically efficient output for desirable outputs and variable input utilization, by using the directional distance function approach, imposing strong disposability (SD), and contracting desirable and undesirable outputs

Directional Distance Function (SD)			Pounds											
	Crew Size	Days at Sea	Monkfish	Cod	Haddock	Yellowtail Flounder	Winter Flounder	Pollock	White Hake	Redfish	Mixed Flounder	Lobster	Scallops	Skates
Capacity Output	1,233	1,644	695,164	1,069,370	2,050,295	1,135,827	712,290	125,292	65,627	55,977	490,859	118,798	136,737	1,568,958
Mean per Trip	4.0	5.4	2,264	3,483	6,678	3,700	2,320	408	214	182	1,599	387	445	5,111
Efficient Output			798,875	1,130,285	2,327,526	1,152,811	723,597	132,460	69,571	65,654	592,799	125,142	93,676	967,740

Table 5.6j. Estimated capacity and technically efficient output for undesirable outputs, by using the directional distance function approach, imposing strong disposability (SD), and contracting desirable and undesirable outputs

Directional Distance Function (SD)				Pounds														
	Skates	Monkfish	Cod	Haddock	Pollock	Redfish	Hakes	Ocean Pout	Sea Robins/ Sea Ravens	Yellowtail Flounder	Winter Flounder	Mixed Flounder	Summer Flounder	Lobster	Mixed Crabs	Seaweed	Starfish
Capacity Output	4,770,287	66,248	113,727	108,288	360	4,071	25,250	30,404	71,554	91,453	6,508	144,060	49,698	44,764	72,193	7,077	47,037
Mean per Trip	15,538	216	370	353	1	13	82	99	233	298	21	469	162	146	235	23	153
Efficient Output	4,968,637	71,046	122,538	126,617	405	4,496	26,809	31,538	76,073	93,879	7,088	147,170	50,342	50,670	87,710	7,470	26,544

Table 5.7a. Estimated capacity and technically efficient output for desirable outputs and variable input utilization, using the hyperbolic ("Graph Efficiency") approach and imposing strong disposability (SD)

Hyperbolic (SD)			Pounds											
	Crew Size	Days at Sea	Monkfish	Cod	Haddock	Yellowtail Flounder	Winter Flounder	Pollock	White Hake	Redfish	Mixed Flounder	Lobster	Scallops	Skates
Capacity Output	1,296	2,521	2,166,364	3,489,863	6,824,161	2,914,653	2,597,799	468,090	188,493	152,408	1,508,129	435,088	191,560	1,568,958
Mean per Trip	4.2	8.2	7,057	11,368	22,229	9,494	8,462	1,525	614	496	4,912	1,417	624	5,111
Efficient Output			2,016,408	3,121,794	5,866,690	2,676,982	2,337,239	443,455	176,482	141,761	1,369,762	398,348	181,299	2,541,281

Table 5.7b. Estimated capacity and technically efficient output for undesirable outputs, by using the hyperbolic ("Graph Efficiency") approach and imposing strong disposability (SD)

Hyperbolic (SD)				Pounds													
	Skates	Monkfish	Cod	Haddock	Pollock	Redfish	Hakes	Ocean Pout	Sea Robins/ Sea Ravens	Yellowtail Flounder	Winter Flounder	Mixed Flounder	Summer Flounder	Lobster	Mixed Crabs	Seaweed	Starfish
Capacity Output	6,093,920	110,944	149,148	142,920	748	7,468	39,449	48,421	112,046	107,890	8,869	241,666	70,952	76,240	133,646	16,781	47,037
Mean per Trip	19,850	361	486	466	2	24	128	158	365	351	29	787	231	248	435	55	153
Efficient Output	6,338,473	113,923	168,812	151,502	782	7,627	40,161	49,814	116,182	110,326	9,528	247,900	73,107	78,968	138,716	17,518	39,415

Table 5.7c. Estimated capacity and efficient output for desirable outputs and variable input utilization, by using the hyperbolic ("Graph Efficiency") approach and imposing weak disposability (WD)

Hyperbolic (WD)			Pounds												
	Crew Size	Days at Sea	Monkfish	Cod	Haddock	Yellowtail Flounder	Winter Flounder	Pollock	White Hake	Redfish	Mixed Flounder	Lobster	Scallops	Skates
Capacity Output	1,316	2,312	1,385,094	2,024,030	3,775,647	1,803,565	1,512,294	339,050	127,724	106,780	879,374	267,059	191,560	1,568,958
Mean per Trip	4.3	7.5	4,512	6,593	12,299	5,875	4,926	1,104	416	348	2,864	870	624	5,111
Efficient Output			1,385,094	2,024,030	3,775,647	1,803,565	1,512,294	339,050	127,724	106,780	879,374	267,059	136,140	1,565,959

Table 5.7d. Estimated capacity and technically efficient output for undesirable outputs by using the hyperbolic ("Graph Efficiency") approach and imposing weak disposability (WD)

Hyperbolic (WD)				Pounds													
	Skates	Monkfish	Cod	Haddock	Pollock	Redfish	Hakes	Ocean Pout	Sea Robins/ Sea Ravens	Yellowtail Flounder	Winter Flounder	Mixed Flounder	Summer Flounder	Lobster	Mixed Crabs	Seaweed	Starfish
Capacity Output	8,088,442	139,932	216,452	194,386	896	8,678	46,936	61,243	147,587	129,071	13,723	310,738	97,422	98,915	174,337	20,201	47,037
Mean per Trip	26,347	456	705	633	3	28	153	199	481	420	45	1,012	317	322	568	66	153
Efficient Output	8,088,442	139,932	216,452	194,386	896	8,678	46,936	61,243	147,587	129,071	13,723	310,738	97,422	98,915	174,337	20,201	47,037

Table 5.8a. Estimated capacity and technically efficient output for desirable outputs by using the Seiford and Zhu Approach, expanding desirable outputs and contracting undesirable outputs

Seiford and Zhu Approach			Pounds											
	Crew Size	Days at Sea	Monkfish	Cod	Haddock	Yellowtail Flounder	Winter Flounder	Pollock	White Hake	Redfish	Mixed Flounder	Lobster	Scallops	Skates
Capacity Output	1,318	2,289	1,385,084	2,023,959	3,774,670	1,803,564	1,512,261	339,049	127,724	106,780	879,320	267,048	136,140	1,565,327
Mean per Trip	4.3	7.5	4,512	6,593	12,295	5,875	4,926	1,104	416	348	2,864	870	443	5,099
Efficient Output			1,385,084	2,023,959	3,774,670	1,803,564	1,512,261	339,049	127,724	106,780	879,320	267,048	136,140	1,565,327

Table 5.8b. Estimated capacity and technically efficient output for undesirable outputs, by using the Seiford and Zhu approach expanding desirable outputs and contracting undesirable outputs.

Seiford and Zhu Approach				Pounds													
	Skates	Monkfish	Cod	Haddock	Pollock	Redfish	Hakes	Ocean Pout	Sea Robins/ Sea Ravens	Yellowtail Flounder	Winter Flounder	Mixed Flounder	Summer Flounder	Lobster	Mixed Crabs	Seaweed	Starfish
Capacity Output	8,091,245	139,945	216,463	194,414	896	8,678	46,936	61,259	147,600	129,079	13,723	310,767	97,432	98,915	174,346	20,201	47,037
Mean per Trip	26,356	456	705	633	3	28	153	200	481	420	45	1,012	317	322	568	66	153
Efficient Output	8,091,245	139,945	216,463	194,414	896	8,678	46,936	61,259	147,600	129,079	13,723	310,767	97,432	98,915	174,346	20,202	47,037

6. Summary and Conclusions

6.1 Overview of Study and Results

The FAO of the United Nations and member nations have become increasingly concerned about the inadvertent capture of nonmarketable marine life (i.e., bycatch and discards). Species may be nonmarketable either because of an absence of economic incentives or because of regulations which prohibit the retention and sale of certain marine species. The FAO and member nations are also concerned about the growing problem of excess capacity, which results in substantial economic waste and the potential for biological overharvesting.

To date, the FAO and various nations have tended to separately address the two issues; namely, to find solutions to reduce the harvesting of nonmarketable species and to determine solutions for addressing excess capacity in fisheries. These aims have led to research which yields estimates of capacity without considering the potential relationship between capacity output and the capture of undesirable (nonmarketable) products. Alternatively, these aims have also led to other research focused only on reducing nonmarketable bycatch without consideration of how capacity output might be affected by various proposals to reduce bycatch.

In this study, we developed numerous approaches for estimating capacity while explicitly recognizing the need to reduce nonmarketable bycatch (i.e., undesirable outputs). Data envelopment analysis was offered as the primary analytical method for estimating capacity. We provided a broad overview of DEA and then various formulations for estimating capacity when there are undesirable outputs. We provided a baseline estimate of capacity for sample trips from the Georges Bank otter trawl fishery; this baseline estimate ignored the undesirable outputs, as has been done by FAO and member nations. This is the standard approach for estimating and assessing capacity output in commercial fisheries and numerous other industries. Next, additional model formulations were introduced and used to estimate capacity, but the estimates were adjusted to reflect various aspects of reducing or expanding undesirable outputs.

6.2 The Methodology and Data Summarized

The initial estimates were obtained from an output-oriented DEA model. In this case, the undesirable outputs are completely ignored and only the desirable (marketable) outputs are considered in the estimation and analysis. A directional distance function approach was next introduced, and corresponding models (which allowed undesirable outputs to be reduced, unchanged, and expanded) were developed. The directional distance function model, however, is limited by the fact that the production of desirable and undesirable outputs must be null joint (i.e., at least one undesirable output must be produced for every observations having at least one desirable output). The directional vector, thus, has limitations for analyzing capacity and efficiency in fisheries in which many observations often have positive desirable outputs and zero levels of undesirable outputs. To counter this problem, the hyperbolic and Seiford and Zhu (2002) approaches were introduced, and models conforming to these specifications were used to estimate capacity and technical efficiency for the sample data observations. These two approaches do not require null jointness in desirable and undesirable outputs (i.e., desirable outputs can be positive while there may be zero levels of undesirable outputs).

The initial directional distance function model imposed strong disposability, which implies it is costless to dispose of unwanted outputs. Next, we imposed weak subvector disposability on the undesirable outputs, which implies that it cost to eliminate undesirable outputs. Capacity was also estimated by using the directional distance function approach but while treating undesirable outputs as inputs which requires an inequality constraint. We also considered strong and weak disposability restrictions for both the directional distance function and the hyperbolic (i.e., graph efficiency) approaches. In addition, the directional distance function approach was modified to allow (1) both desirable and undesirable outputs to expand, (2) desirable outputs to expand and undesirable outputs to be decreased, (3) desirable outputs to expand and undesirable outputs to remain unchanged, and (4) both desirable and undesirable outputs to be contracted. The Seiford and Zhu (2002) approach only allows for the expansion of desirable outputs and contraction of undesirable outputs.

The sample data set contained 307 fishing vessel trips, which represented production activities for a total of 129 vessels operating between 2003 and 2005. The data set was unbalanced in that trips were not available for all 129 vessels in each of the three years. Onboard observers collected the data. There were 12 desirable outputs and 17 undesirable outputs.

6.3 Results and Discussion

Since there were a total of 29 outputs, we summarize only the total desirable and undesirable levels for each of the methods in this summary and conclusions section. We further restrict the summary to mean values per trip. The total mean reported desirable output per trip equaled 45,345 pounds, and the mean undesirable output per trip equaled 31,918 pounds (Table 6.1). The corresponding mean desirable and undesirable outputs per trip by each method used to estimate capacity are as follows (Table 6.1): (1) for the standard output-orientation with no undesirable outputs, the total desirable outputs equal 80,032 pounds; (2) for the directional distance function, which allowed desirable and undesirable outputs to expand, the total desirable output equaled 66,613 pounds and the undesirable output equaled 46,052 pounds; (3) for the directional distance function, which allowed desirable outputs to expand and undesirable outputs to contract, while treating undesirable outputs like inputs, the total desirable output equaled 45,492 pounds, and the undesirable output equaled 31,763 pounds; (4) for the directional distance function, which allowed desirable outputs to expand and undesirable outputs to contract, but imposed weak subvector disposability on the undesirable outputs, the total desirable output equaled 45,351 pounds and the undesirable output equaled 31,907 pounds; (5) for the directional distance function, which allowed desirable outputs to expand and no change in undesirable outputs, the total desirable output equaled 45,716 pounds, and the undesirable output equaled 31,918, the same as the reported mean output per trip of undesirable outputs; (6) for the directional distance function, which allowed both desirable and undesirable outputs to contract, the total desirable output equaled 24,637 pounds and the undesirable output equaled 18,324 pounds; (7) for the hyperbolic approach with strong disposability, the total desirable output equaled 77,745 pounds and the undesirable output equaled 24,032 pounds; (8) for hyperbolic approach with weak subvector disposability, the total desirable output equaled 45,351 pounds and undesirable output equaled 31,821 pounds; and (9) for the Seiford and Zhu (2002) approach, the total desirable output equaled 45,345 pounds, and the undesirable output equaled 31,918 pounds.

Table 6.1 Comparison of mean desirable and undesirable outputs resulting from using different capacity models

	Disposability Assumption for Undesirable Output	Direction for Desirable Expansion	Direction for Undesirable Expansion	Desirable (Mean per Trip)	Undesirable (Mean per Trip)
Data				45,345	31,918
Model					
1. Standard				80,032	31,918
2. Directional Distance Function	Strong	Expand	Expand	66,613	46,052
3. Directional Distance Function	Strong	Expand	Contract	45,492	31,763
4. Directional Distance Function	Weak	Expand	Contract	45,351	31,907
5. Directional Distance Function	Strong	Expand	None	45,716	31,918
6. Directional Distance Function	Strong	Contract	Contract	24,637	18,324
7. Hyperbolic	Strong			77,745	24,032
8. Hyperbolic	Weak			45,351	31,821
9. Seiford and Zhu	Strong			45,345	31,918

We also find that improvements in technical efficiency produced capacity output for the majority of the trips, rather than increased crew size and days at sea per trip. Not surprisingly, however, capacity output requires increasing days at sea per trip with strong disposability in desirable and undesirable outputs or with the standard model (which ignores undesirable outputs). Also, the hyperbolic approach suggests a need to increase days at sea when weak subvector disposability is imposed. This conclusion is not unexpected because the hyperbolic approach expands desirable outputs by a scalar but contracts undesirable outputs by the inverse of the scalar (i.e., the expansion and contraction factors are not the same as in the directional distance function approach).

6.4 Concluding Assessment of Methods

Overall, the various methods for explicitly treating undesirable outputs, and the methods that attempt to expand desirable outputs and contract undesirable outputs yielded equivalent results. This is encouraging because the hyperbolic and Seiford and Zhu (2002) approaches facilitate estimation of capacity and technical efficiency when some observations have zero levels of undesirable outputs, which is likely to characterize most fisheries data on production activities at the trip level. In addition, the two latter approaches are relatively easy to use to estimate capacity output. The directional distance function, while being relatively easy to implement, requires all observations to satisfy null-jointness.

Acknowledgments

We would like to thank Fred Serchuk and Jarita Davis for extremely insightful comments and suggestions. This research was sponsored by the National Marine Fisheries Service, Office of Science and Technology, Economics & Social Analysis Division.

Endnotes

1. Additional early research includes works by Havlicek et al. (1969), Kneese et al. (1970), and Kneese (1971).

2. Extensive discussions on production theory, input sets, and output sets are available in Chambers (1988), Färe et al. (1985, 1994), and Coelli et al. (2005).

3. For additional information on production frontiers, see Färe et al. (1994).

4. This function is defined as $f(x) = \max\{y: y \in P(x)\}$.

5. See pages 12 and 13 of Coelli et al. (2005) for an indepth discussion of these basic properties.

6. See Pages 44 and 45 of Coelli et al. (2005) for an indepth discussion of input sets.

7. Färe et al. (1985,1994) and Coelli et al. (2005) provided detailed explanations of the properties of the input and output sets.

8. Färe et al. (1985, 1994), Kumbhakar and Lovell (2000), and Coelli et al. (2005) provide extensive discussions about various notions of efficiency.

9. Technical efficiency may also be assessed in terms of both a contraction in inputs and an expansion in outputs. For additional information, see Färe and Grosskopf (2004a).

10. Here, we seek radial contractions and expansions relative to all inputs or outputs. Numerous alternative expansions and contractions are possible (e.g., the notions of Russell (1985), which permits either each input to contract by a different percentage, or each output to expand by a different percentage). For additional information on alternative notions, see Russell (1985), Färe et al. (1994), Zhu (2003), Färe and Grosskopf (2004a), Ray (2004), and Cooper et al. (2006).

11. Coelli et al. (2005) note that the definition of the distance function could be made more rigorous by replacing max (maximum) with sup (supremum), which allows for the possibility that a maximum may not exist.

12. As was the case for the input distance function, we can replace min (minimum) with inf (infimum) to allow for the possibility that a minimum may not exist. For addition information, see Coelli et al. (2005).

13. Luenberger (1992, 1995) introduced the notion of a directional technology distance function and referred to it as a shortage function. Chambers et al. (1996), Chung (1996), and Chung et al. (1997) introduced the application of the directional distance function for assessing efficiency in the presence of (1) desirable, or (2) desirable and undesirable outputs.

14. Returns to scale indicate the percentage by which outputs change in response to a given percentage change in all inputs. If all inputs are doubled and output doubles, we have constant returns to scale; if outputs increase by less than the proportional expansion of all inputs, we have decreasing returns to scale (sometimes referred to as nonincreasing returns to scale); and if outputs exhibit multiple responses or returns to scale for given changes in input levels, we have variable returns to scale.

15. Corbo and de Melo (1986) provide an introduction and overview of various methods used to estimate technical efficiency.

16. The advantages and disadvantages are discussed in greater detail in Corbo and de Melo (1986), Kumbhakar and Lovell (2000), and Coelli et al. (2005).

17. Corbo and de Melo (1986) argue that all parameters should be constrained to greater than or equal to zero, and the objective function should be specified as absolute value. Kumbhakar and Lovell (2000), however, suggest that it is not necessary to constrain the objective function to the absolute value, and the parameters need not be constrained to greater than or equal to zero.

18. Kumbhakar and Lovell (2000) and Coelli et al. (2005) provide extensive discussion about the potential distributions of the inefficiency term.

19. These are discussed in more detail in Kumbhakar and Lovell (2000), Coelli et al. (2005), and Coelli (undated).

20. Chambers (1988) and Coelli et al. (2005) provide a summary and overview of the most frequently used flexible functional form specifications of production functions.

21. We can also specify an input distance function; for additional information, see Coelli (undated) and Paul and Nehring (2005).

22. There is extensive literature on DEA; see, for example, Färe et al. (1985, 1994), Charnes et al. (1994), Zhu (2003), Färe and Grosskopf (2004a), Ray (2004), and Coelli et al. (2005). Also observe that we discuss only the notion of technical efficiency; DEA has also been widely used to assess allocative and economic efficiency, along with a wide array of other economic performance metrics.

23. Expansion of outputs and contraction of inputs, however, need not be restricted to radial projections. Ray (2004) and Cooper et al. (2006) provide extensive discussion about non-radial DEA models. Also, see Färe and Lovell (1978) and Russell (1985) for nonradial DEA models.

24. Slacks represent the potential additional expansion in desirable outputs and contraction in undesirable outputs. Alternatively, a positive slack indicates the potential for additional increase in outputs, and a negative slack (e.g., in an input-oriented problem) represents the potential for additional reduction in an input.

25. Färe et al. (1994), Zhu (2003), Ray (2004), and Cooper et al. (2006) provide detailed discussions of alternative models for addressing strong efficiency. Coelli (1996) provides free DEA software, which contains an algorithm for estimating strong efficiency or dealing with nonzero slacks.

26. Some researchers reverse the signs and inequalities of the restrictions in both the input and output orientations; these differences, however, yield the same results and estimates of efficiency.

27. A detailed summary of the restrictions necessary to impose various returns to scale is presented on page 13 of Zhu (2003).

28. Some available software calculates θ in such a way that θ is less than or equal to 1.0. In this case, $1/\theta - 1.0$ indicates the proportion by which outputs can be expanded.

29. Other specifications appear in the literature, but they are the same problem with only some minor differences in the specifications of the constraints; see for example page 92 of Ray (2004) and pages 12-13 of Färe and Grosskopf (2004a).

30. Berndt and Morrison (1981), Morrison (1985a,1985b, 1986), Berndt and Fuss (1986, 1989), and Kirkley and Squires (1999) provide a comprehensive review of the various concepts of capacity, and the methods used to estimate and assess capacity. A relatively nontechnical discussion of capacity is presented in Grafton et al. (2006).

31. Simar and Wilson (2000) offer one framework for dealing with noise, but Coelli et al. (2005) have argued that the approach of Simar and Wilson really addresses issues relating to sampling variation and sample size and does not adequately address the issue of noise. Gstach (1998) offers an alternative DEA approach (DEA+), but this approach has not been widely adopted or used by other researchers to assess efficiency or capacity.

32. The appeal of DEA is that a wide array of performance metrics can be estimated by using only linear programming. For additional details about DEA, see Färe et al. (1985, 1994), Zhu (2003), Ray (2004), Coelli et al. (2005), and Cooper et al. (2006).

33. More recent discussions on estimating efficiency with undesirable outputs appear in Vencheh et al. (2005), Jahanshahloo et al. (2005), and Zhou et al. (2006). These discussions, however, mostly provide summaries of existing methods for estimating technical efficiency when production involves undesirable outputs.

34. Details of the modifications appear in Färe et al. (1989a, 1994) and Ray (2004).

35. The directional distance technology approach is extensively discussed in Färe and Grosskopf (2004a) and Ray (2004).

36. Zhu (2003) provides a more detailed treatment of their proposed approach.

37. Trawl gear is a relatively nonselective gear with respect to species and size. Increasing the mesh size does allow some escapement of smaller fish, but few modifications can be made to trawl gear to avoid the capture of many species.

38. We note that some undesirable outputs are because of regulations rather than nonmarketability or nonutilization. That is, some of the outputs, such as juvenile yellowtail and summer flounder, could be landed and utilized as pet food or fish meal. Landings are restricted, however, because if left to grow these juveniles will become more important as larger fish for human consumption, and they contribute to the future stock abundance and biomass.

39. Sum represents total over all vessels in sample.

40. The total summaries are based on aggregating over the three year period.

41. The estimated values are different when expressed in terms of two or three decimal places. For convenience, we express the estimated full-utilization levels of the variable factors using one decimal place.

42. The same estimates would be obtained with the traditional output-oriented approach if all desirable and undesirable outputs were included.

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