Data Envelopment Analysis (DEA): A Framework for Assessing Capacity In Fisheries When Data are Limited

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Abstract: The Sustainable Fisheries Act (SFA) and Code of Conduct for Responsible Fisheries Management require restoration of fishery resources and a matching of capacity to desired resource levels. There is, thus, a need to reduce harvesting capacity throughout many of the fisheries of the world. Yet, even the term capacity is not well defined, and it is even more complicated to measure. In this paper, we introduce several definitions and measures of capacity that are consistent with economic theory and empirical analyses. Since economic data on production activities are usually unavailable, we introduce the concept of data envelopment analysis (DEA) which may be used to calculate a physical or primal-based concept of capacity in fisheries. We initially introduce DEA and dispel many of the myths believed to be problems of DEA. We discuss how DEA may be used to calculate capacity in single and multiple-species fisheries. We also introduce how the DEA-derived measure of capacity may be formulated to include undesirable outputs (e.g., bycatch).

Keywords: Capacity, capacity utilization, data envelopment analysis

1. Introduction

In 1997, the Food and Agriculture Organization (FAO) of the United Nations (1997) reported that nearly 60% of the world's major fisheries were either mature or senescent. An earlier report by FAO (1995) stated that of the 44% of the fish stocks for which formal stock assessments were available, 16% were overfished, 6% were depleted, and 3% were slowly recovering. Excess harvesting capacity has been cited as a major factor contributing to overfishing in many of the world's fisheries (FAO 1997). Since 1996, there has been an international effort to reduce harvesting capacity, and subsequently, match capacity to resource levels.

Yet, even the basic concept, capacity, is neither uniquely defined nor easily assessed. There is debate about whether or not capacity should be defined from an economic perspective or relative to a technological or primal perspective (Morrison 1985a; Kirkley and Squires 1999). A broad and practical economic definition of capacity is that it is the output level that would be produced if the producer realized a given behavioral objective (e.g., maximized profits) and operated under customary and usual operating procedures. This economic definition is relatively consistent with that used by the U.S. Census Bureau which reports annual assessments of capacity to the Federal Reserve, the Federal Emergency Management Administration, the International Trade Commission,, and the Bureau of Export Administration. Alternative definitions and potential measures based on other criteria are summarized in Morrison (1985a), Kirkley and Squires (1999), and Färe et al (2000).

An alternative definition, and one which is receiving increasing attention by individuals interested in estimating harvesting capacity for a fishery, is a technological-engineering, or more formally a technological-economic definition. Following Johansen (1968), capacity is the maximum potential output that could be produced given that the availability of the variable factors is not limiting. Kirkley et al. (2000) offer a modified definition of Johansen's definition by considering customary and usual operating procedures.

In the case of fisheries, estimation of the economic concept of harvesting capacity is complicated because appropriate economic data (e.g., costs and earnings information) are not widely available. The absence of appropriate economic data and a national and international urgency to calculate harvesting capacity in fisheries has increased research interest in options for estimating capacity.

In this paper, we present data envelopment analysis (DEA) as one approach for estimating and assessing capacity and capacity utilization (CU) in fisheries. Initially, we provide an introduction and overview of DEA—a mathematical programming approach that may be used to estimate technical efficiency (TE), capacity, and CU. We subsequently discuss the various restrictions often thought to characterize the technology with the DEA framework. We next provide an overview and discussion of many of the typical criticisms of DEA. Potential modifications of the DEA framework that might be useful for exploring other issues in fisheries (e.g., capacity reduction programs and bycatch mitigation strategies) are next discussed. We then introduce the Johansen (1968) concept of capacity that was made operational by Färe et al. (1989) and later modified by Färe et al. (2000) to better accommodate economic concerns and multi-product technologies. We conclude the paper with an empirical analysis, based on DEA, of a small fleet of sea scallop vessels.

2. Data Envelopment Analysis

Data envelopment analysis (DEA) is a mathematical programming approach for estimating the relative technical efficiency (TE) of production activities. The term DEA was originally proposed by Charnes et al. (1978). The Charnes et al. work extended the Farrell (1957) multiple input, single output measure of TE to the multiple-output, multiple input technology. Since the early Charnes et al. work, however, DEA has developed and expanded to include a wide variety of applications. DEA has been used to assess TE, scope, scale, and allocative efficiency. It has also been used to estimate optimal input utilization, productivity, identify strategic groups, determine benchmarks and total quality management programs, estimate social and private costs of regulating undesirable outputs and capacity (Kirkley et al. 2000). The DEA models have been extended from the static, deterministic models to include dynamics and stochastic aspects (Färe and Grosskopf 1996; Banker 1990; and Resti 2000). Procedures have been developed to deal with temporal aspects and balanced panel data (e.g., the window analysis approach of Charnes et al. (1994)).

In addition to being a mathematical programming approach for estimating TE, what can we say about DEA? It is non-statistical and non-parametric. When we say it is non-statistical, we are implying that estimates are not based on any statistical distribution (e.g., the normal) and noise is not explicitly considered in the estimation.; that does not mean, however, that statistical tests of the various estimates cannot be performed. An alternative view is that DEA is deterministic. When we refer to DEA as being non-parametric, we are referring to the fact that we do not have to assume a particular functional relationship between the inputs and outputs; we do not have to assume any statistical distribution; and we do not have to estimate parameters based on assumed statistical distributions.

The DEA technique permits an assessment of the performance or TE of an existing technology relative to an ideal, “best-practice,” or frontier technology (Coelli et al. 1998). The frontier or best-practice technology is a reference technology or production frontier that depicts the most technically efficient combination of inputs and outputs (i.e., output is as large as possible given the technology and input levels, or input levels are as small as possible given the output levels). The frontier technology is formed as a non-parametric, piece-wise linear combination of observed “best-practice” activities. Data points are enveloped with linear segments, and TE scores are calculated relative to the frontier technology.

The DEA technique may be used to estimate TE scores or efficient levels of inputs or outputs from either an input or output orientation or from an orientation that allows both input and output levels to simultaneously change. The input-orientation provides estimates of the amount by which inputs could be proportionally reduced and still produce a given output level. The output-orientation provides estimates of the amount by which outputs could be proportionally expanded given existing input levels. The orientation that allows both inputs and outputs to change by the same proportion (inputs are proportionally decreased while outputs are proportionally increased) provides a measure of what is referred to as hyperbolic graph efficiency; it may be generalized by what is called a directional distance function.

Following Färe et al. (1994), we have a production technology transforming inputs $x = (x_1, x_2, \ldots, x_N) \in R_+^N = \{x : x \in R_+^N,\ x \geq 0\}$ into outputs $u = (u_1, u_2, \ldots, u_M) \in R_+^M$ which can be represented by the output correspondence, P, the input correspondence, L, or the graph (GR) of the technology. The output correspondence

$$P:\ R_+^N \to 2^{R_+^M} \tag{1}$$

maps inputs $x \in R_+^N$ into subsets $P(x) \subseteq R_+^M$ of outputs. The set P(x) is referred to as the output set; it indicates the collection of all outputs $u \in R_+^M$, which can be produced from the input vector $x \in R_+^N$. There is also an input correspondence that maps outputs $u \in R_+^M$ into subsets of inputs $L(u) \subseteq R_+^N$

$$L:\ R_+^M \to 2^{R_+^N} \tag{2}$$

The input set L(u) indicates all inputs $x \in R_+^N$ that yield at least outputs $u \in R_+^M$. With (1) or (2), we can depict the technology from either the input correspondence or the output correspondence (Färe et al. 1994).

The input and output sets provide representations of the technology in terms of input and output quantities. Input substitution possibilities are modeled with the input set, and output substitution possibilities are modeled by the output set. We can also derive the relationship between the input and output sets (i.e., the Graph (GR) of the technology) (Färe et al. 1994). The graph models input substitution, output substitution, and the input-output transformation. The graph may be derived from either an input or output correspondence, and the input and output correspondences, respectively, may be derived from the GR as

$$P(x) = \{u: (x,u) \in GR\} \tag{3}$$

$$L(u) = \{x: (x,u) \in GR\} \tag{4}$$

The relationship between inputs, outputs, and the graph (GR) may be summarized as

$$u \in P(x) \Leftrightarrow x \in L(u) \Leftrightarrow (x,u) \in GR \tag{5}$$

Thus far, no assumptions have been imposed on the underlying technology. The GR specification and the input and output correspondences allow the technology to be specified from either an input orientation, an output orientation, or directly in terms of the input-output transformation frontier. Numerous alternative specifications are presented in Färe et al. (1994).

Two very important aspects of the input and output correspondences that we need for understanding TE are returns to scale and disposability. Thus far, we have not imposed any returns to scale or disposability conditions. A technology may exhibit constant, non-increasing, and non-decreasing returns to scale. Disposability actually refers to assumptions about economic regions that are often assumed for a normal technology. From an input orientation, we normally assume that isoquants cannot bend backwards; this assumption is the case of strong disposability for an input orientation. From an output orientation, we normally assume the technology cannot have an upward sloping portion of the transformation frontier; this is the case of strong disposability from an output orientation. In contrast, we can have weak disposability from either an input or output orientation. From an input orientation, if the technology is weakly, but not strongly, disposable, input usage may be excessive and we may have congestion. Strong disposability implies weak disposability, but weak disposability does not imply strong disposability. If the technology is weakly, but not strongly, disposable in outputs, it may not be possible to reduce the level of one output without reducing the level of another output. For most production analysis, strong disposability in inputs is assumed (Reinhard et al. (1999) provides a listing of research on weak disposability).

Returning to our input and output orientation and DEA framework, consider J producers that use N inputs to produce M outputs. We let u_{jm} equal the quantity of the mth output produced by the jth producer, and x_{jn} the level of the nth input used by the jth producer. Inputs and outputs are assumed to satisfy the following conditions:

(i) $u_{jm} \geq 0,\ x_{jn} \geq 0$

(ii) $\sum_{j=1}^{J} u_{jm} > 0,\ m = 1,2,\ldots,M$

(iii) $\sum_{n=1}^{N} x_{jn}, > 0,\ j = 1,2,\ldots,J$

(iv) $\sum_{j=1}^{J} x_{jn}, > 0,\ n = 1,2,\ldots,N$

(v) $\sum_{m=1}^{M} u_{jm} > 0,\ j = 1,2.,\ldots,J$

Condition (i) imposes the assumption that each producer uses nonnegative amounts of each input to produce nonnegative amounts of each output. Conditions (ii) and (iii) require total or aggregate production of positive amounts of every output, and total or aggregate employment of positive amounts of every input. Conditions (iii) and (v) require that each firm employ a positive amount of at least one input to produce a positive amount of at least one output. Zero levels are permitted for some inputs and outputs.

We next introduce the vector $z = (z_1,z_2,\ldots,z_J) \in R_{+}^{J}$ which denotes the intensity levels at which each of the J firms or activities are operating. The z vector allows us to decrease or increase observed production activities (input and output levels) in order to construct unobserved but feasible activities. More important, the z vector provides weights that are used to construct the linear segments of our piece-wise, linear technology (i.e., the technology constructed by DEA). As previously stated, we can model our technology from either an input or output orientation. We can also model the technology relative to various returns to scale. Models may also be constructed to reflect different disposability conditions.

Starting with the piece-wise formulation of the input set representation of the technology given constant returns to scale (C) and strong disposability (S) of inputs and outputs, we have

$$\begin{aligned} L(u \mid C,S) = \{x: u_m \leq \sum_{j=1}^{J} z_j u_{jm},\ m = 1,\ldots,M \\ \sum_{j=1}^{J} z_j x_{jn} \leq x_n,\ n = 1,\ldots,N,\ z \in R_{+}^{J}\} \end{aligned} \tag{6}$$

Non-increasing returns to scale (NIRS) and strong disposability require imposing the additional constraint on the intensity values

$$L(u|N,S) = \{x: u_{jm} \le \sum_{j=1}^{J} z_j u_{jm},\ m = 1,\ldots,M \quad (7)$$

$$\sum_{j=1}^{J} z_j x_{jn} \le x_n,\ n = 1,\ldots,N,\ z \in R_+^J,\ \sum_{j=1}^{J} z_j \le 1.0\},\ u \in R_+^M$$

Variable returns to scale (VRS), $L(u|V,S)$, requires changing the constraint on the summation of the intensity variables from $\le$ 1.0 to = 1.0.

Specifying the piece-wise formulation of the input set representation of the technology $L(u|(C,N,V),W)$ subject to weak disposability of inputs, (W), requires changing the inequality constraint in Eq. (6) to an equality constraint

$$\sum_{j=1}^{J} z_j x_{jn} = x_n,\ n = 1,\ldots,N \quad (8)$$

which is the case when all inputs are weakly disposable. The more likely case, however, is when only a subset of the inputs is weakly disposable. This latter case can be accommodated by partitioning the input variables into those that are strongly disposable and those that are only weakly disposable, and reformulating the technology with $\le$ constraints on the strongly disposable inputs and equality constraints on the weakly disposable inputs.

The output possibilities set can also be used to construct a piece-wise technology. Under constant returns to scale and strong disposability, we have the following

$$P(x \mid C,S) = \{u: u_m \le \sum_{j=1}^{J} z_j u_{jm},\ m = 1,\ldots,M \quad (9)$$

$$\sum_{j=1}^{J} z_j x_{jn} \le x_n,\ n = 1,\ldots,N,\ z \in R_+^J\}$$

Non-increasing and variable returns to scale can be modeled by imposing the same constraints on the summation of the intensity variables as done from the input orientation. Weak disposability in all outputs requires the following equality constraint

$$u_m = \sum_{j=1}^{J} z_j u_{jm},\ m = 1,\ldots,M \quad (10)$$

Weak disposability in a subvector of outputs can be accomplished in the same fashion as done for weak disposability in a subvector of inputs (i.e., partition the outputs into strong and weak disposable sets and impose the necessary inequality and equality conditions).

Given a large range of options for specifying the technology, TE may be estimated using DEA from either an input or output orientation. The input orientation permits us to measure TE as the largest proportion that inputs could be reduced and still produce the same level of output. The output orientation permits us to measure TE as the largest proportion by which outputs could be increased without changing the level of inputs.

Using the piece-wise technology, $L(u|C,S)$, given by Eq. (6), an input-oriented measure of TE can be calculated for a given decision making unit (DMU) or observation as the solution to a linear programming (LP) problem

$$TE_{ij}(u_j,x_j \mid C,S) = \min_{\lambda,z} \lambda \quad (11)$$

$$\text{subject to } u_{jm} \le \sum_{j=1}^{J} z_j u_{jm},\ m = 1,\ldots,M,$$

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

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

where $TE_{ij}(u_j,x_j \mid C,S)$ is technical efficiency of any jth observation given constant returns to scale and strong disposability; λ is the measure of TE and equals the reciprocal of an input distance function which equals the ratio of the minimal feasible input usage to the current input usage, $0 \le \lambda \le 1.0$; z is the intensity vector which enables the benchmark or "best-practice" frontier to be constructed; J is the number of DMUs; M is the number of outputs; and N is the number of inputs. The solution to problem (11) provides a measure of TE and the potential radial or proportional reduction in all inputs with no change in the output level (e.g., a TE of 1.0 implies technically efficient production; a value of TE < 1.0 (e.g., .75) implies that production is technically inefficient and all inputs corresponding to the DMU could be scaled back by the TE score (e.g., by 25% or to 75% of their original value)). The LP problem is solved for every observation. Modifications to reflect NIRS and VRS only require imposing the constraints presented in Eq. (7) and that required for VRS. Weak disposability requires the constraint in Eq. (8).

The piece-wise technology corresponding to the output set, $P(x \mid C,S)$, is similarly constructed

$$TE_{oj}(u_j,x_j \mid C,S) = \max_{\lambda,z} \theta \quad (12)$$

$$\text{subject to } \theta u_{jm} \le \sum_{j=1}^{J} z_j u_{jm},\ m = 1,\ldots,M,$$

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

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

where TE_o is TE for an output orientation and indicates the maximum feasible or proportional expansion in all outputs; θ is the inverse of an output distance function and equals the ratio of the maximum potential output to the observed output level; and the zs are used to construct the reference technology. The value of θ is restricted to $\geq$ 1.0; some existing software packages, however, solve problem (12) in terms of $1/\theta$, where θ - 1.0 is the potential proportionate increase in outputs. If θ = 1.0, production is technically efficient; if θ > 1.0, production is inefficient and output levels could be increased by θ - 1.0. Imposing NIRS and VRS requires imposing the same constraints identified for the input oriented problem; weak disposability requires the constraint of Eq. (10).

A remaining aspect of DEA is that of scale efficiency (SE). Scale efficiency is a measure of whether or not a producing unit is operating at an optimal scale of operation. Measures of SE offer information that may be particularly useful for formulating fishery management plans; that is, what should be the optimal scale of operation? Scale efficiency equals the ratio of TE_{CRS} to TE_{VRS}. Production is scale efficient if SE = 1.0, or if the $TE_{CRS} = TE_{VRS}$. Scale efficiency may be calculated from either an input or output-orientation.

The measure of SE, however, only indicates whether or not a firm is scale efficient. The measure does not indicate whether or not scale inefficiency occurs because a production activity is operating at too large or too small a scale (i.e., is production characterized by decreasing or increasing returns to scale?). Assessing whether or not an activity, which is scale inefficient, is operating at too large or too small a scale only requires solving another DEA problem—the NIRS model. By comparing TE_{NIRS} to TE_{CRS}, we can determine whether or not the inefficiency is because of increasing or decreasing returns to scale. In general, and without proof, we have the following conclusions regarding scale efficiency: (1) if $SE_I < 1.0$ from an input-orientation, we have scale inefficiency; (2) for $SE_I < 1.0$ and $TE_{iNIRS} = TE_{iCRS}$, scale inefficiency is because of increasing returns to scale (i.e., the producing unit is operating at an inefficiently small scale); (3) for $SE_I < 1.0$ and $TE_{iNIRS} > TE_{iCRS}$, scale inefficiency is caused by operating at an inefficiently large scale or in the region of decreasing returns to scale; (4) if $SE_o > 1.0$ from an output-orientation, production is scale inefficient; (5) if $SE_o > 1.0$ and $TE_{oNIRS} = TE_{oCRS}$, production is scale inefficient because of increasing returns to scale; and (6) if $SE_o > 1.0$ and $TE_{oNIRS} > TE_{oCRS}$, production is scale inefficient because of decreasing returns to scale.

3. Perceived Restrictions on Technology and Myths

Perhaps because of misunderstanding, numerous researchers have criticized DEA for assuming various restrictions on the underlying technology. In this section, we discuss some of the typical criticisms of DEA relative to perceived restrictions and attempt, without mathematical proof, to dispel these criticisms.

In words, we assume that the underlying technology satisfies certain basic properties or axioms (Färe and Grosskopf 1996). We initially assume that it is always possible to produce no output, and it is not possible to produce an output without an input. Our technology may be subject to weak or strong disposability in inputs or in outputs. We also assume that the output correspondence or set (P(x)) is bounded for any input vector x; only finite amounts of output can be produced by finite amounts of inputs. In practice, we assume convexity of the input and output sets. We also typically assume a specific returns to scale (CRS, NIRS, and VRS). We impose assumptions (i) through (v). The preceding properties are the minimal required set.

A common criticism of DEA is that it assumes the technology has either fixed input proportions or fixed output proportions. This criticism is likely because TE scores represent radial contractions of inputs or expansions of outputs. The radial change simply provides a convenient way to examine changing inputs or outputs relative to efficient production. The technology is not, however, assumed to have fixed input or output proportions. In fact, inclusion of slacks, calculation of the Russell (1985) TE measure, or the directional distance function explicitly permit a nonradial change in inputs or outputs (Färe et al. 1994; Coelli et al. 1998). Slacks occur whenever sections of the piece-wise frontier run parallel to the axes. The non-radial measure of TE is consistent with Koopmans' (1951) notion of TE, which requires a firm to operate on the frontier and have zero slacks.

Another common assumption often thought to characterize the technology relative to a multiproduct, multiple input technology is separability between inputs and outputs. As illustrated in Färe and Primont (1995), however, input-output separability is not imposed by the basic DEA model.

Another perceived assumption is that DEA imposes zero input and output substitution possibilities. This is likely a result of early texts on LP, which often stated that the LP specification of the technology imposed zero substitution possibilities. Numerous recent texts, however, have demonstrated that zero substitution possibilities need not be imposed by the LP specification. Moreover, the isoquants or production possibility curves corresponding to the DEA-derived best-practice frontiers explicitly permit substitution.

4. Common Criticisms of DEA

Of the many objections to DEA, it is perhaps the non-stochastic nature that generates the most criticism. With DEA, all deviations from the frontier are attributed to inefficiency. The DEA does explicitly account for stochastic events such as bad weather, poor luck, or measurement error in the data. In contrast, the oft-used stochastic production frontier (SPF) does specifically accommodate the possible influence of measurement errors and other noise upon the frontier. In the case of measurement error, however, the SPF also may be an inappropriate specification; Goldfeld and Quandt (1972) have shown that if the dependent variable, but not the independent variable, is observed with error, the stochastic error term should be additive in the specification of a multiplicative technology. If so, it may difficult to construct the appropriate maximum-likelihood function necessary to estimate TE with the SPF.

To address the issue of DEA being non-stochastic, there has been an increasing emphasis on developing a stochastic DEA (Banker 1990; Resti 2000). Resti offers multiplicative and heteroscedastic multiplicative stochastic DEA models; Resti also presents a detailed comparison of deterministic and stochastic DEA and SPF models. At the present time, however, developments in stochastic DEA appear to be too limited to adequately evaluate, and thus, the criticism of DEA being non-stochastic will likely remain.

Another criticism of DEA is that it is non-statistical. This may be an appropriate criticism. DEA does not yield estimates that can be easily validated with conventional statistical procedures. To address this problem, some researchers have recommended bootstrapping, which does permit confidence intervals to be estimated. In addition, a wide variety of non-parametric techniques have been employed to examine various properties of the TE estimates (Banker 1990).

Sensitivity to outliers has been another criticism of DEA (Coelli et al. 1998). Thompson et al. (1990) and Burgess and Willson (1993), however, offer evidence to the contrary. Sensitivity to outliers may also pose problems for estimating the SPF or any regression relationship. As such, the sensitivity issue is probably over-exaggerated.

Another common but erroneous criticism is that DEA does not adequately address the underlying economics. It is a primal approach. This is a serious misconception of DEA. DEA can easily accommodate economic behavior by using cost and revenue specifications. Färe et al. (1997) offer one approach for estimating profit efficiency using a DEA model. More important, the economic-based DEA models allow decomposition of economic efficiency into technical and allocative components (Färe et al. 1994; Coelli et al. 1998). From a cost or revenue-based framework, total economic efficiency (EE) can be decomposed into the product of allocative (AE) and technical efficiency (TE). Moreover, TE can be further decomposed into scale efficiency (SE), congestion (CN), and a residual TE component ($TE(u,y|V,W)$), where the residual is a TE measure given variable returns to scale and weak disposability. Overall, EE can subsequently be decomposed into the product of AE, SE, CN, and $TE(u,y|V,W)$ relative to a cost (input) orientation or revenue (output) orientation (Färe et al. (1994) and Coelli et al. (1998) provide detailed discussions on EE and the relative decompositions).

Coelli et al. (1998) offer 11 possible limitations that one may encounter in conducting a DEA, and a comparison of the advantages and disadvantages of DEA and the SPF approach. They also note that the 11 problems are likely applicable to the SPF approach. Coelli et al. conclude that the SPF approach may be more applicable in situations where the data are heavily influenced by measurement error and random effects.

5. Fisheries and Potential Modifications to DEA

For all the potential disadvantages of DEA, it offers a powerful framework for analyzing various issues in fisheries. First, it can model multiple output-multiple input technologies. DEA models do not impose any specific functional form on the underlying technology and technical interactions. Last, DEA permits an assessment of congestion efficiencies.

The technology of many fisheries involves multiple outputs and multiple inputs. Management and regulation are increasingly focusing on the multi-species nature of most fisheries. DEA offers a convenient framework for analyzing TE in multi-species fisheries. Concurrently, managers are becoming increasingly concerned with controlling bycatch and preventing habitat damage; these two issues may be equated to the case of undesirable outputs and weak disposability in outputs. The DEA framework can easily accommodate analysis of TE and issues related to undesirable inputs or outputs. The disposability properties can also be used to model input or output congestion (e.g., the case of using too much of an input). The concept of congestion in DEA may have applicability to the examination of the possible relationship between fleet size and technological externalities in production.

6. DEA, Capacity, and Fisheries

DEA offers a particularly convenient framework for estimating capacity in fisheries because it allows maximum output to be estimated conditional only on the fixed factors. Alternatively, DEA easily facilitates the calculation of the concept of capacity proposed by Johansen (1968). Färe et al. (1989) recognized the potential consistency between the Johansen definition of capacity and DEA. Johansen (p. 50) defined capacity as "the maximum output that can be produced per unit of time with the existing plant and equipment provided that the availability of the variable factors is not restricted." Färe et al. (1989) illustrated that capacity at the plant level could be estimated by partitioning the fixed (F_x) and variable inputs (V_x) and solving the following output-oriented, DEA problem:

$$TE_{ocj} = \underset{\theta,z,\lambda}{Max}\,\theta \tag{13}$$

$$\text{subject to } \theta u_{jm} \le \sum_{j=1}^{J} z_j u_{jm}, \; m = 1,\ldots,M,$$

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

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

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

$$\lambda_{jn} \ge 0,$$

where θ is a measure of TE ($\theta \ge 1.0$). If we multiply the observed output by θ, we obtain an estimate of capacity output. Capacity can also be estimated by solving problem (13) without the variable input constraints.

Problem (13) imposes strong disposability in outputs and constant returns to scale. Problem (13) was initially proposed by Färe et al. (1989) as an approach for assessing capacity when data were limited to input and output quantity information; that is, economic data such as cost and earnings information and information on input and output prices were not available. As such, problem (13) is a technological-engineering concept. Since estimates are based on actual data, however, estimates of capacity obtained from solutions to problem (13) implicitly reflect the underlying economics. We offer, therefore, that an estimate of capacity derived from problem (13) should be referred to as a technological-economic measure of capacity.

In addition to obtaining an estimate of capacity, problem (13) together with problem (12) may be used to estimate an unbiased measure of capacity utilization (CU). Färe et al (1989) demonstrated that the ratio of an output oriented measure of TE, with fixed and variable inputs included, to an output-oriented measure of TE, with variable inputs excluded, yielded a relatively unbiased measure of CU:

$$CU = \frac{TE_o}{TE_{oc}} \tag{14}$$

Although the focus of Färe et al. was on obtaining an unbiased estimate of CU, the Färe et al. CU measure permits an assessment of whether or not deviations from full capacity are because of inefficient production or less than full utilization of the variable and fixed inputs. In contrast to the CU measure in Eq. (14), the conventional practice for measuring CU has been to divide observed output by capacity output.

Solutions to problem (13) may be used to estimate a variable input utilization rate. The ith variable input utilization rate is estimated as follows (Färe et al. (1994)):

$$\lambda^*_{jn} = \frac{\sum_{j=1}^{J} z^*_j x_{jvi}}{x_{jvi}}, \; n \in V_x \tag{15}$$

where λ^* equals the ratio of the level of the ith variable input required to produce the capacity level to the observed usage of the ith variable input; the numerator equals the optimal level; and the denominator equals the observed usage of the ith variable input. A value of $\lambda > 1.0$ indicates a labor shortage relative to capacity production; $\lambda < 1.0$ implies excess labor.

The use of DEA to estimate capacity need not be restricted to the primal or technological-engineering concept of capacity. If sufficient data on input or output prices are available, it is possible to estimate TE, capacity, CU, and optimal variable input usage using a cost or revenue-based DEA problem. Färe et al. (2000) illustrate how TE, capacity, and CU for a multiproduct, multiple input technology can be estimated either directly by solving respective revenue maximization or cost minimization DEA problems similar to problem (13) or by exploiting the properties of duality.

A potential criticism of the DEA-based assessment of capacity, particularly relative to fisheries, is that capacity is estimated subject to radial expansions of outputs. The use of a radial measure may understate capacity and subsequently lead to management that permits excess harvesting of some species. This is a fair criticism, but not one that cannot be overcome. One may use Koopmans definition of TE, which indicates that a firm is TE only if it operates on the frontier, and there are no slacks. The multi-stage DEA algorithm of Coelli (1997) may then be used to estimate TE. The Coelli routine involves a sequence of radial DEA models to identify projected efficient points which have input and output mixes as similar as possible to those of the inefficient points; unlike many other DEA routines, the Coelli approach is invariant to the units of measurement. The Coelli multi-stage routine, however, may not yield solutions if there are some zero outputs. A modified Russell measure may also be used to estimate a non-radial measure of TE when there are zero outputs (Färe and Lovell 1978).

6. Capacity in Fisheries: An Empirical Illustration

In this section, we illustrate the use of DEA to estimate capacity in a fishery. Our data set consists of trip level observations on output, days at sea, crew size, stock abundance, and vessel characteristics for nine U.S. northwest Atlantic, sea scallop, *Placopecten magellanicus*, dredge vessels operating between 1987 and 1990. For the purposes of illustrating DEA, however, we restrict our analysis to annual observations. We first solve problem (12) subject to CRS, VRS, and NIRS; we do this to examine TE and scale efficiency. We then solve problem (13) imposing CRS to be consistent with the long-run competitive equilibrium. We then obtain estimates of capacity, CU and the variable factor, full input utilization levels.

Sea scallops are harvested offshore between Maine and North Carolina. The primary gear is the dredge. The primary landed form is shucked meats (i.e., the muscle). The major U.S. fishing areas are Georges Bank, Mid-Atlantic, and what is referred to as DelMarVa (Delaware, Maryland, and Virginia). There are approximately 334 vessels licensed to harvest scallops in the Exclusive Economic Zone (EEZ) (Kirkley et al. 2000). There are approximately 215 full-time, scallop vessels. As of 1998, there were 120 vessels between 5 and 50 gross registered tons (GRT); 82 vessels between 51 and 150 GRT; and 132 vessels larger than 150 GRT.

Vessel size, measured by GRT, ranged from 124 to 181 (Table 1). Engine horsepower (HP) ranged from 520 to 620. Dredge sizes were 13 and 15 feet. Vessel characteristics served as the fixed factors of production in our analysis. Average annual output ranged from 127,733.3 pounds of sea scallop meats for vessel 2 to 172,269.0 pounds for vessel 1 (Table 2). The average annual number of days ranged from 226.5 for vessel 3 to 258.8 for vessel 6. Average manpower, measured in man-days, ranged from a low of 2,270.0 for vessel 9 to 2,474.7 for vessel 1. We used days at sea and man-days as measures of our variable inputs. We also included a measure of stock abundance, which was measured in terms of baskets per tow and weighted by number of days per trip to obtain an annual measure (Kirkley et al. 2000).

Table 1. Vessel characteristics of 9 sea scallop vessels[a]

Vessel	GRT	HP	Dredge
1	181	620	15
2	125	520	13
3	190	520	15
4	124	620	13
5	130	520	15
6	135	520	15
7	129	520	15
8	137	520	15
9	131	520	13

[a] GRT is gross registered tons; HP is engine horsepower; and Dredge is the width of the dredge in feet.

Because we have panel data, we averaged our annual estimates of TE, capacity, and CU to smooth the abnormally high or low production levels. The TE scores for CRS, VRS, and NIRS varied considerably among vessels and years (Table 3). Under CRS, production was technically efficient for only seven observations; production was efficient for considerably more observations under VRS. Relative to scale efficiency only ten observations were scale efficient between 1987 and 1990. We also found that for observations that were not scale efficient, production was operating at too small a scale or in the range of increasing returns to scale.

Table 2. Average days, man-days, catch, and abundance[a]

Vessel	Catch	Days	Man-days	Abundance
1	172,229.0	255.3	2,474.7	3.3
2	127,733.3	248.5	2,410.4	2.5
3	140,726.5	226.5	2,260.2	3.1
4	135,843.3	255.8	2,443.9	2.6
5	143,256.5	239.3	2,231.4	2.9
6	169,924.8	258.8	2,336.0	3.2
7	142,264.0	244.0	2,294.1	2.8
8	137,132.5	242.5	2,357.8	2.8
9	129,667.5	235.0	2,227.0	2.6

[a]Days at sea is a measure of the number of days a vessel was at sea; Man-days equals the product of crew size and days at sea per year; stock abundance is a measure of number of baskets per tow per trip weighted by days per trip to obtain an annual measure.

Because we have panel data, we averaged our annual estimates of TE, capacity, and CU to smooth the abnormally high or low production levels. The TE scores for CRS, VRS, and NIRS varied considerably among vessels and years (Table 3). Under CRS, production was technically efficient for only seven observations; production was efficient for considerably more observations under VRS. Relative to scale efficiency, only ten observations were SE between 1987 and 1990. We also found that for observations that were not SE, production was operating at too small a scale or in the range of increasing returns to scale.

Overall, we found that production was typically less than the capacity output levels (Table 4). Annual average production by vessels 1,2, 4,6, and 7 did nearly equal the capacity output. Overall, the nine-vessel fleet had the capability to harvest approximately 9% more per year than it actually did between 1987 and 1990. Besides being technically inefficient, there was a general tendency to operate too few days and with a relative shortage of labor; most of the utilization ratios exceed 1.0 in value.

Given that CU and the optimum input utilization ratios were close to 1.0, a Wilcoxon signed rank test was conducted to assess whether or not the estimated values were any different than the observed values. We used the non-parametric Wilcoxon signed rank test because we could not assume a normal distribution for our estimates. The corresponding z scores and two-tailed asymptotic significance levels () for capacity and utilization of days and man-days equaled, respectively, -4.86 (0.000), -3.252 (0.001), and –0.487 (0.626). We concluded that the mean difference between observed output and capacity output and between days and optimal days did not equal 0.0; we could not, however, reject that the mean difference between observed man-days and the man-days at full utilization equaled 0.0.

Table 3. TE by sea scallop vessel and year, 1987-1990

Year	Vessel	TE-CRS	TE-VRS	TE-NIRS
1987	1	1.01	1.00	1.01
	2	1.05	1.00	1.05
	3	1.11	1.00	1.11
	4	1.16	1.00	1.16
	5	1.10	1.00	1.10
	6	1.00	1.00	1.00
	7	1.09	1.00	1.09
	8	1.05	1.00	1.05
	9	1.18	1.00	1.18
1988	1	1.00	1.00	1.00
	2	1.16	1.10	1.16
	3	1.08	1.03	1.08
	4	1.01	1.00	1.01
	5	1.01	1.01	1.01
	6	1.02	1.01	1.02
	7	1.09	1.07	1.09
	8	1.02	1.01	1.02
	9	1.01	1.01	1.01
1989	1	1.06	1.02	1.06
	2	1.08	1.06	1.08
	3	1.04	1.04	1.04
	4	1.00	1.00	1.00
	5	1.08	1.05	1.08
	6	1.05	1.01	1.05
	7	1.08	1.05	1.08
	8	1.02	1.00	1.02
	9	1.15	1.00	1.15
1990	1	1.02	1.02	1.02
	2	1.00	1.00	1.00
	3	1.00	1.00	1.11
	4	1.02	1.00	1.02
	5	1.06	1.02	1.06
	6	1.01	1.00	1.01
	7	1.07	1.00	1.07
	8	1.11	1.04	1.11
	9	1.00	1.00	1.00

Table 4. Annual mean capacity, CU, and input utilization

Vessel	Capacity	CU	Utilization Ratio	
			Days	Man-days
1	178,347	0.99	1.14	1.08
2	137,937	0.99	1.02	0.95
3	170,459	0.87	1.51	1.35
4	142,927	1.00	1.01	0.96
5	158,504	0.96	1.11	1.06
6	173,701	1.00	1.02	1.01
7	155,161	0.99	1.07	1.01
8	154,424	0.95	1.08	1.00
9	143,879	0.97	1.10	1.03

7. Summary and Conclusions

Estimation of harvesting capacity in fisheries will become increasingly important as nations address the problems associated with overharvesting. Acceptable and practical definitions of capacity and methods for estimating capacity will have to be developed. In this paper, we proposed the Johansen (1968) definition of capacity as a short-run concept. We subsequently demonstrated how this concept could be estimated using the DEA framework proposed by Färe et al. (1989). We demonstrated that the DEA framework imposes minimal assumptions on the underlying technology. We also noted a limitation of DEA—it attributes all deviations from the frontier to technical inefficiency. We suggested, however, that DEA might be useful for estimating capacity in fisheries. We demonstrated many useful decompositions of TE that can provide information for fisheries management. We concluded with an illustration of how DEA could be used to estimate and assess TE, capacity, CU, and optimum input utilization.

An issue not discussed in this paper and that may be important for assessing capacity in fisheries is capacity at the fishery or industry level. That is, how can we assess capacity at a more aggregate level such as the fishery or industry. If we only had aggregate time-series data, we could estimate capacity using DEA after adjusting for technical change; this approach, however, would likely yield estimates similar to those obtained from the peak-to-peak approach (Kirkley and Squires 1999). If detailed firm level data on input and output quantities were available, we could use the DEA approaches of Färe et al. (1992) and Dervaux et al. (2000) to estimate capacity at a higher level of aggregation. These approaches not only facilitate the estimation of industry capacity for the short and long-run, they also provide information about the optimum allocation of inputs and outputs. Considerably more work and analyses will have to be conducted, however, before we can conclude that these industry models are appropriate for assessing capacity in fisheries.

7. References

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